Grenze International Journal of Engineering and Technology, January Issue

A Comprehensive Analysis of Federated-Learning-Based Methodologies for Brain Tumor Diagnosis

Kavitha C R[1], Maya B. S[2] and Asha T[3]
[1-3]Computer Science & Engineering Bangalore Institute of Technology Bangalore, India
Email: kavigani2008@gmail.com, mayabs@bit-bangalore.edu.in, ashat@bit-bangalore.edu.in

***Abstract*— Brain tumors have become a severe medical complication in recent years due to their high fatality rate. Radiologists detect the tumor manually, which is time-consuming, error-prone, and expensive. In recent years, automated detection based on deep learning has demonstrated promising results in solving computer vision problems such as image classification and segmentation. Many researchers have worked on various machine and deep learning approaches to determine the most optimal solution using the convolutional methodology. In this review paper, we discuss the most effective segmentation techniques based on the datasets that are widely used and publicly available. This study provides an overview of recent research on the diagnosis of brain tumors using federated and deep learning methods. We also proposed a survey of federated learning methodologies to enhance global segmentation performance and ensure privacy. A comprehensive literature review is suggested after studying more than 100 papers to generalize the most recent techniques in segmentation and multi-modality information. Based on this review, future researchers will understand the powerful learning ability of deep learning mechanisms has been reviewed for their performance, and a comparison between them is presented to encourage its applications.**

***Keywords*— Brain Tumor, Deep Learning, Federated Learning, Convolution Neural Network, Magnetic Resonance Imaging.**

I. INTRODUCTION

Brain tumor (BT) refers to an unwanted and uncontrollable development or growth of cells in the brain. A life-threatening situation could be generated due to such development because it tends to affect other body parts. Also, the human brain has physical limitations to endure this unwanted development of cells. In the treatment and diagnosis of this disease, a pivotal role is played by advancements in imaging technology. Various imaging methods are available today for brain tumors that may vary from MRI to CT scans. A great deal of information is contained in a Brain magnetic resonance (MR) image regarding the multi-dimensional structure of the human brain. Brain tumors are known to be the most complex and dangerous among all forms of tumors. Various methods have been developed to identify tumors from MR images of the brain [1]. An image analysis technique is used in machine learning research to construct a system to classify the tumor's type. For research purposes, two paths are taken: classification and segmentation [2]. The segmentation approach may identify the tumor from pictorial data. Segmentation is becoming an increasingly popular study topic in medical imaging analysis. Tumor or glioma diagnosis and therapy both heavily rely on image segmentation.

Grenze ID: 01.GIJET.11.1.304_2

Astrocytomas and oligodendrogliomas are the least aggressive and common gliomas, but HGG (GBM grade IV) is among the most destructive. High-grade gliomas cause more damage than lower-grade glioblastomas.Usually, gliomas are treated with surgery, chemotherapy, and radiotherapy. Early detection can help improve patient medical diagnoses and treatment policies. First and foremost, imaging data from the patient must be collected. There are numerous types of scanning available to detect abnormalities. Such methods are known as computed tomography (CT), X-ray, SPECT, PET, MRS, and MRI [3]. An MRI imaging system analyses different types of tumors in different plane show in Fig.1.

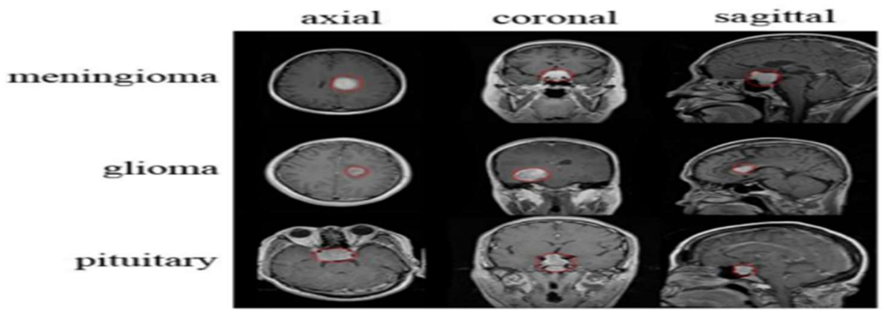

Fig. 1. Representation of normalized magnetic resonance imaging (MRI) images showing distinct kinds of tumors in different planes

Various efforts, there remains a gap in the current literature for inclusive representation of recently developed deep learning-based classification methods. The current study attempts to fill this gap by briefly reviewing the current state of the art on brain tumor segmentation and classification methods while focusing on deep learning methods. The variation among reviewed techniques can be accounted for through an understanding of differences in performance parameters revealed by the previous scholars [8].

