Threats and Vulnerabilities in Social Media: A Review of Cyber Security Perspectives

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***Abstract*—**Brain tumors are a severe medical problem due to their high mortality rate, necessitating improved diagnostic and therapeutic procedures. Radiologists must manually segment patients, which is expensive, time-consuming, and prone to error. Deep learning-based automated segmentation has recently demonstrated the potential to address these challenges, especially in the areas of image segmentation and classification. Brain tumor segmentation is essential in medical imaging to evaluate the size, location, and shape of tumors. This paper starts with an overview of multi-modal brain tumor segmentation techniques. After that, it reviews pertinent literature to evaluate how deep learning and machine learning are applied in diverse modalities. In addition, the review offers an overview of federated learning strategies that enhance global segmentation efficiency while maintaining data privacy. Lastly, the paper assesses the level of multi-modal brain tumor segmentation algorithms at the moment and looks ahead to potential developments in this area.

Keywords—*Brain Tumor, Segmentation, Modality, Deep Learning, Federated Learning*

1. Introduction

Over the past ten years, brain tumors have been the subject of extensive research in medical image processing [1, 2]. Because these tumors are the result of abnormal cell growth in the human brain, they represent a serious risk to healthy brain tissue [3, 4]. The location along with the size of a brain tumor varies depending on its type [5]. Brain tumors come in two varieties: benign and malignant. Benign tumors are not malignant, but their cells may cause damage to adjacent healthy brain tissue. [6]. They rarely recur and are typically treatable. Conversely, malignant tumors which are cancerous and likely to come back even after treatment. They can spread to other brain regions, often with disastrous consequences [7]. Numerous imaging techniques, most notably CT and MRI, are used to diagnose medical infections [8]. But MRI turns out to be a better option than CT due to its reduced risk profile and better clarity. Radiofrequency and magnetic fields are used in MRI, while X-rays are mostly used in CT. Moreover, MRI scans are able to distinguish between healthy and diseased organs with greater accuracy than CT images. MRI is the most sophisticated imaging technique in biomedical imaging, according to [9] [10]. Using MRI, brain tumors are categorized into four groups: T1, T1CE, T2, and Flair. T1-weighted MRI can be used to differentiate tumors from healthy tissue, and T2-weighted MRI makes edema areas easy to identify.

There had been a recent rise in research on brain tumor segmentation due to Deep Learning (DL) techniques showing impressive performance in both segmentation along classification tasks [11]. The integration of AI technology into e-healthcare has greatly enhanced medical research and allowed subject matter experts to deliver more efficient healthcare services. The novel approaches development for the early identification along the diagnosis of brain cancers have been facilitated by the integration of AI and ML, particularly with the use of DL techniques. This has made timely medicines possible, some of which could even save lives [12]. A decrease in DL performance is known to be caused by smaller training and testing datasets. Federated Learning (FL) offers a way around this issue by allowing data privacy to be maintained while building a shared global model using data from multiple sources [13]. This article examines the latest advancements in brain cancer segmentation using MRI data, with a focus on FL algorithms and fundamental DL techniques. Despite the recent surge in interest in automated brain tumor diagnosis using DL approaches, few papers have explored FL strategies [14].

2. Related Literatures

An efficient automated approach for brain tumor categorization in an effort to assist radiologists in making diagnoses of brain tumors more quickly and reliably while requiring less time to review numerous images. To optimize the benefits of using multiple techniques, the proposed method merged the outputs of five separate

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models with 3064 T1W-CE MRIsfrom 233 patients. The outcomes of this procedure were significantly improved, and its overall accuracy was an amazing 99.31%. [15]

A U-Net based segmentation model as well as a deep CNN architecture for automatic brain image classification into 4 different categories. They evaluated the segmentation model and trained the classification model through experimentation with six benchmark datasets, allowing a direct comparison of segmentation's effect on tumor classification in MRI brain scans. Additionally, they evaluated two categorization strategies utilizing crucial metrics like recall, accuracy, precision, and AUC. Their classification model demonstrated optimal performance, with a 98.7% overall dataset accuracy and a 98.8% segmentation accuracy. Among the four datasets, the one with the highest recorded classification accuracy, at 97.7%, was discovered. Consequently, this innovative approach demonstrated potential utility in clinical contexts by offering MRI scan inputs for automated brain tumor segmentation and diagnosis. [16]

