Brain Tumor classification based on Federated Learning

Muntasir Al-Asfoor
School of Creative and Digital Industries
Buckinghamshire New University
Queen Alexandra Road, High Wycombe, UK
muntasir.al-asfoor@bnu.ac.uk

Mohammed Hamzah Alsalihi
Department of Telecommunication and Artificial Intelligence
Budapest University of Technology and Economics
Budapest, Hungary
malsalihi@qu.edu.iq

Kevin Maher
School of Creative and Digital Industries
Buckinghamshire New University
Queen Alexandra Road, High Wycombe, UK
kevin.maher@bnu.ac.uk

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***Abstract*—This paper investigates the challenges of brain tumor classification and focuses on diagnostic performance while preserving the patient's privacy by investigating decentralized using federated learning. Brain tumor are considered one of the significant health risks and a widespread cancer disease, and the more accurate classification methods will help to diagnose the disease and for effective treatment planning. Conventional methods encounter many difficulties because of the limited availability of diverse medical imaging data as well as privacy regulations. To address these challenges, this method allows for decentralised training across multiple data centres by using the Federated Learning method. The proposed method utilises a pre-trained DenseNet model within an FL environment. This approach guarantees effective feature selection, improving the overall performance of the classification model. The training data remains localised at each node, and only the trainable weights and model updates are shared, therefore preserving data confidentiality. The FL model collects these updates to build a model that is capable of classifying MRI images.The study assesses the efficacy of the FL model through the utilisation of three publicly accessible MRI datasets, thereby substantiating a notable enhancement in classification accuracy when compared to single-institution models. The results indicate that the FL approach not only enhances diagnostic accuracy but also facilitates multi-institutional collaborations without compromising patient data privacy. This solution holds promise for widespread clinical adoption, enabling better management and treatment of brain tumors through advanced, privacy-preserving AI techniques.**

***Index Terms*—Federated Learning , brain tumor, classification, MRI**

I. Introduction

Malignant brain tumors are among the most lethal types of tumors and are associated with a high mortality rate. As reported by Cancer Research UK (CRUK), the incidence of malignant tumors has increased by approximately 39% in the UK over the past four decades. Brain tumors have the potential to grow rapidly and become highly aggressive, ultimately resulting in death. There are numerous categories of brain tumor, with glioma representing one of the most prevalent. The Global Health Organization classifies glioma into four degrees (1, 2, 3 and 4) [1], [2]. It is of the utmost importance to differentiate between healthy and unhealthy brains, as this significantly impacts recovery phases. In the field of medical applications, deep neural networks (DNNs) have demonstrated promising results. However, the success of DNNs is heavily reliant on the availability of diverse and voluminous training data [3]. The scarcity of MRI images in medical institutions is due to several reasons, including the privacy of patients who refuse to share their data and the lack of infected cases in the location of the medical centre. These reasons made the process of collecting data a great challenge. In the midst of this situation, Federated Learning (FL) has emerged as a promising technology for decentralized training of deep neural networks without revealing and sharing patient data [4], [5].The federated learning approach involves developing local models on each participating machine or organization (node) and sending only the resulting trained parameters to a central server. The individual contributions are then combined to create a global model that works on mostly unseen data to do the specific task of the training [6]. The training data itself is never shared throughout the learning and training process, and each node maintains its own copy [7], [8]. Only trained weights and model updates are made public, protecting patient information. It allows multi-organizational collaboration while avoiding many data security concerns. FL allows for multi-institutional partnerships without centralising data [9]. Additionally, FL is suitable for brain tumor classification tasks due to the challenges associated with creating consolidated public datasets from medical imaging data. An effective classification model is developed by iteratively combining locally trained models at the centralized server. This model learns the variation across many institutions without exchanging patient data. The model employs a deep convolutional neural network (CNN)

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architecture and FL techniques for supervised classification. The article presents a deep learning structure in the context of federal learning to classify brain tumors from brain MRI images while maintaining confidentiality. This work classifies MRI images into two categories: normal or abnormal while preserving medical data privacy.