The main contributions of this study are as follows.

- A systematic review is presented in which various recent methodologies for brain tumor segmentation are discussed.
- The best deep learning segmentation methodologies are identified through multiclass tumor recognition comparison.

II. RELATED WORK

Authors studied on support vector machines, k-nearest neighbors, multi-layer perceptrons, Naive Bayes, and random forest algorithms were among the ML and DL strategies for brain tumor identification [9] and segmentation [14] that were surveyed. The maximum classification accuracy for the traditional SVMs was 92.4%. The researchers also represented a 97.2% accuracy for BT identification in MRI using a custom CNN architecture with five layers.Similarly, A method utilizing MRI scans, the VGG19 CNN architecture, and K-means clustering [15] was developed for the classification and segmentation of brain tumors. This approach pre-processed the intensities of the input MRI picture by employing modalities that were later transformed to samples using a statistical normalization strategy. Its overall accuracy leads to 94%. By carrying experimentations on BraTS 2015 dataset the recommended CNN [16] based scheme is evaluated. Here the innovators were conducted experimentations on datasets of different sizes and BT classifications was propounded [17] using ML classifiers and a deep CNN feature ensemble. The SVM using a radial basis function evaluated as best when compared with other ML and DL classifiers. Researchers investigated numerous pre-trained CNN algorithms [18] depends on DL to determine how benign differ malignant BTs and the objectives would accomplish by using the optimizers, like Adam, RMSprop, and stochastic gradient descent (SGD).

AlexNet might have given the best accuracy of 99.04% when it was correctly estimated. A specific CNN architecture which uses VGGNet [19] to categorize 253 BT images (155 tumors and 98 non-tumors).By using data augmentation and preprocessing methods Overfitting problems were alleviated and CNN model provided the validation accuracy about 86%, VGGNet provided the 97% on one dataset. The authors reviewed several image preprocessing methods like Sobel filter, the high-pass filter, median blurring, histogram equalization, dilations Global thresholding and adaptive thresholding, which leads to the enormous improvement in classification accuracy and the pre-trained Resnet101 V2 [10]. model that depends on transfer learning achieved 95% of accuracy. A new scheme that collaborated a stacked classifier with the VGGNet architecture known as VGG-Scnet [20] and The dataset's class imbalance would fixed by using augmentation methods. This research yielded three well defined outcomes. First, the best performed ML model was identified when compared ML algorithms SVM, RF, DT, NB, and KNN with CNN having 7 fine-tuned layers gives performance (88.7% F1 Score) to categorize BTs from MRI images on the named dataset. Second, VGG-16 (F1 Score 97.8%) was found as the best pre-trained model amongst 14 pretrained DL models for classifying BT images. Third, from the second last layer of the VGG-16_CNN transfer learning model the features were excerpted the four different hybrid models were proposed. The recommended Stacked Classifier (SC) hybrid model yields the better accomplishment than the other model and by adopting a layered classifier finally the tumor detection in imaging was accomplished.