A novel approach to recognizing and classifying brain tumors aimed to solve the issues facing the field at the time. The technique included pretreatment with a 17-layered CNN architecture for tumor segmentation and postprocessing with linear contrast stretching to improve image edge detail. The study used an entropy-based controlled approach for feature selection and a modified MobileNetV2 architecture for transfer learning-based feature extraction. Brain tumors were identified using the MC-SVM architecture. Testing the suggested approach on the BraTS 2018 and Figshare datasets revealed improved quantitative and graphic performance. The accuracy of the findings was higher than that of other existing methodologies, with 97.47% and 98.92%, respectively. [17]

A cutting-edge DL system intended to categorize brain tumors using a variety of data modalities. The study employed the BRATS datasets for evaluation. At first, a hybrid approach that blended ant colony optimization with histogram equalization was used to boost contrast. Subsequently, a nine-layer novel CNN model was trained for classification. Following the second fully connected layer's feature extraction, moth flame optimization, and differential evolution were used to optimize the result. A matrix length methodology was used to fuse the outputs of multiple optimization techniques, and the resulting outputs were then fed into an MC-SVM. In the BRATS 2013, BRATS 2015, BRATS 2017, and BRATS 2018 datasets, the suggested approach demonstrated remarkable accuracy of 99.06%, 98.76%, 98.18%, and 94.6%, respectively, during the experimental phase. [18]

Three CNN models were used in this study: Inception V3, AlexNet, and ResNet 50. The preparation step involved resizing the photos, normalizing them between 0 and 1, and augmenting them with fill-up, rotation, flips, translation, and shear transformation, among other techniques. The study showed how successfully CNN structures identify enhanced MRI images of brain tumors. The outcomes revealed that the accuracy rates of Inception V3, AlexNet, and ResNet50 were 92.07%, 98.24%, and 93.51%, respectively. However, the study discovered many drawbacks: (1) CNN operations like max-pooling could make processing sluggish; (2) CNN training with many layers could be time-consuming, particularly if GPU support isn't sufficient; and (3) ConvNets required a training data significant amount. [19]

A feature fusion-based approach for categorizing brain cancers. The minimum-maximum normalization method was used to preprocess source photographs to overcome the data scarcity problem. Following this, the photos were extensively enhanced with data. Transfer learning was performed on deep CNN models ResNet18 and GoogLeNet in order to produce a single feature vector. Following that, SVM and KNN classifiers were used to create the final output, which generated an astonishing 97.7% accuracy. [20]

By combining the distinctive qualities of four MRI modalities, represented a novel paradigm for BraTS. A CNN model that focused on the region around the tumor outperformed human observers. In addition, a cascade CNN design was proposed to gather both local and global data with varying patch sizes. Thorough tests on the BRATS 2018 dataset proved the competitiveness of the suggested approach, resulting in mean dice scores for tumor core segmentation, improved tumor segmentation, and whole tumor segmentation of 0.9203, 0.9113, and 0.8726, respectively. [21]

A semantic segmentation technique using CNN to automate brain tumor segmentation using 3D BraTS image files with 4 various imaging modalities (T1, T1C, T2, and Flair). Utilizing semantic segmentation, the study trained DL networks on 257 BraTS image datasets. With the use of training, validation, and test pictures, the labels were predicted and compared with ground truth labels. The results showed a mean tumor prediction of 91.72 and a mean background forecast of 99.75. Additional characteristics, including mean accuracy (95.74), mean IoU (86.95), and weighted IoU (99.42), were examined using five photographs. The Mean BFScore, a crucial metric, was discovered to be 92.94. [22]

Using a CNN architecture intended for multiscale processing, an automated approach for segmenting and classifying brain tumors. They used T1-weighted, contrast-enhanced MRI data that was available to the general public to evaluate its performance. They used data augmentation by elastic transformation to reduce overfitting and improve the training dataset. The approach was found to have performance metrics that positioned it among the top 10 of the BRATS 2013 benchmark. Their method achieved the best accuracy of 0.973 for tumor categorization. Their multiscale CNN technique, which used three processing paths, was successful in segmenting and classifying 3 types of brain cancer: meningioma, gliomas, and pituitary tumors. It's interesting to note that their approach resulted in excellent segmentation performance measures, including average pttas values of 0.967, average Dice index of 0.828, and average sensitivity of 0.940. [23]

