IAES International Journal of Artificial Intelligence (IJ-AI)
Vol. 15, No. 6, December 2026, pp. 5703~5712
ISSN: 2252-8938, DOI: 10.11591/ijai.v15.i6.pp5703-5712

Federated transfer learning with label integration for glioma and brain tumor classification under data heterogeneity

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Article Info

Article history:

Received Sep 11, 2025
Revised Aug 10, 2026
Accepted Sep 20, 2026

Keywords:

Brain tumor
Deep learning
Federated learning
Image classification
Image processing
Non-independent and identically distributed problem

ABSTRACT

Accurate detection and classification of brain tumor using magnetic resonance imaging (MRI) is important for early diagnosis and treatment planning, especially in the fact of glioma, one of the most aggressive tumors. The centralized training where medical data is aggregated at one central place from different institutions is not feasible in most cases because of privacy and data exchange laws. The proposed research work introduces a privacy-preserving federated transfer learning framework. In this framework, each client is represented by a local hospital with their own subset of a brain tumor MRI dataset. To handle the non-independent and identically distributed (non-IID) problem, an adaptive client weighting technique and a label integration method are proposed to train the model in a collaborative manner. The experimental outcomes demonstrated that the proposed federated transfer learning with label integration (Fed-LI) method showed 95% accuracy, which closely matches the centralized model performance of 98% while ensuring robust glioma detection under heterogeneous data conditions.

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1. INTRODUCTION

The reliable and timely screening of brain tumors is a significant challenge in medical imaging research as it directly affects clinical outcomes and patient well-being [1]. Magnetic resonance imaging (MRI) is considered the predominant visualization strategy for identifying and classifying brain tumor, due to its effectiveness in providing high-resolution information about tumor structure without the use of ionizing radiation [2]. Among all brain tumor types, gliomas are considered to be a one of the critical concerns due to their aggressiveness and poor prognosis, followed by meningiomas and pituitary tumor [3]. Deep learning (DL) models have shown promising scope in the early and accurate classification of this tumor. However, in the centralized model training practice, where images from different hospitals are combined into a one training repository, although effective in terms of performance, it introduces serious privacy concerns, especially in the healthcare domain [4], [5]. In the healthcare sector, the exchange of patient MRI data is often difficult to obtain due to data security requirements and ethical concerns. Another issue is that medical data are often large, and their transfer or sharing into a centralized storage system also makes it an arduous chore due to the risk of security risks such as data leaks and hacking. These barriers make it difficult to build centralized models that truly represent diverse patient populations [6]. The recent advances in federated learning (FL) have enabled collaborative model development excluding interchanging unrefined patient data, where healthcare organizations retain patient data locally, train models independently, and communicate

merely paradigm parameters to a central server for aggregation [7]. The aggregated model parameters are integrated by the central server to produce a global model that grabs information from diverse institutions without compromising data privacy. However, the major crucial issues associated with FL is the non-independent and identically distributed (non-IID) data across medical institutions, as in real-world healthcare, data are rarely distributed identically, and few hospitals might have only specific types of tumors represented in their records, such as glioma and no-tumor, whereas others may hold cases of meningioma and pituitary tumor [8], [9].

In the recent literature, various reviews were explored FL as a privacy-preserving alternative for brain tumor analysis using MRI images. The work carried out by Islam *et al*. [10] addressed the challenge of restricted data sharing using an ensemble learning mechanism within an FL setup, and the study outcome showed 91.05% accuracy using FL compared to 96.68% by a centralized model. However, this work needs a reduction in the computational complexities associated with the methodology adopted. Another work done by Albalawi *et al*. [11] presented an FL transfer learning scheme by implementing a modified visual geometry group 16-layer network (VGG16) model. The study outcome reported 98% accuracy with high class-specific precision for tumor classification. However, the performance analysis needs to be validated in the context of client heterogeneity. Zhou *et al*. [12] applied FL with an efficient network baseline 0 (EfficientNet-B0) and federated averaging (FedAvg), demonstrating greater performance compared to residual network (ResNet) under non-IID distributions. Yahiaoui *et al*. [13] presented a segmentation framework using the U-Net model with an FL setup for tumor segmentation with a differential privacy scheme on the brain tumor segmentation challenge 2020 (BraTS-2020) dataset. The outcome reported Dice scores above 86%. However, the usage of the differential privacy scheme introduces noise that degraded fine-grained predictions. The study of Lee *et al*. [14] developed an FL model for segmentation and classification of pediatric tumor, which achieved a 30% improvement in performance, but coordination complexity across clients was significant. Mahlool and Abed [15] tried to improve the model's weight aggregation by ranking client contributions instead of utilizing the FedAvg method. The experimental outcome reported 98% accuracy for binary-class datasets. Onaizah *et al*. [16] introduced a peer-to-peer model framework using a Siamese neural model under FL for tumor similarity detection. However, this framework raised concerns about communication overhead in hospital networks. Al-Saleh *et al*. [17] developed a custom learning model by combining ResNet-50, capsule networks, and blockchain-secured updates to achieve comprehensive privacy. The result showed an accuracy of 99.07% on computed tomography (CT) scans, but at a higher computational cost. Awotunde *et al*. [18] suggested an FL with CNNs and transfer learning that outperformed conventional centralized methods, nevertheless, those people didn't fully test performance under non-IID data. There are further research attempts towards enhancements integrating optimization techniques. The work done by Kani and Ayothi [19] presented an FL approach using a nature-inspired optimization algorithm and fitness-based aggregation, which achieved over 98% accuracy. However, the adoption of a multi-level optimization strategy added a significant computational overhead. The work carried out by Sivakumar *et al*. [20] combined FedAvg and federated proximal (FedProx) to stabilize training on heterogeneous data, and showed higher accuracy on a four-class dataset, but restricted analysis to a non-IID problem with their advanced approach. The work done by Yang *et al.* [21] extended the FL approach to a multi-modal learning context by using progressive distillation and an optimal transport scheme for achieving robust segmentation performance. However, this method requires a significant reduction in computational complexity. Anish and Ajitha [22] provided an extensive analysis of the existing learning-based schemes and identified the gaps in dataset availability, privacy, and heterogeneity, which highlights the need for frameworks like FL to address the non-IID problem without much computational overhead.