The proposed a model deep convolutional neural network (DCNN) is similar to the general VGG-16 model but the architecture has been modified where the final max-pooling layer from a general VGG-16 architecture is replaced by an average- pooling layer. The average pooling layer, also called as Global Average Pooling Layer (GAP), performs spatial pooling of the feature map to reduce overfitting by limiting the overall amount of parameters in the model [21]. However, the reduction in the spatial dimensions by average-pooling is more significant than that of max-pooling and within the afflicted human brain, MRI images were employed to recognize and locate tumor cells. In this paper [11], to spot brain cancers in 3D MRI scans, the inventors were presented a special approach which uses multimodal detail blended in tandem with CNNs and this approach was enhanced by using more imaging methodologies upon multimodal 3D-CNNs in order to capture the unique features of BT lesions. The real normalization layer is added between the convolution layers and pooling layer to enhance the convergence speeds of the network and alleviate the trouble of overfitting. Finally, the loss function was refined, and the weighted loss function was used to strengthen the feature learning of the lesion area. Additionally [12], the connection of BT classification, the researchers investigated the use of VGGNets, GoogleNets, and ResNets, amongst other CNN designs and ResNet-50 outperformed GoogleNet and VGGNets, with an accuracy rate of 96.50%, compared to 93.45% and 89.33%, respectively. In [22], the authors built a YOLOv5l model where they have applied YOLOv5's different variant algorithm on Brats 2020 annotated dataset to detect BT location and achieved 82-92 percent accuracy for the YOLO variant where the YOLOv5l model provides the best accuracy than YOLOv5n and YOLOv5s. In [13], the researcher put forward the AO based TL model such as AlexNet, ResNet18, DenseNet and MobileNet method for an efficient BT detection and the AO based TL DenseNet achieved maximum accuracy compared to other models. The FL [14] model using the ensemble architecture and was trained with weights from the local model without sharing the client's data . Here the six CNN models, VGG16, VGG19, Inception V3, ResNet50, DenseNet121, and Xception were trained with MRI data ,among these VGG1,Inception V3 and DenseNet121 were selected to form he averages CNN model and it achieved better accuracy 96.68% compared to FL where it achieves the privacy of data with 91.05% accuracy. Proposed Federated Averaging (FEDAVG) algorithm [23] of choice for federated learning because of its simplicity and less communication cost. However, the FEDAVG suffers from 'client-drift' when the data would be heterogeneous (non-id), results in unstable and slow convergence and to overcome this problem proposed a new algorithm (SCAFFOLD) which uses control variates (variance reduction) to correct for the 'client-drift' in its local updates and proved that SCAFFOLD [24] needed outstandingly lesser communication rounds and is not affected by data heterogeneity or client sampling. Propose a new framework, MIME [25] , that mitigates client drift(FedAvg) and could adapt an arbitrary centralized optimization algorithm, e.g. SGD with momentum or Adam, to the federated setting .

A summary showing the number of surveyed on the brain tumor segmentation is shown in Fig. 2.