Initially, nonlinear methods and contrast optimization were employed to enhance the input image's visual quality. Tumor sites were then identified by applying segmentation along with the clustering approaches. After scoring, these locations were combined with the matching input image and EfficientNet was used to extract features. Ultimately, the optimal spots were aligned to identify tumor classes and their matching locations. The study employed fivefold cross-validation on the T1W-CE MRI dataset to achieve an accuracy of 98.04%. However, this technique has the drawback of requiring more processing power due to the need to train additional networks. [24]

A CNN with a RELU activation function based on a hard switch. Their recommended approach consisted of three essential steps: To improve the brain image viewing, normalization procedures were first applied during the image pre-processing step. Ultimately, CNN classified meningiomas, pituitary cancers, and gliomas using a hard-swish-based RELU activation function. With an impressive 98.6% accuracy rate, they were able to classify brain cancers using the T1W-CE MRI dataset. [25]

The multi-stage DCNN approach for the diagnosis and classification of brain tumors was described. The preprocessing steps involved applying N4ITK, normalizing, and figuring out the mean intensity value and SD for each pixel before parameter initialization and updating. Next, techniques for augmenting data were applied, including translation, flipping, and rotation. Following that, classification was done using a variant of the GoogleNet model. Labels and pixel features were assigned using back-propagation as a post-processing step, both with and without CRF. The model accuracy on the T1W-CE MRI dataset was 95.1% and 97.3%, respectively, with and without CRF. However, there were certain shortcomings with the model, such as its insufficiency for jobs requiring sparse data and its susceptibility to a reduction in classification performance upon exposure to erroneous data from various patient imaging modalities. Additionally, a large number of pre-processing procedures were needed. [26]

Three important steps in the classification of brain tumors. They created annotations initially so that the regions of interest could be correctly identified. They then retrieved deep features from questionable data using a proprietary CornerNet architecture and a DenseNet-41 base network. Ultimately, they were able to identify and classify several forms of brain cancer by utilizing CornerNet in combination with a one-stage detector. Using the T1W-CE MRI dataset, 98.8% accuracy was obtained using this approach. Notably, this method offered an inexpensive choice for brain tumor classification by employing CornerNet's one-stage object identification architecture. [27]

An approach for brain tumor detection that combines fuzzy logic along with the U-NET CNN architecture was presented. First, as a preprocessing step, contrast enhancement was applied to the original photos. Then, edges in the enhanced images were identified using fuzzy logic-based edge detection. Characteristics were then produced by deconstructing sub-band images and applying a dual tree-complex wavelet transform at several scale levels. The U-NET CNN technique was then used to classify these features in order to distinguish between brain imaging that showed meningioma and that which did not. The suggested approach showed an astounding accuracy rate of 98.59% when compared to other current algorithms. [28]

A well the networks under consideration removed significant characteristics from MRI slices using two transfer learning strategies: freeze and fine-tune. Using the U-Net architecture with ResNet50 as the backbone and a commonly utilized segmentation technique, the tumor location was determined, yielding an IoU score of 0.9504. The Figshare dataset was used to multiclassify brain tumors in order to further distinguish between different types of tumors. Transfer learning was applied to the NASNet design in contrast to the DenseNet201, ResNet50, MobileNet V2, and Inception V2 architectures. The NASNet architecture has shown superior efficacy compared to other architectures, achieving a 99.6% classification accuracy on the target dataset. [29]

TumorGAN, a novel GAN-based framework for improving pictures of brain tumors, in their study. By mixing tumor locations and brain tissue from various people, the approach created numerous virtual data sets, significantly increasing the amount of the dataset. They also added a regional L1 loss and a regional perceptual loss with a local discriminator to enhance generation performance. TumorGAN demonstrated that it could generate high-quality image pairs with a minimal quantity of paired data, which set it apart from earlier GAN-based picture-to-image translation frameworks. Experimental results demonstrated the usefulness of the synthesized picture pairings from TumorGAN, particularly in terms of enhancing tumor segmentation across multi-modal and single-modality datasets. [30]