A. Contributions

The main contributions of this work is: Build a deep learning model using Federated learning for brain tumor classification into healthy and unhealthy based on MRI images in a distributed environment using Federated Learning as following:

- Utilities a pretrained model for use in the federated learning framework.
- Use a Federated Learning environment to aggregate the sharing weight of each client (clinic or hospital).
- Evaluating the performance of brain tumor diagnosis in the case of FL and a single client.

The article is structured as follows: The paper is categorized as the following: Related work illustrated in the second section describing the most recent literature on brain tumors over FL environment were illustrated. The materials and methods explained in section three and section four show the result and discussion section. Finally, section five concludes the work and result.

II. Related work

Many researchers used different methods of machine and deep learning to classify MRI brain images. This section introduces some literature surveys on machine learning and Federated Learning. In the last decade, the use of Deep learning and AI tools has increased. Arunachalam and Savarimuthu [10] proposed a brain MRI classification model that distinguishes between healthy and unhealthy images. The suggested algorithm consists of several phases, including the enhancement of brain MRI images using shift-invariant shearlet transform (SIST), followed by the extraction of features using two techniques: Gabor grey level co-occurrence matrix and Discrete Wavelet Transform. then, the selected features are passed to a feed-forward back-propagation neural network; the suggested model achieves high performance. Shree and their research team [11] proposed a binary classification of a brain tumor based on brain MRI images. The model employed GLCM to extract a proper feature and a PNN classifier for the two classes (normal and abnormal). The suggested model achieved 95% accuracy. Additionally, the researchers in [12] proposed an automatic tumor detection and segmentation method based on a hybrid energy-efficient approach. The method comprises seven phases and achieved 98% accuracy. However, the primary limitation of this method is its high computation time.

III. Materials and Methods

This section presents the workflow of the brain tumor classification model. The framework of the federated model is illustrated in Figure 1. The model entails the processing of data at the client side, commencing with pre-processing, followed by training of the local model, and ultimately sharing the training weight with the global model deployed in the cloud.

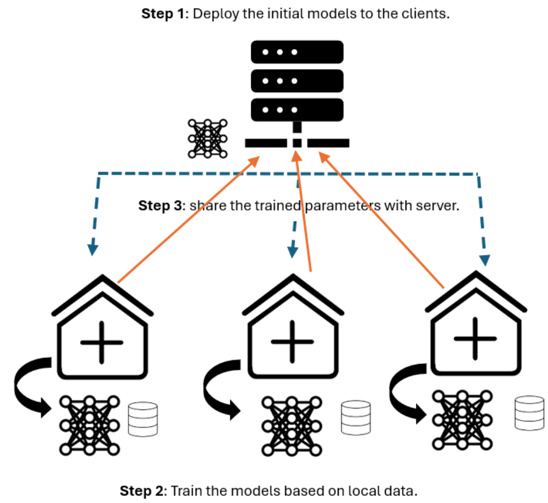

Fig. 1. Workflow of the Federated learning environment

A. Dataset

Three publicly available magnetic resonance imaging (MRI) datasets were used to conduct experiments aimed at classifying brain tumors (BTs). The first dataset, BT-large-1c, includes a total of 3000 brain images sourced from Kaggle [13]. It consists of 1500 each class (normal and abnormal) images. The second dataset, Brain Tumor Classification (MRI), was obtained from Kaggle [14] and contains 405 images without tumors and 906 images with diagnosed brain tumors. The third dataset, the Brain Tumor MRI Dataset [15], contains 253 images categorized into two classes: 155 images with tumor and 98 images without tumor. figure 2 shows example of one brain tumor.