From the literature review, it has been observed that FL approach is promising for ensuring privacy-preserving in brain tumor analysis, yet several gaps remain to address: i) in most works, the issue of non-IID data is only partly handled, as many works are subjected to non-IID scenarios or semi-balanced partitions; ii) strategies such as weighted averaging, personalization, and regularization improved the model convergence but often failed when clients lack complete tumor classes, which causes label space mismatch; iii) also most existing studies prioritize accuracy but give less attention to reducing the computational complexity, and communication overhead, and optimizing hospital-level coordination; and iv) very few works have tried to ensure that clients with partial or imbalanced datasets contribute effectively to the global model.

To address the above-mentioned research issues, this paper presents an FL framework for automated brain tumor recognition utilizing image processing and DL based approach under heterogeneous label distributions. The core and unique contributions are: i) federated transfer learning with label integration (Fed-LI) and adaptive client weighting at the central server for fairer weight aggregation; ii) adoption of a fine-tuned ResNet-50 for robust local feature learning on limited client datasets; and iii) introduction of a label

integration mechanism at each local client for global label space mapping to address the non-IID problem. The proposed framework is evaluated using extensive analysis on a public multi-class brain MRI dataset.

2. METHOD

The research work introduces an FL transfer learning framework and for automatic brain tumor classification using MRI, and a label integration (Fed-LI) has been proposed. By considering a client-server architecture, a framework was created, wherein every client is designated as a local medical institution that host its own MRI dataset. Here, each client independently trains their local model and shares only the model parameters (weights) with the central server. Afterwards, the server aggregates model parameters obtained from all clients to get an updated global model, and broadcasts it to all local clients. The workflow of the proposed system implementation is illustrated in Figure 1. The suggested Fed-LI system considers input brain MRI images from distinct hospitals, which are subjected to comprehensive preprocessing operations that include morphological filtering, Gaussian blur, contour-based cropping, resizing, and normalization to prepare clean and standardized input for the DL based local models. The data is then subjected to train, validation (val), and test subsets, where augmentation is applied on the train set to improve model training robustness.

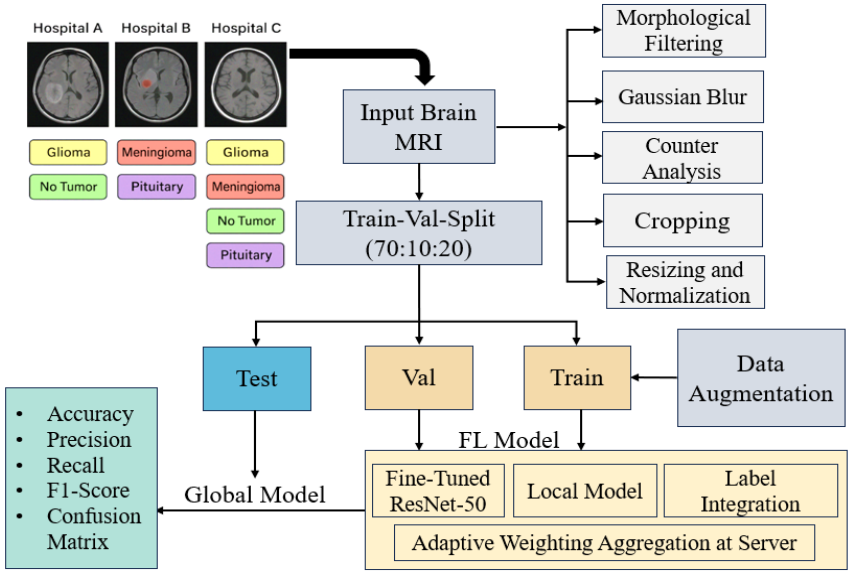

Figure 1. Exhibits the design and implementation process of the proposed Fed-LI system

In Figure 1, the FL setup each hospital acts as a local client and trains a fine-tuned ResNet-50 model [23] on its own data. To mimic and simulate a real-world scenario, a non-IID distribution is created by allocating different tumor classes to different clients. A label integration mechanism is included in the weight aggregation process to match the partial label space of each client with the global classification problem. Post-training on the local level, the model's weights are shared with the central server for adaptive weight aggregation. Once the process converges, the global model is validated on the unseen samples for glioma detection and multi-class tumor classification using standard performance metrics.

