OPEN ACCESS JOURNALS
Indiana Journal of Multidisciplinary Research
Abbreviated Tittle- Ind J Multi Res
ISSN *(Online)*- 2583-3820
Journal Homepage Link- https://indianapublications.com/Journals/IJMR
DOI: https://doi.org/10.5281/zenodo.21610697

INDIANA PUBLICATIONS
PRODUCTIVE AND QUALITY RESEARCH

Research Articles
Volume-06|Issue-04|2026

Brain Tumor Detection in MRI Images via Federated Learning Technique

Nithin Kumar B[1] and Maya B S[2]

[1]Student, Department of Computer Science and Engineering, Bangalore Institute of Technology Bengaluru, India.
[2]Associate Professor, Department of Computer Science and Engineering, Bangalore Institute of Technology Bengaluru, India.

Article History
Received: 05.05.2026
Accepted: 22.06.2026
Published: 25.07.2026

Citation
Nithin, K. B. & Maya, B. S. (2026) Brain Tumor Detection in MRI Images via Federated Learning Technique. *Indiana Journal of Multidisciplinary Research, 6*(4), 457-464.

Abstract: Brain tumors are some of the most serious issues affecting the central nervous system. They need to be detected early and correctly. Traditional machine learning techniques rely on collecting data in one place, which raises significant privacy and security concerns. This work proposes a federated learning (FL)-based framework for classification of tumors from MRI, enabling decentralized training while preserving patient confidentiality. Multiple healthcare institutions collectively train deep learning models (VGG16, DenseNet) using the Federated Averaging algorithm, where only the model parameters are shared with a central server. The workflow includes preprocessing, feature extraction, local training, aggregation, and evaluation. Brain tumors are classified into glioma, pituitary, meningioma, and no-tumor classes. Experimental results are measured by precision, accuracy, recall, and F1-score and demonstrate robustness and strong classification performance. The paper highlights the scalability and usability of FL in medical imaging and introduces a secure federated approach to facilitate AI-driven healthcare applications.

Keywords: Brain Tumor Classification, Federated Learning, Deep Learning, Medical Imaging, VGG16, DenseNet.

INTRODUCTION

Brain tumors are some of the most intricate and life-threatening medical disorders, rendering correct and timely diagnosis crucial for optimal treatment. Imaging modalities like MRI and CT scans are invaluable in detection, but interpretation is complicated by heterogeneity in tumor size, shape, and image quality. These shortcomings can result in delayed or false diagnoses, adversely affecting patient outcomes. In recent times, machine learning has emerged as **a** powerful tool to augment medical image analysis, providing faster and more precise assessments compared to traditional methods. However, most ML approaches rely on centralized data storage, which raises serious privacy concerns. Patient data is highly sensitive and subject to strict regulations such as HIPAA and GDPR, making data sharing across institutions difficult. This limits access to diverse datasets, which are essential for building robust and generalizable machine learning models.

Federated Learning (FL) has recently emerged as a privacy-preserving answer to this problem. FL differs from traditional ML in that it enables multiple institutions to train models jointly without sharing raw patient data. In an FL configuration, the models are trained locally at each institution on that institution's own data, and model updates (e.g., weights or gradients) are exchanged with a server, rather than the raw data. The server combines these updates, often via the Federated Averaging algorithm, producing a central model that leverages distributed, heterogeneous data while preserving privacy. This distributed framework maintains legal compliance, supports cross-institutional collaboration, and improves model generalization across heterogeneous sources of data. The system presented in the present work utilizes convolutional deep neural models including VGG16 and DenseNet optimized for brain tumor detection. For improving privacy further, other mechanisms like secure aggregation and differential privacy can be used. The framework is built to handle data heterogeneity between institutions, allowing for differences in imaging quality, protocols, and patient demographics. Additionally, an intuitive interface allows physicians to simply upload MRI scans and obtain automatic predictions, while the backend handles federated updates and synchronization.

By integrating deep learning and federated learning, this project seeks to provide high evaluation performance for brain tumor diagnosis while maintaining patient confidentiality. Successful adoption of such a system can lead the way for secure collaborative AI solutions in healthcare. Systematic comparative evaluation of VGG16 and DenseNet121 under controlled federated settings for multi-class brain tumor classification. Explicit modeling and evaluation of IID and non-IID data distributions, with quantitative heterogeneity analysis. Detailed federated optimization configuration including communication rounds, local epochs, and convergence stability analysis. Comparative benchmarking against centralized training to quantify the federated performance gap. Integration of explainable tumor localization visualization aligned with CNN prediction outputs. Presentation of both client-level and aggregated global confusion matrices.