B. DenseNet Models

A Densely Connected Convolutional Network (DenseNet) [16] has been utilized in a workflow system to demonstrate the effectiveness of federated learning in brain tumor classification. It is commonly employed in classification tasks, in this configuration, the architecture of each layer is connected to every other layer in a feed-forward manner. This connectivity is intended to facilitate effective feature selection and enhance the flow of gradients across the network. Figure 3 illustrates the structure of the DenseNet model proposed by [16].

C. federated learning framwwork

The objective function for the conventional machine learning problem can be represented asf_i(w)=l(x_i,y_i,w),, where $l(x_i, y_i, w)$ denotes the prediction loss for a given model w, with respect to the case (x_i, y_i). In a federated environment,

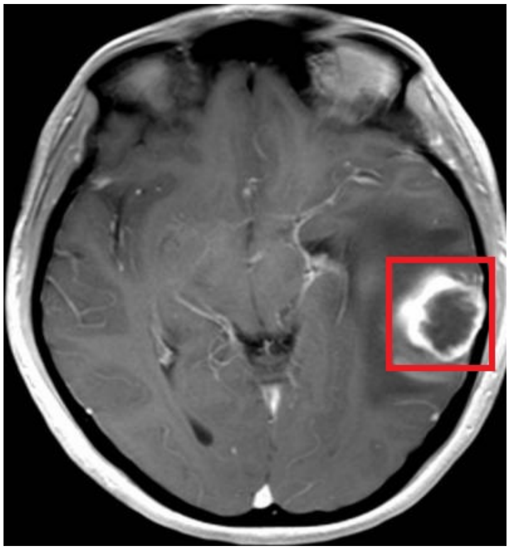

Fig. 2. example of brain tumor

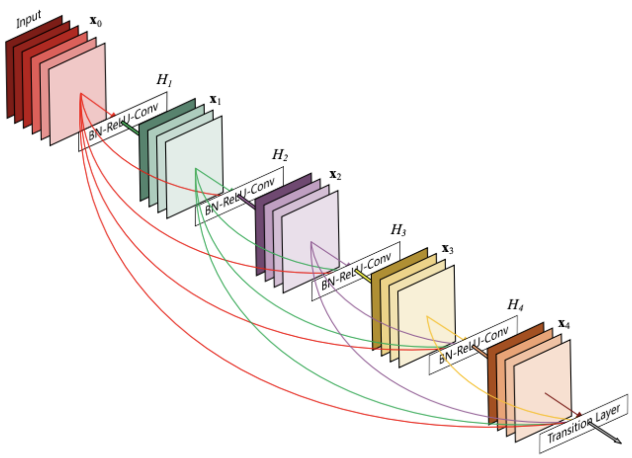

Fig. 3. Five layers of dense blocks [16]

the data points i are assumed to be distributed among C clients, where P_c represents the collection of data points held by client C, and n_c represents the number of data points held by client C, defined $n_c = [P_c]$.

D. Evaluation

A variety of evaluation methods have been employed to assess the performance of models in the context of federated learning (FL). The evaluation of brain tumour classification has been conducted using a number of metrics, including accuracy, precision, recall and F1-score. The accuracy metric calculated using Equation(1) quantifies the ratio of correctly classified instances. Precision, calculated by using Equation (2), represents the proportion of true positive prediction rate, while recall is calculated by Equation (3). finally, The F1 score calculated using Equation(4) is the harmonic mean of precision and recall.