2.1. Dataset description

The dataset used to build the proposed FL framework is adopted from Kaggle [24], which has been created by integrating three openly accessible brain MRI repositories such as Figshare, SARTAJ, and Br35H. Four classes are included in the dataset, namely glioma, meningioma, pituitary tumor, and no-tumor, and is divided into train, val, and test subsets considering an 80:10:10 split ratio. The train-set is utilized to train the model; the val-set is used during the training phase to observe performance and fine-tune the model. The test-set serves as unseen data to validate the robustness of the trained model for tumor classification. The detailed distribution of MRI images across classes and splits is highlighted in Table 1.

Table 1. Details of dataset distribution

Class	Train set	Val set	Test set	Total
Glioma	1,321	132	300	1,753
Meningioma	1,339	134	306	1,779
No-tumor	1,595	160	405	2,160
Pituitary	1,457	146	300	1,903
Total	5,712	571	1,311	7,594

2.2. Data preprocessing

The proposed study adopts multi-level data preprocessing operations to perform enhancement over the input brain MRI images and extract the region of interest (ROI) for effective feature representation to the DL model. This phase of the proposed framework ensures noise reduction, preservation of important brain structures, and normalization of the input images to a consistent size and intensity scale. The detailed computational steps involved in the preprocessing operations are described in Algorithm 1.

Algorithm 1. Multi-level data preprocessing
Input: input brain MRI image B_I
Output: enhanced image I_E
Start
1: Read brain MRI B_I stored on local storage
2: Transform B_I to a single-channel intensity representation → I_g
3: Perform smoothening over I_g using Gaussian blur to reduce noise
4: Perform image binarization using adaptive thresholding
5: Apply morphological filtering followed by erosion and dilation to remove structural noise
6: Perform contours analysis of the brain mask
Retain largest connected component as brain mask
Identify extreme points
7: Extract region of interest by cropping image around bounding box defined by extreme points
8: Resize the extracted ROI to a dimension of 224 × 224 pixels
9: Normalize ROI by scaling pixel intensities to [0,1]
10: Generate output: I_E
End

In Algorithm 1, the first step performs grayscale conversion to reduce the data dimensionality without compromising the structural and clinical characteristics of the brain MRI. In the next step, a Gaussian blurring operation is used to eliminate high-frequency noise and smoothing of local intensity variations. Afterwards, an adaptive thresholding operation is used to generate a binary representation of the input image, and morphological operations such as erosion and dilation are further applied to remove small artefacts and isolated noise regions. To ensure accurate localization, only the largest connected component is retained, as it corresponds to the brain region. The next step is carried out towards achieving a refined image mask using contour analysis that detects the brain boundary and the extreme points, which are useful to define the bounding box for ROI extraction. The cropped ROI is resized to 224 × 224 pixels, and its pixel intensities are normalized to the [0,1] range to make the input image compatible to ResNet-50 input layer. The proposed multi-step preprocessing strategy aims to standardize the input MRI data across all federated clients, which is important to ensure uniformity and reliable classification under heterogeneous data conditions. Figure 2 illustrates the sequential outcome of the multi-level preprocessing operation that exhibits grayscale conversion, noise suppression, binarization, and morphological refinement of the brain MRI image. The contour detection and extreme-point localization enable accurate ROI extraction, thereby obtaining a standardized cropped image for reliable feature learning.

2.3. Deep local model and federated learning setup

The proposed framework adopts an FL scheme where each hospital acts as a client node, and the central server orchestrates the global training. Figure 3 displays the federated working process, where each hospital acts as a local hospital with its own MRI dataset with different tumor class distributions, thereby creating a non-IID scenario. To address this, local models are trained on fine-tuned ResNet-50 backbones using a transfer learning approach. A label integration module is incorporated during weight sharing to ensure better alignment between partial local label spaces and the global label space. The base layers of ResNet-50 basically extract low-level features (edges and textures), where the deeper layers are fine-tuned to adapt to the domain-specific representations for brain tumor classification. To reduce overfitting, dropout regularization is considered, and dense layers are used, followed by a global average pooling (GAP) operation.