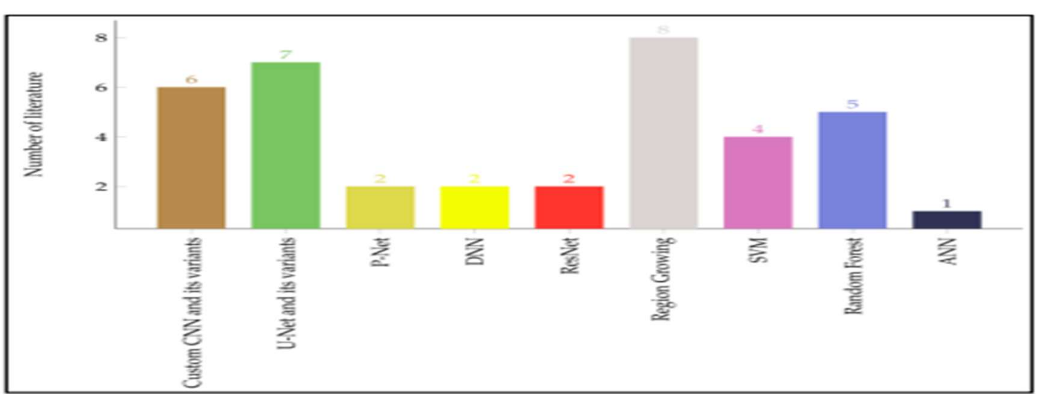

Fig. 2. Brain tumor segmentation techniques survey

TABLE I. DIFFERENT APPROACHES USED FOR BRAIN TUMOR DETECTION AND CLASSIFICATION

Year	Brain Tumor Type	Classifier Model	Methods	Performance
2023		Multiscale CNN	Pituitary, Glioma and Meningioma	98.3%
2022	Gliomas	RF Classifier	Intensity Normalization, Contrast enhancement	96.59%
2022	Meningioma, Glioma and Pituitary	Inception resnetV2	Binary based boundary box detection	96.78%
2022	Glioma	ResNet50	Randomly rotating augmentation and scaling augmentaion	83.4%
2023		Softmax Classifier	Scalable range based adaptive bilateral filter and noise reduction	
2023	Glioma	DL model with IGWT technique	GBF filtering technique	87.3%
2021	Meningioma, Glioma and Pituitary	Support Vector Machine		95.67%
2022		CNN based		98.97%
2021	Class1: Meningioma, Glioma and Pituitary, metastatic and normal Class2: Grade II,III,IV	Custom CNN Model	Oligodendroglioma, Astrocytoma, Glioblastoma	92.66%
2019	Benign Tumors and Malign Tumors	CNN + SVM, CNN +KNN	Filters Methods	93.1%
2020		CNN(alexNet,GoogleNet,VGG-16)		97.23%
2020	HGG &LGG	Pre-trained DenseNet201	Meningioma, Glioma and Pituitary	98.3%

III. CONCLUSION

Brain tumor classification from MRI images is a challenging and complex task as a high level of accuracy is in demand to provide the best insights for clinicians. It can be concluded from this research that despite the barrier to its adoption, Deep learning-based classification methods show a promising future in diagnosing and treating brain tumors. Recent developments in this area are recorded in this study, and outcomes in precise classification are evaluated.

A gap remains in developing standard procedures to incorporate the potential of deep learning-based models in the diagnostic procedures carried out in real cases. Furthermore, there is a huge gap in the current literature regarding identifying security challenges posed to the computer systems during the classification of tumors from Brain MRI and the potential of tempered results through malicious intents.

Future researchers can work on the cost and resource optimization for CNN networks to encourage their widespread adoption in the medical field. Furthermore, they can work on developing standards for preprocessing techniques and improving the overall architecture.

REFERENCES

[1] L. Rundo, C. Militello, V. Conti, F. Zaccagna, and C. Han, ‘‘Advanced computational methods for oncological image analysis,’’ J. Imag., vol. 7, no. 11, p. 237, Nov. 2021

[2] Bauer, S., Wiest, R., Nolte, L.-P., Reyes, M., “A survey of MRI-based medical image analysis for brain tumor studies”, Phys. Med. Biol. 58, R97–R129,2023

[3] Menze, B.H., van Leemput, K., Lashkari, D., Weber, M.-A., Ayache, N., Golland, P., Jiang, T., Navab, N., Pluim, J.P.W., Viergever, M.A. (Eds.),” A Generative model for brain tumor segmentation in multi-modal images BT -in medical image computing and computer-assisted intervention – MICCAI 2010. Springer ,pp. 151–159,2024

[4] H. Mohsen, E.-S.-A. El-Dahshan, E.-S.-M. El-Horbaty, and A.-B.-M. Salem, ‘‘Classification using deep learning neural networks for brain tumors,’’ Future Comput. Informat. J., vol. 3, no. 1, pp. 68–71, Jun. 2022

[5] J. Wang, Y. Yang, J. Mao, Z. Huang, C. Huang, and W. Xu, ‘‘CNNRNN: A unified framework for multi-label image classification,’’ in Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR), Las Vegas, NV, USA, pp. 2285–2294, Jun.2021

[6] S. Pereira, A. Pinto, V. Alves, and C. A. Silva, ‘‘Brain tumor segmentation using convolutional neural networks in MRI images,’’ IEEE Trans. Med. Imag., vol. 35, no. 5, pp. 1240–1251, May 2022

[7] Z. Zhan, J.-F. Cai, D. Guo, Y. Liu, Z. Chen, and X. Qu, ‘‘Fast multiclass dictionaries learning with geometrical directions in MRI reconstruction,’’ IEEE Trans. Biomed. Eng., vol. 63, no. 9, pp. 1850–1861, Sep. 2023

[8] M. M. Badža and M. Č. Barjaktarović, ‘‘Classification of brain tumors from MRI images using a convolutional neural network,’’ Appl. Sci., vol. 10, no. 6, p. 1999, Mar. 2020