A deep autoencoders in combination with a fuzzy clustering-based segmentation method to categorize brain tumors. MRI scans were segmented by utilizing the fuzzy clustering method in order to get the best characteristics. The Jaya optimization method was applied to a deep auto encoder to classify healthy brain cells from malignancies. When the recommended technique had been tested with the BRATS 2015 dataset, a 98% accuracy rate was achieved. [31]

In order to classify glioma, meningioma, and pituitary tumors in the T1W-CE MRI dataset, formed a CNN architecture with 22 layers. They carried out tenfold cross-validation at the subject and record levels for network testing on both the original and improved photo datasets. The highest accuracy, 96.56%, was attainedby utilizing record-wise tenfold cross-validation with an additional dataset on the 3064 T1W-CE MRI dataset. [32]

A combined DL and ML techniques to categorize brain cancers. To extract features, they first optimized an Inception-v3 model. Subsequently, the data was classified by a range of approaches, including ensemble methods, SVM, RF, KNN, and softmax layer replacement for the last layer. In a similar spirit, following feature extraction from an improved Xception model, the same classification methods were applied. Of all the proposed approaches for classifying brain tumors, the Inception-v3-Ensemble approach formed the highest testing accuracy of 94.34% on the T1W-CE MRI dataset. It's crucial to remember, though, that the recommended methods have problems with drawn-out processes and costly computers. [33]

A unique CNN architecture with two fully linked layers along with five convolutional layers is presented by Max pooling, a ReLU activation function, and a batch normalization layer came after each convolutional layer. The dataset was preprocessed by standardizing it between 0 and 1, then shrinking it to (256×256). Using a fivefold cross-validation approach, they ran two tests: the first used he CNN with a softmax classifier, and the second used the CNN with an SVM. The T1W-CE MRI dataset was split into 70–30percent for trainingas well as testing, using this strategy, which raised the classification accuracy from 94.2% to 95.8%.[34]

In order to improve tumor identification and classification efficiency, a DL-based feature selection method. During the preprocessing stage, saliency maps and contrast were created. Using Inception V3, deep feature extraction was carried out. Following the fusion of these deep features with DRLBP features, the PSO software has been utilized to optimize the fused features. The BRATS 2017 & 2018 datasets have been utilized to confirm the effectiveness of the recommended approach. In both BRATS 2017 and 2018, the total tumor dice score was 93.7% and 91.2%, respectively. [35]

A pre-trained GoogleNet models were modified using the Adam optimizer in conjunction with DL and ML techniques. It's noteworthy to observe that accuracy increased when the transfer learning framework's classification layer was replaced with SVM or KNN algorithms. Specifically, GoogleNet, SVM, and KNN achieved accuracy rates of 92.3%, 97.8%, and 98%, respectively, by applying fivefold cross-validation to the T1W-CE MRI dataset. This study demonstrated how the suggested method could be utilized to successfully classify three various kinds of brain tumors. However, it also clarified a number of boundaries. First off, as an independent classifier, the transfer-learned model did terribly. 2nd, numerous obvious misclassifications were found, particularly in the data pertaining to the meningioma class. [36]

A pre-trained DCNN to apply a Deep Convolutional GAN (DCGAN), a kind of Generative Adversarial Network (GAN), as a discriminator. This discriminator may be able to extract and learn robust features from MR image structures. A softmax layer was added in place of the GAN discriminator's last fully connected layer. Using the T1W-CE MRI dataset, their approach attained an impressive accuracy of 95.6% in brain tumor classification. However, one study constraint was GANs, particularly the 64x64 input size restriction. Because pre-trained architectures required larger input sizes, they were challenging to use as discriminators. [37]

As part of a hybrid feature extraction methodology, a RELM. During pre-processing, min–max normalization was initially applied to the brain images in order to enhance the contrast of the brain edges. Following that, a hybrid technique known as PCA-NGIST was used to extract features from brain tumors. This method combined Principal Component Analysis (PCA) with the Normalized GIST descriptor to identify significant features. Finally, a RELM has been utilized to classify the different kinds of brain tumors. They obtained 94.23% accuracy using the T1W-CE MRI dataset and fivefold cross-validation. [38]