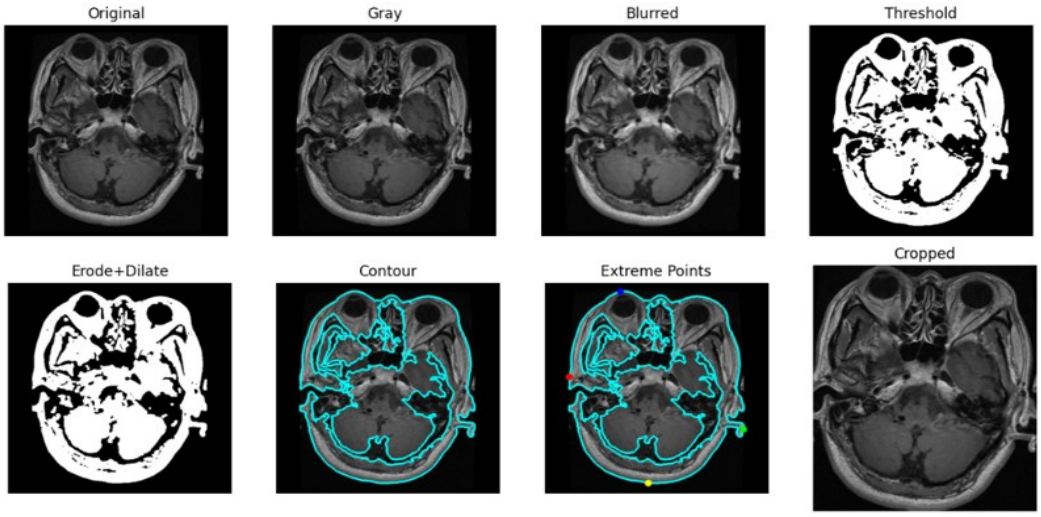

Figure 2. Illustrates the visualization outcome of Algorithm 1

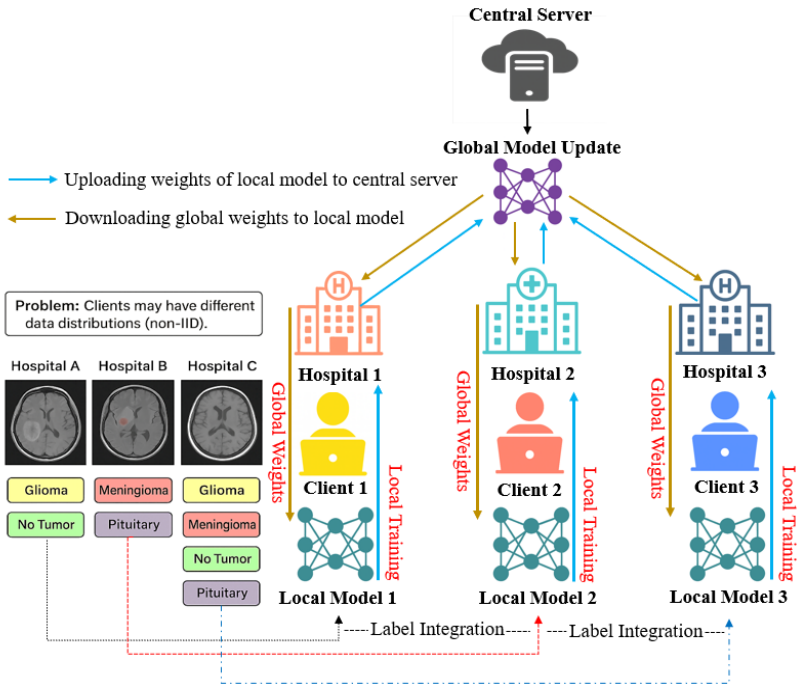

Figure 3. Shows the process flow of the FL tasks

The kth client maintains their local data $D_k = \{(x_i, y_i)|i = 1,2,\cdots,n_k\}$, where variable x_i denotes MRI samples and, and $y_i \in Y_k$ is the corresponding class label with $Y_k \subseteq Y$, that presents the client-specific label space. Here, a local ResNet-50 model is trained by every client using cross-entropy loss as expressed in (1).

$$L_k = -\frac{1}{n}\sum_{i=1}^{n_k}\sum_{c=1}^{C} 1_{[y_i=c]} log\hat{p}_\theta(y_i|x_i) \quad (1)$$

Where $\hat{p}_\theta(y_i|x_i)$ indicates the probability that sample x_i belongs to class c and θ denotes the trainable parameters of the model. During the local optimization process, the input images I_e are processed in mini-batches, which are then fed to cthe onvolutional layer of local ResNet-50 model to extract disease specific patterns and then represented a feature map $F = \{f_1, f_2 \cdots f_C\} \in \mathbb{R}^{h\times w\times C}$, where C denote the number

of feature channels and every feature map had its own height h and width w that corresponds to the spatial activation map produced by the c-th convolutional filter.