[9] Amishi Agrawal. “Classification and detection of brain tumors by aquila optimizer hybrid deep learning based latent features with extreme learner,” ICDSIA ,ITM Web of Conferences,pp.1-14,2023.
[10] Durgham Hassan Mahlool,Mohamed Hamzah Abed. “Distributed brain tumor diagnosis using a federated learning environment,” Bulletin of Electrical Engineering and Informatics, Vol. 11, pp. 3313-3321 , December 2022.
[11] Muharat Barat Ali,Irene yu-Hua Gu,Mitchel S.Berger and Asgeir Store Jakola, “A novel federated deep learning scheme for glioma and its subtype classification,” Frontiers in Neuroscience, pp.1-16, 23 May 2023.
[12] Md Ishtyaq Mahmud, Muntasiramun and Ahmed Abdelgawad. “ A Deep Analysis of Brain Tumor Detection from MR Images Using Deep Learning Networks,” Algorithms,pp.1-19,23 March 2023.
[13] Shubhangi Solanki,Udaya pratap Singh,Siddharth singh chouhan and sanjeev jain. “Brain Tumor Detection and Classification Using Intelligence Techniques:An Overview,”IEEEAccess,vol.11,pp.1-17,10 February2023.
[14] Kumar G., Kumar P, Kumar D. “ Brain tumor detection using convolutional neural network,” In Proc.ICMNWC ,pp. 1–6,2021
[15] Amjad Rehman Khan,Siraj Khan, Majid Harouni , Rashid Abbasi,Sajid Iqbal and Zahid Mehmood. “Brain tumor segmentation using K-means clustering and deep learning with synthetic data augmentation for classification,” Microscopy Research and Technique,pp.1-12,27 November 2020.
[16] Jaeyong Kang, Zahid Ullah and Jeonghwan Gwak. “MRI-Based brain tumor classification using ensemble of deep features and machine learning classifiers,” Sensors,pp.1-21,22 March 2021
[17] Y. Yorozu, M. Hirano, K. Oka, and Y. Tagawa, “Electron spectroscopy studies on magneto-optical media and plastic substrate interface,” IEEE Transl. J. Magn. Japan, vol. 2, pp. 740–741, 2021
[18] Mehrotra R.,Ansari M.A.,Agrawal R. and Anand R.S.“A transfer learning approach for AI-based classification of brain tumors,” Machine Learning Application, pp.1-12, 14 September 2020
[19] Venkamma Shalavadi, Vaishnavi R. Dhotargavi, Megha Kudari and Mrs Soumya Jolad. “Brain tumor detection using deep learning models,” In Proc. IEEE INDISCON,pp. 129–134, , October 2020
[20] Mohammad Shahjahan Majib, MD. Mahbubur Rahman, T.M. shahriar Sazzad, Nafizimtia Khan and Samrat kumar Dey. “VGG-SCNet: A VGG net-based deep learning framework for brain tumor detection on MRI images”, IEEE Access ,vol. 9,pp.1-11,27 August 2021.
[21] Siddique, M.A.B.; Sakib, S.; Khan, M.M.R.; Tanzeem, A.K.; Chowdhury, M.; Yasmin, N. Deep convolutional neural networks modelbased brain tumor detection in brain MRI images. In Proc. I-SMAC , pp. 909–914, 7–9 October 2022.
[22] Tejas Shelatkar,Dr.Urvashi,Mohammed Shofuzzaman, Abdulmajeed Alsufyani and Kuruva Lakshmanna. “Diagnosis of brain tumor using light weight deep learning model with fine-tuning approach,” Hindawi, Computational and Mathematical Methods in Medicine,Vol. 2,pp.1-9,July 2022.
[23] Shubhangi Solanki,Udaya pratap Singh,Siddharth singh chouhan and sanjeev jain. “Brain tumor detection and classification using intelligence techniques:An overview,”IEEEAccess,vol.11,pp.1-17,10 February2023.
[24] Mehrotra R.,Ansari M.A.,Agrawal R. and Anand R.S.“A transfer
[25] learning approach for AI-based classification of brain tumors,” Machine Learning Application, pp.1-12, 14 September 2020
[26] Marcin Woz niak, Jakub silka and Michal Wieczorek. “ Deep Neural network correlation learning mechanism for CT brain tumor detection,” Neural Computing and Applications, vol. 35,pp.4611–14626, 16 March 2021.