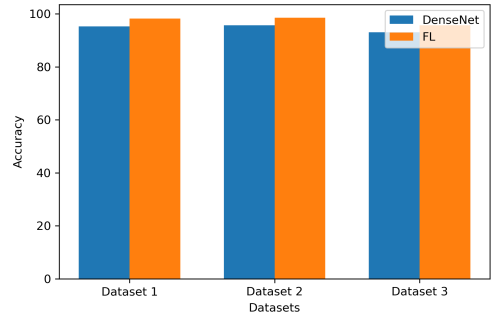

Fig. 4. Comparsion of Accuracy between a DenseNet and FL model

TABLE I
PERFORMANCE RESULTS OF THE THREE DIFFERENT DATASET (FEDERATED LEARNING SCENARIO)

Dataset	Accuracy	Precision	Recall	F1-Score
Dataset1	0.9823	0.9833	0.9813	0.9823
Dataset2	0.9855	0.9911	0.9879	0.9895
Dataset3	0.9565	0.9394	0.9480	0.9437

$$Accuracy(Acc) = \frac{TP + TN}{TP + FP + TN + FN} \tag{1}$$

$$Precision(Prc) = \frac{TP}{TP + FP} \tag{2}$$

$$Recall(Rcl) = \frac{TP}{TP + FN} \tag{3}$$

$$F1score(F1) = 2\frac{Precision * recall}{Precision + recall} \tag{4}$$

IV. RESULTS AND DISCUSSION

In this study, we examined the effectiveness of the FL model when applied to DenseNet. We evaluated its performance using the metrics outlined in section III-D. Table I presents the performance measurements based on three datasets assessed within a Federated Learning environment. The results indicate that the FL model, based on DenseNet, achieved better performance compared to the initial model without FL, as illustrated in Figure 4. The accuracy of FL was higher across all the datasets analyzed in this study.

Furthermore, Figures 5, 6, and 7 display the confusion matrix of the three datasets in the presence of FL. All three figures show significant improvement when FL is employed. In this work, FL achieved good results compared to the Deep learning model and kept the privacy of the data unshared and without use it by other clients. these results give a promising achievement for future work direction to establish such a high privacy model with a limited a communication channel between server and clients and in the performance was neer from the central model and in worst case scenario the FL model achieved same performance.

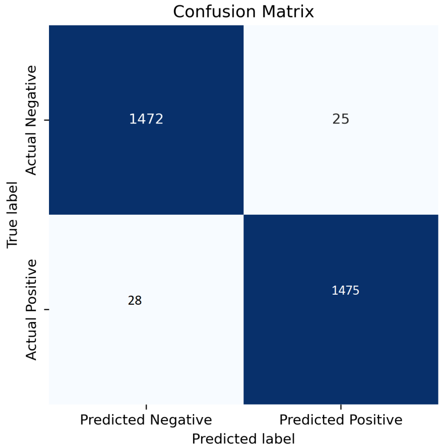

Fig. 5. Confusion Matrix of first MRI dataset [13]

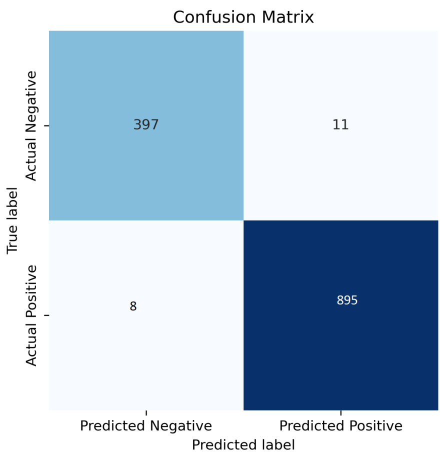

Fig. 6. Confusion Matrix of second MRI dataset [14]

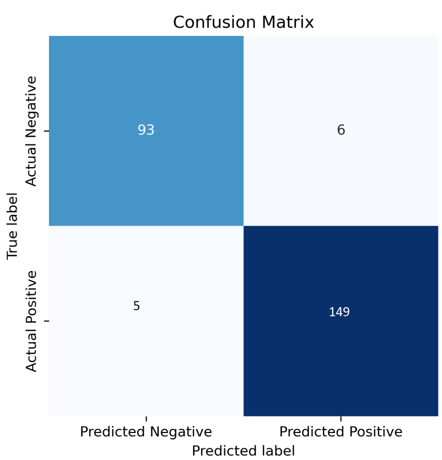

Fig. 7. Confusion Matrix of third MRI dataset [15]