The obtained feature F are forwarded to customized output layers consisting of GAP followed by dropout regularization to reduce overfitting. Afterwards, the pooled feature is then fed to a fully-connected classifier for computing class probability using the softmax activation. The training process and model weights are optimized using adaptive moment estimation (Adam) with a learning rate of 0.001 and categorical cross-entropy (CCE). In the federated setup, the datasets distributed across clients follow a non-IID setting, where hospital 1 contains only glioma and no-tumor cases, hospital 2 contains meningioma and pituitary cases, while hospital 3 contains all four classes. Since certain classes are absent at some clients, direct aggregation of local models can lead to inconsistent classifier outputs. To overcome this issue, each client maps its local label space Y_k to the global label space Y through a label integration module, where placeholder probabilities are assigned for the missing classes before transmitting the local model to the server, thereby maintaining a consistent output space during global aggregation. After successful execution of local training, only the updated model parameters θ_k are transmitted from each client to update the global model, which utilized adaptive federated averaging mechanism, where the aggregation weight for every client is estimated by employing using its dataset size and validation accuracy, as given in (2) and (3).

$$\theta^{(t+1)} = \sum_{k=1}^{K} \alpha_k \theta_k^{(t)} \tag{2}$$

$$\alpha_k = \frac{n_k \times Acc_k}{\sum_{j=1}^{K} n_j \times Acc_j} \tag{3}$$

Where, α_k denotes the adaptive weight for client k, which combines the data size n_k and validation accuracy Acc_k. The upgraded global model $\theta^{(t+1)}$ is shared to every participating client to initiate the subsequent communication round. This iterative exchange of local updates and global aggregation will continue until the convergence criterion is satisfied, and the final global model is assessed using held-out test data for glioma detection and multi-class brain tumor classification.

3. RESULTS AND DISCUSSION

The proposed Fed-LI framework was designed and executed using Python in the Anaconda environment configured on a Windows Core i7 system with 16 GB RAM, and a graphics processing unit (GPU) with 6 GB VRAM. The training of the global model was done for the 30 epochs, with a batch size of 32. The initial learning rate of 0.001 was considered, with a dropout rate of 0.5 after the pooling layer, and a weight decay of 1×10^{-5} were used during training. A quantitative evaluation of model with confusion plot is illustrated in Figure 4 for the centralized model, Figure 5 for the standard FL approach, and Figure 6 for the proposed Fed-LI model.

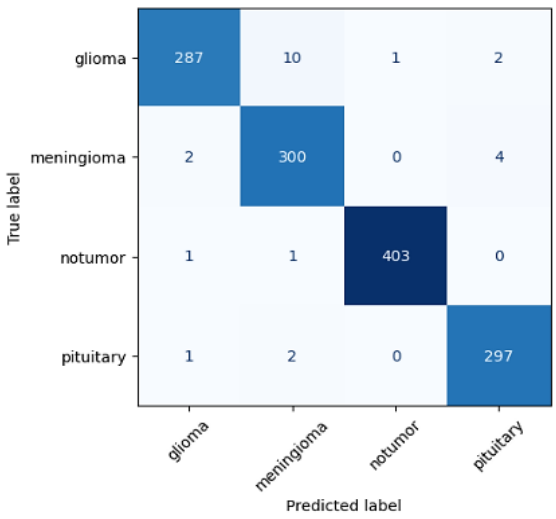

Figure 4. Shows prediction outcomes of the centralized model via confusion matrix

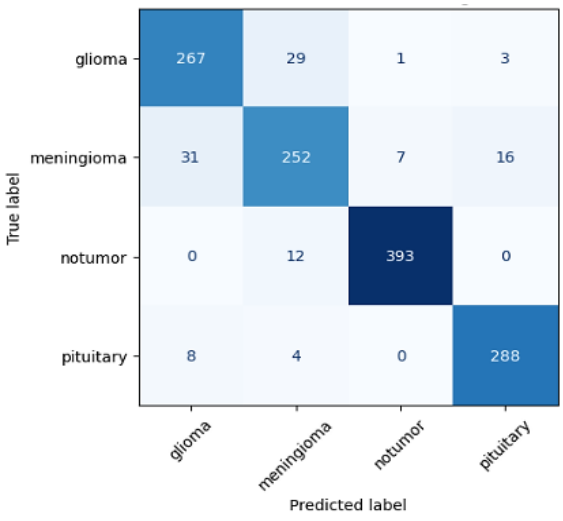

Figure 5. Shows prediction outcomes of the standard FL model via confusion matrix

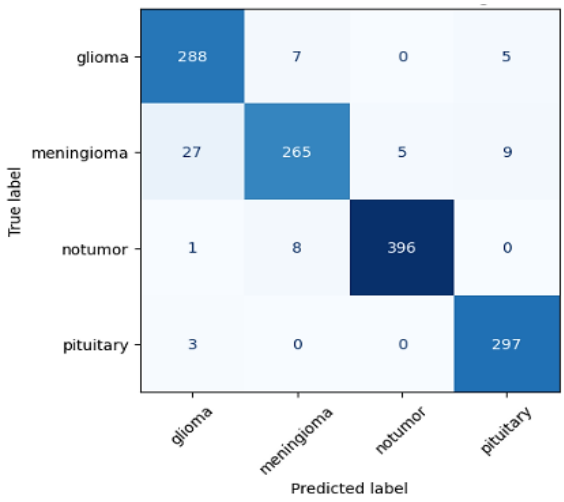

Figure 6. Shows prediction outcomes of the proposed Fed-LI model via a confusion matrix