A DCNN-based SE-ResNet-101 architecture and modified the model to fit the training set. Among their pre-processing techniques were ROI segmentation, intensity normalization, intensity zero-centering, and the application of data augmentation techniques like flipping, rotation, elastic transform, and shear with varying degrees of transformation. Next, the SE-ResNet-101 model, which is a combination of ResNet-101 and squeeze and excitation (SE) blocks, underwent training using the T1W-CE MRI dataset. The purpose of this training was to classify three specific types of brain tumors: gliomas, meningiomas,and pituitary tumors. With and without data augmentation, overall accuracy was reached at 89.93% and 93.83%, respectively. [39]

3. Methodology

This section outlines the procedure for locating relevant papers for the survey inquiry. Following the collection of a substantial number of papers, only the most pertinent publications were extracted through a thorough screening procedure. This filtering method involved a number of parameters. First, publications matching the keywords were found. Next, articles with appropriate titles about brain tumor segmentation were selected. The most recent article that best reflected the state of the art at the time was selected when multiple titles could be found. The final step was evaluating the selected articles' progress based on their abstracts and datasets. Following that, a thorough full-text analysis was conducted to find out more about advancements in the sector. Extra consideration was paid to contributions and references to ensure that no significant research articles were overlooked. Following a comprehensive evaluation of the references, three additional publications were included, as seen in Fig. 1.

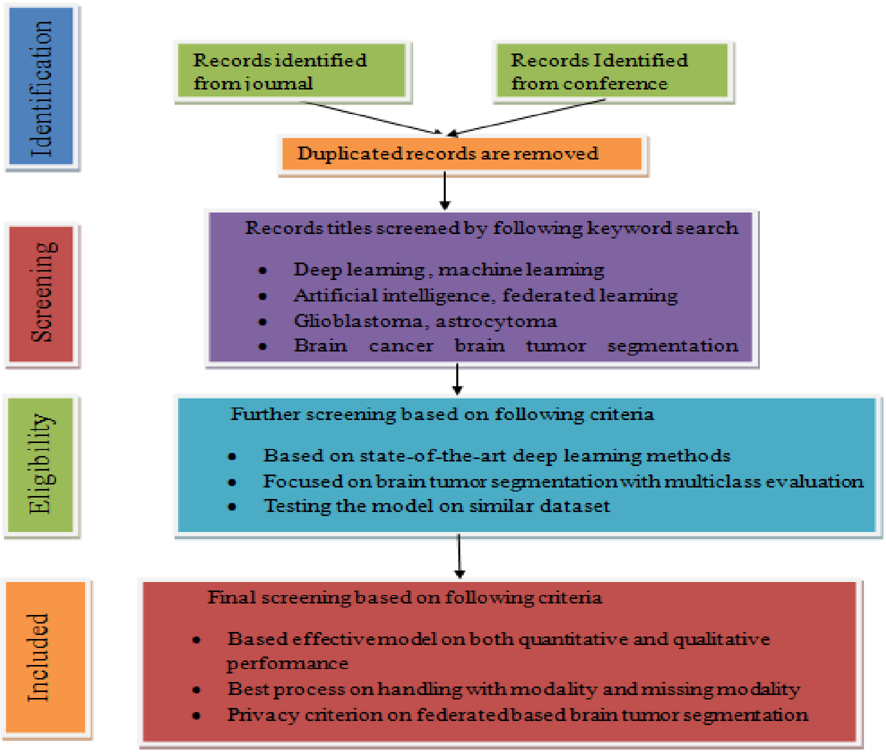

Fig. 1 Presents the identification, screening, eligibility, and selection procedures.

4. Results and discussion

Reviews of the literature have shown that centralized datasets are frequently utilized as the training set for DL and ML models. This centralized approach has additional disadvantages, including scalability, data localization, and privacy challenges. Centralized datasets may contain sensitive data, and the risk of data breaches or unauthorized access is heightened when such data is collected in one location. Additionally, there are circumstances in which obtaining and maintaining such centralized datasets may be challenging or even impossible, particularly in cases where data is scattered across multiple sources or sharing of data is prohibited by data protection regulations. Conversely, FL allows model training on decentralized data sources directly, removing the requirement for data centralization as well as addressing related privacy and scalability challenges. Moreover, in edge computing settings or on devices with limited processing and storage capacity, centralized model training might not be feasible. FL solves these resource limitations by utilizing local computing and storage resources to facilitate distributed model training across several edge devices or client devices. This decentralized approach increases ML's effectiveness and accessibility in resource-constrained environments by decreasing the load on centralized infrastructure and improving scalability and performance.