V. Conclusion

This study highlights the effectiveness of the federated learning (FL) environment for classifying brain tumor based on MRI images. Three different datasets were used to demonstrate the concept of FL using a deep learning model. The results show that the FL architecture can significantly improve the performance of MRI brain tumor classification while maintaining the privacy of the clinic and the patients. The comparison between DenseNet and FL indicates that FL achieved higher accuracy than the central deep learning model. This is considered a good result in cases where datasets cannot be shared, and only learnable parameters are shared between the server and client to find optimal parameters suitable for all clients.

References

[1] Stupp, R., et al. "High-grade malignant glioma: ESMO Clinical Practice Guidelines for diagnosis, treatment and follow-up." Annals of oncology 21 (2010): v190-v193.

[2] Hassan, M.F., Al-Zurfi, A.N., Abed, M.H. et al. "An effective ensemble learning approach for classification of glioma grades based on novel MRI features", Sci Rep 14, 11977 (2024).

[3] Moore, K., & Kim, L. (2010). Primary brain tumors: Characteristics, practical diagnostic and treatment approaches. Glioblastoma: Molecular Mechanisms of Pathogenesis and Current Therapeutic Strategies, 43-75.

[4] David, D. S., & Arun, L. (2020). Classification of brain tumor type and grade using MRI texture and shape in a machine learning scheme. Artech J. Eff. Res. Eng. Technol, 1, 57-63.

[5] Brown, T. J., Bota, D. A., van Den Bent, M. J., Brown, P. D., Maher, E., Aregawi, D., ... & Glantz, M. (2019). Management of low-grade glioma: a systematic review and meta-analysis. Neuro-oncology practice, 6(4), 249-258.

[6] Mahlool, D. H., & Abed, M. H. (2022). Distributed brain tumor diagnosis using a federated learning environment. Bulletin of Electrical Engineering and Informatics, 11(6), 3313-3321.

[7] Mahlool, D. H., & Abed, M. H. (2022). A comprehensive survey on federated learning: Concept and applications. Mobile Computing and Sustainable Informatics: Proceedings of ICMCSI 2022, 539-553.

[8] Al-Asfoor, M., & Abed, M. H. (2022, April). Deep learning approach for COVID-19 diagnosis using X-ray images. In Proceedings of International Conference on Information Technology and Applications: ICITA 2021 (pp. 161-170). Singapore: Springer Nature Singapore.

[9] Althnian, A., AlSaeed, D., Al-Baity, H., Samha, A., Dris, A. B., Alzakari, N., ... & Kurdi, H. (2021). Impact of dataset size on classification performance: an empirical evaluation in the medical domain. Applied Sciences, 11(2), 796.

[10] Arunachalam, M., & Royappan Savarimuthu, S. (2017). An efficient and automatic glioblastoma brain tumor detection using shift-invariant shearlet transform and neural networks. International Journal of Imaging Systems and Technology, 27(3), 216-226.

[11] Varuna Shree, N., & Kumar, T. N. R. (2018). Identification and classification of brain tumor MRI images with feature extraction using DWT and probabilistic neural network. Brain informatics, 5(1), 23-30.

[12] Rajan, P. G., & Sundar, C. (2019). Brain tumor detection and segmentation by intensity adjustment. Journal of medical systems, 43(8), 282.

[13] https://www.kaggle.com/datasets/ahmedhamada0/brain-tumor-detection/data

[14] Msoud Nickparvar. (2021). Brain Tumor MRI Dataset [Data set]. Kaggle. https://doi.org/10.34740/KAGGLE/DSV/2645886

[15] https://www.kaggle.com/datasets/navoneel/brain-mri-images-for-brain-tumor-detection/data

[16] Huang, Gao, et al. "Densely connected convolutional networks." Proceedings of the IEEE conference on computer vision and pattern recognition. 2017.