The analysis of the classification matrix shown in Figure 4 revealed that the centralized model achieved higher performance for all four classes with an overall accuracy of 98%. This model shows very low misclassification rates, and the no-tumor class showed near-perfect recall (403 correctly classified out of 405 samples). This analysis represents the upper-bound performance scenario, as data centralization maximizes diversity but compromises privacy. On the other hand, from Figure 5, compared to the centralized setup, the model depends on standard FL showed degraded performance, with an overall accuracy of 92% was viewed and some perplexity was noticed among glioma and meningioma. The classification matrix in Figure 6 revealed that the proposed Fed-LI demonstrated highly competent performance with an accuracy of 95%, despite being trained in a privacy-preserving distributed environment with heterogeneous label distributions, which reduces cross-class errors and aligns predictions closer to the centralized baseline. The Fed-LI system achieved near-centralized performance without requiring patient data to leave local hospitals, thereby showing its feasibility of serving as a support tool for clinical decisions. The quantitative classification assessment in terms of precision, recall, and F1-score is presented in Table 2.

Table 2. Presents the quantified classification outcomes

Class	Metric	Centralized (%)	FedAvg (%)	Fed-LI (%)
Glioma	Precision	99	87	90
	Recall	96	89	96
	Specificity	99.3	97	97.9
	F1-score	97	88	93
Meningioma	Precision	96	85	95
	Recall	98	82	87
	Specificity	98.6	97.5	98.8
	F1-score	97	84	90
No-tumor	Precision	100	98	99
	Recall	100	97	98
	Specificity	100	99.3	99.5
	F1-score	100	98	98
Pituitary	Precision	98	94	95
	Recall	99	96	99
	Specificity	99.3	98.1	98.7
	F1-score	99	95	97

The comparative analysis shown in Table 2 highlights clear trends in both strengths and limitations of each approach. The model with centralized training reported the highest classification performance, whereas the standard FedAvg model showed slightly degraded precision and recall performance for glioma and meningioma because of heterogeneous client data. The proposed Fed-LI framework improved the classification performance by introducing label integration and adaptive client weighting during aggregation. For glioma, the recall rate matched the performance of the centralized model at 96%, which is critical for clinical reliability, though precision reached 90%. Similarly, for the meningioma class, the precision increased to 95% from 85% in FedAvg, although the recall remained at 87%. The closer analysis reveals that

Fed-LI achieved a better trade-off by narrowing the performance gap with centralized training while preserving privacy. The next analysis in Figures 7 and 8 is shown in terms of the ROC curve and precision vs recall comparison.

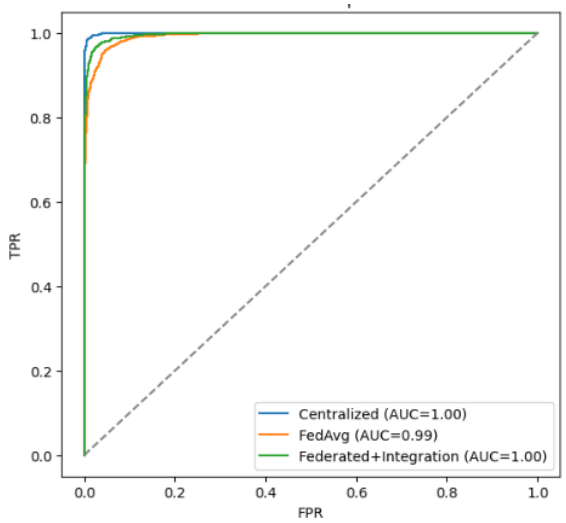

Figure 7. Comparison in terms of ROC curve

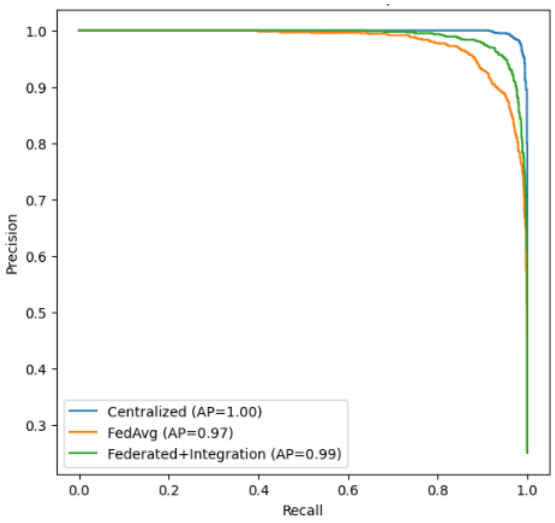

Figure 8. Comparison with precision vs. recall

The analysis shown in Figures 7 and 8 further provides additional evidence of better performance by the proposed Fed-LI framework compared to standard FedAvg and centralized training methods. The ROC curve shows that the centralized model achieved an AUC of 100%, which demonstrated its effectiveness in perfect separation of classes, whereas FedAvg slightly lagged with an AUC of 99% due to non-IID effects. The proposed Fed-LI framework also achieved an AUC of 100%, indicating that the label integration and adaptive aggregation strategy reduced the effect of heterogeneous class distributions across clients. A similar trend was observed in the precision–recall analysis, where the proposed framework reported an average precision (AP) of 99% and produced better performance for minority classes than the standard FedAvg model. Although the centralized model remained the best-performing approach, the proposed Fed-LI framework produced comparable results under the privacy-preserving FL setting. The comparative analysis presented in Table 3 further showed that the proposed model outperformed the hybrid CNN–LSTM model [25] and the autoencoder-based CNN model [26], which reported accuracies of 92% and 93.4%, respectively.