Table 1 represents a comparative analysis of several studies based on the datasets, techniques, and performance indicators used.

Table I : Recent deep learning techniques for brain tumor segmentation are compared using different techniques, datasets, modalities, and assessment accuracy.

Author(s)	Dataset	Modality	Methods	Accuracy %
[15]	Figshare	MRI	AlexNet	96.08
			GoogleNet	95.16
			ShufeNet	96.84
			SqueezeNet	97.17
			NASNet	97.50
			Majority-Voting	99.31
[16]	BraTS	MRI	Deep CNN	96.7
[17]	BraTS	MRI	Naïve bayes	97.18
			KNN	96.33
			DT	97.42
			MC-SVM	99.06
[18]	Figshare and BraTS	MRI	The proposed method (17-layered CNN, MobileNetV2 , M-SVM)	97.47
[19]	Figshare	MRI	AlexNet	98.24
			ResNet 50	93.51
			Inception V3	92.07
[20]	Figshare	MRI	Proposed method (AlexNet, GoogLeNet, ResNet18)	99.7
			Proposed (CNN, SVM, and KNN)	99.7
[21]	BraTS	MRI	Dice score	87.26
[22]	BraTS	MRI	Mean prediction	91.71
			Mean(IOU)	86.94
			Meab BF	92.93
[23]	BraTS	MRI	CNN	97.3
[24]	Figshare	MRI	CNN- 5-fold cross-validation	98.04
[25]	BraTS	MRI	CNN	98.60
[26]	Figshare and BraTS	MRI	CNN- Figshare dataset	97.3
			CNN- BraTS dataset	96.5
[27]	Figshare and BraTS	MRI	DenseNet-41-based CornerNet framework – Figshare dataset	98.8
			Brats	98.5
[28]	BraTS	MRI	U-NET CNN	98.45
[29]	Figshare	MRI	NASNet.	99.6
			DenseNet201	93.1
			ResNet50	92.9
			Inception V3	92.8
			MobileNet V2	91.8
[30]	BraTS	MRI	Cascaded Net	77.8
			U-Net	70.6
			Deeplab-v3	72.5
[31]	BraTS	MRI	DAE with JOA and softmax regression	98
[32]	BraTS	MRI	CNN 10 FOLD cross validation	96.56

[33]	BraTS	MRI	Ensemble model Inception-v3 (SVM,KNN,RF)	94.34
[34]	Figshare, Radiopaediat, Harvard medical dataset	MRI	CNN (softmax)	94.2 , 95.7, 94.5,
			CNN with SVM	95.8, 99, 98.7
[35]	BraTS	MRI	Dice score	93.7
[36]	Figshare	MRI	GoogleNet	92.3
			SVM	97.8
			KNN	98
[37]	BraTS	MRI	GAN	95.60
[38]	BraTS	MRI	PCA-NGIST with RELM	94.23
[39]	Figshare	MRI	CNN based SE-ResNet-101	93.83

5. Conclusion

It is very challenging to automatically segment brain tumors in order to diagnose cancer, but recent developments in publicly accessible datasets and the well-known BRATS benchmark have provided researchers with a common platform to develop and critically evaluate new methods in addition to those that are currently in use. With a focus on FL and DL in particular, this paper offers a thorough evaluation of the literature on the evolution of BraTSduring the previous few decades. An extensive review of previously published information summarizes common approaches and multimodality strategies. FL appears to be a promising approach, particularly when privacy is protected by restricting access to medical records. FL preserves data privacy while resolving the issue of scarce datasets for testing and training. Because this field of study promises to produce models that are reliable, safe, impartial, stable, and useful, many researchers are interested in it. Accurate medical picture classification is essential, and using benchmark datasets like the BraTS challenge datasets has made it simpler to assess publically available data. It is anticipated that FL will be used in medicine more frequently in the future, necessitating the creation of more complex protocols that offer greater security as well as privacy guarantees. FL will soon be used to address real-world issues in the healthcare industry.

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