Table 3. Comparative analysis with existing similar work

References	Dataset	Method	Accuracy (%)
Vankdothu *et al*. [25]	MRI	CNN + LSTM	92.0
Saeedi *et al*. [26]	MRI	CNN + autoencoder	93.4
Proposed	MRI	Label integration + weighted integration	95.0

The reason behind achieving a better performance by the proposed model is the integrated effect of multi-level preprocessing, transfer learning, and the proposed FL with label space integration strategy. The multi-level preprocessing (morphological filtering, contour-based cropping, and normalization) has ensured that only precise inputs are passed to the model for better feature learning, while fine-tuned ResNet-50 with transfer learning enabled robust representation of complex tumor structures. The proposed Fed-LI framework reduced the influence of heterogeneous label distributions through label integration before global aggregation. Also, adaptive client weighting assigned greater importance to reliable local model updates, which further contributed to better global model convergence and improved classification performance.

4. CONCLUSION

The research work presented a Fed-LI for brain tumor detection and classification from MRI under heterogeneous data distributions. Here combined the transfer learning, adaptive client weighting, and label

integration to support collaborative model training without sharing patient data. The experimental evaluation exhibited that the proposed methodology attained better classification performance comparable to centralized learning without compromising data privacy features in the collaborative setup. The study also demonstrated that clients with incomplete class distributions can effectively participate in global model training through the proposed label integration strategy. Despite these promising results, additional communication overhead and the availability of multi-institutional clinical datasets remain practical challenges. Future work will investigate stronger privacy-preserving mechanisms, communication-efficient aggregation methods, and validation of the proposed framework on larger real-world clinical datasets.

FUNDING INFORMATION

The authors confirm that no funding was involved in carrying out this research.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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Maya Bevinahalli Somashankaregowda		✓				✓		✓	✓	✓	✓	✓		

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no conflict of interest.

DATA AVAILABILITY

The datasets generated and/or analyzed during this study are available from the corresponding author, [KCR], upon reasonable request.

REFERENCES

[1] A. B. Abdusalomov, M. Mukhiddinov, and T. K. Whangbo, "Brain tumor detection based on deep learning approaches and magnetic resonance imaging," *Cancers*, vol. 15, no. 16, Aug. 2023, doi: 10.3390/cancers15164172.

[2] S. Khalighi, K. Reddy, A. Midya, K. B. Pandav, A. Madabhushi, and M. Abedalthagafi, "Artificial intelligence in neuro-oncology: advances and challenges in brain tumor diagnosis, prognosis, and precision treatment," *npj Precision Oncology*, vol. 8, no. 1, Mar. 2024, doi: 10.1038/s41698-024-00575-0.

[3] M. Cè *et al.*, "Artificial intelligence in brain tumor imaging: a step toward personalized medicine," *Current Oncology*, vol. 30, no. 3, pp. 2673–2701, Feb. 2023, doi: 10.3390/curroncol30030203.

[4] E. Chukwujindu, H. Faiz, S. AI-Douri, K. Faiz, and A. De Sequeira, "Role of artificial intelligence in brain tumour imaging," *European Journal of Radiology*, vol. 176, Jul. 2024, doi: 10.1016/j.ejrad.2024.111509.

[5] R. Kaifi, "A review of recent advances in brain tumor diagnosis based on AI-based classification," *Diagnostics*, vol. 13, no. 18, Sep. 2023, doi: 10.3390/diagnostics13183007.

[6] J. Amin, M. Sharif, A. Haldorai, M. Yasmin, and R. S. Nayak, "Brain tumor detection and classification using machine learning: a comprehensive survey," *Complex & Intelligent Systems*, vol. 8, no. 4, pp. 3161–3183, Aug. 2022, doi: 10.1007/s40747-021-00563-y.

[7] S. M. A. Monisha and R. Rahman, "Brain tumor detection in MRI based on federated learning with YOLOv11," Mar. 2025, *arXiv: 2503.04087*.

[8] M. Z. Muntaqim and T. A. Smrity, "Federated learning framework for brain tumor detection using MRI images in non-IID data distributions," *Journal of Imaging Informatics in Medicine*, vol. 38, no. 6, pp. 3909–3927, Mar. 2025, doi: 10.1007/s10278-025-01484-9.

[9] M. I. Khan, E. Kontio, S. A. Khan, and M. Jafaritadi, "Election of collaborators via reinforcement learning for federated brain tumor segmentation," Dec. 2024, *arXiv: 2412.20253.*

[10] M. Islam, M. T. Reza, M. Kaosar, and M. Z. Parvez, "Effectiveness of federated learning and CNN ensemble architectures for identifying brain tumors using MRI images," *Neural Processing Letters*, vol. 55, no. 4, pp. 3779–3809, Aug. 2023, doi: 10.1007/s11063-022-11014-1.

[11] E. Albalawi *et al.*, "Integrated approach of federated learning with transfer learning for classification and diagnosis of brain tumor," *BMC Medical Imaging*, vol. 24, no. 1, May 2024, doi: 10.1186/s12880-024-01261-0.
[12] L. Zhou, M. Wang, and N. Zhou, "Distributed federated learning-based deep learning model for privacy MRI brain tumor detection," Apr. 2024, *arXiv: 2404.10026*.
[13] M. E. Yahiaoui *et al.*, "Federated learning with privacy preserving for multi-institutional three-dimensional brain tumor segmentation," *Diagnostics*, vol. 14, no. 24, Dec. 2024, doi: 10.3390/diagnostics14242891.
[14] E. H. Lee *et al.*, "An international study presenting a federated learning AI platform for pediatric brain tumors," *Nature Communications*, vol. 15, no. 1, Sep. 2024, doi: 10.1038/s41467-024-51172-5.
[15] D. H. Mahlool and M. H. Abed, "Optimize weight sharing for aggregation model in federated learning environment of brain tumor classification," *Journal of Al-Qadisiyah for Computer Science and Mathematics*, vol. 14, no. 3, Aug. 2022, doi: 10.29304/jqcm.2022.14.3.989.
[16] A. N. Onaizah, Y. Xia, and K. Hussain, "FL-SiCNN: an improved brain tumor diagnosis using Siamese convolutional neural network in a peer-to-peer federated learning approach," *Alexandria Engineering Journal*, vol. 114, pp. 1–11, Feb. 2025, doi: 10.1016/j.aej.2024.11.063.
[17] A. Al-Saleh, G. G. Tejani, S. Mishra, S. K. Sharma, and S. J. Mousavirad, "A federated learning-based privacy-preserving image processing framework for brain tumor detection from CT scans," *Scientific Reports*, vol. 15, no. 1, Jul. 2025, doi: 10.1038/s41598-025-07807-8.
[18] J. B. Awotunde, C. O. Abikoye, B. Brahma, E. T. Oladipupo, and A. Bandyopadhyay, "Federated learning augmented with convolutional neural networks for brain cancer classification," *Procedia Computer Science*, vol. 258, pp. 2617–2626, 2025, doi: 10.1016/j.procs.2025.04.523.
[19] J. S. N. Kani and S. Ayothi, "Enhancing medical image analysis with FL brain-HOA: a federated learning and hybrid optimization approach," *Iranian Journal of Science and Technology, Transactions of Electrical Engineering*, vol. 49, no. 4, pp. 1793–1818, Dec. 2025, doi: 10.1007/s40998-025-00877-4.
[20] N. Sivakumar *et al.*, "A hybrid brain tumor classification using FL with FedAvg and FedProx for privacy and robustness across heterogeneous data sources," *IEEE Access*, vol. 13, pp. 57705–57719, 2025, doi: 10.1109/ACCESS.2025.3549440.
[21] Q. Yang, M. Zhu, P. Y. M. Woo, L. L.-H. Chan, and Y. Yuan, "Progressive distillation with optimal transport for federated incomplete multi-modal learning of brain tumor segmentation," *IEEE Journal of Biomedical and Health Informatics*, vol. 29, no. 5, pp. 3159–3170, May 2025, doi: 10.1109/JBHI.2025.3525854.
[22] J. J. Anish and D. Ajitha, "Exploring the state-of-the-art algorithms for brain tumor classification using MRI data," *IEEE Access*, vol. 13, pp. 118033–118054, 2025, doi: 10.1109/ACCESS.2025.3579727.
[23] M. B. Hossain, S. M. H. S. Iqbal, M. M. Islam, M. N. Akhtar, and I. H. Sarker, "Transfer learning with fine-tuned deep CNN ResNet50 model for classifying COVID-19 from chest X-ray images," *Informatics in Medicine Unlocked*, vol. 30, 2022, doi: 10.1016/j.imu.2022.100916.
[24] M. Nickparvar, "Brain tumor MRI dataset: a dataset for classifying brain tumors," *Kaggle.com*, 2019. Accessed: Aug. 11, 2025. [Online]. Available: https://www.kaggle.com/datasets/masoudnickparvar/brain-tumor-mri-dataset
[25] R. Vankdothu, M. A. Hameed, and H. Fatima, "A brain tumor identification and classification using deep learning based on CNN-LSTM method," *Computers and Electrical Engineering*, vol. 101, Jul. 2022, doi: 10.1016/j.compeleceng.2022.107960.
[26] S. Saeedi, S. Rezayi, H. Keshavarz, and S. R. N. Kalhori, "MRI-based brain tumor detection using convolutional deep learning methods and chosen machine learning techniques," *BMC Medical Informatics and Decision Making*, vol. 23, no. 1, Jan. 2023, doi: 10.1186/s12911-023-02114-6.

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