RELATED WORK

Recent experiments using CNNs, VGG16, and DenseNet for tumor classification show strong performance but raise concerns about privacy due to centralized data storage. In response, decentralized learning has been used in medical imaging to enable institutions to collaborate and train models without accessing raw data. Techniques like FedAvg gather model updates to ensure their proper functioning across different datasets. However, most studies still lean toward centralized frameworks or limited datasets, highlighting the necessity of effective FL methods in brain tumor detection.

Machine learning (ML) and deep learning (DL) have greatly improved the neuroimaging diagnosis of brain tumors. Centralized training methods create significant risks to patient data and information security. Federated Learning offers a solution by allowing multiple institutions to train models simultaneously without sharing raw data [1]. FL has received a lot of attention in the health community, with surveys noting challenges and limitations such as non-independent and identically distributed (non-IID) data distributions, communication costs, and the lack of personalization [2]. To improve performance with non-IID datasets, online or adaptive weight aggregation methods have been suggested and have significantly improved results in segmentation tasks [3]. Optimized weight-sharing strategies have also proven to boost aggregation effectiveness in classification within brain tumor federated frameworks [4]. Additionally, multi-convolutional neural network (multi-CNN) ensemble-learned federated systems achieved better accuracy compared to individual systems, further demonstrating the value of ensemble learning in decentralized health imaging [5]. The overall FL pipeline for healthcare solutions emphasized privacy protection, scalability, and the challenges and barriers at the regulatory and technology fronts [6]. Experimental research utilizing deep learning models such as VGG16, ResNet50, and ConvNeXt in federated contexts confirmed high accuracy in the categorization of brain tumors under IID and non-IID settings [7]. Later studies focused on optimized segmentation performance through the consolidation of scalable FL and advanced security and privacy measures [8]. Alternative deep learning models that combine attention mechanisms and ResNet50 improve classification effectiveness, but they require a lot of computation [9]. The FL system through strengthened domain alignment and customized predictors improved multi-site adaptability for the identification of diseases in the brain [10]. Recent work covers privacy-preserving implementations using DenseNet architectures [11], reduced FL models using AlexNet for low-resource devices [12], and CNN-enabled federated architectures reaching near-centralized performance [13]. DenseNet121 combined with MLPs enhanced tumor identification accuracy while maintaining data confidentiality [14].

Newer methods such as federated adversarial learning frameworks were employed for MRI reconstruction to obtain high-resolution images while maintaining data privacy [15]. Peer-to-peer FL using Siamese CNNs provided better robustness to adversarial attacks while maintaining diagnostic accuracy [16]. Transfer learning using FL with adjusted CNNs has also led to better classification results. Large-scale surveys focusing on federated learning for classifying brain tumors noted significant challenges. These challenges include interpretability, communication overhead, and dealing with non-IID datasets [18]. Secure and robust MRI classification using FL and VGG networks was obtained at multiple institutions [19]. Finally, FL and transfer learning integrated systems and customized CNNs obtained high classification accuracy in brain tumors and had inherent potential for deployment in the clinical setting [20].

PROPOSED WORK

The paper discusses a privacy-friendly framework for detecting tumors using Federated Learning (FL) and deep learning models. Conventional machine learning approaches rely on central data storage. This reliance raises serious privacy and compliance issues, especially in medicine. Our framework tackles these concerns. It lets different institutions work together on training the model without sharing sensitive MRI data while staying within ethical and legal guidelines.

The system employs two powerful CNN models, VGG16 and DenseNet, for categorization and feature extraction. VGG16, by virtue of its simple and uniform architecture designed through the use of stacked 3×3 filters, provides good hierarchical feature representation. DenseNet, through the use of dense connectivity and feature reuse, accelerates gradient flow and reduces overfitting and, therefore, facilitates improved classification performance. To gather the learning from different clients, the FedAvg (Federated Averaging) algorithm is used. It calculates the weighted average of the model parameters locally. This approach results in a global model while taking advantage of decentralized training data.

Five clients are involved in this configuration. The dataset consists of 15,000 T1-weighted contrast-enhanced MRI images, distributed across five institutional clients, and each of them has a dataset of 3,000 MRI images labelled as glioma, pituitary, meningioma, and no-tumor classes. Each client

***Corresponding Author:** Nithin Kumar B

preprocesses its data individually by normalizing it, resizing it, and augmenting it, then trains the local model. Only the model weights are uploaded to the master server. The data is partitioned from a publicly available brain MRI dataset and distributed artificially to simulate multi-institution collaboration. The global model is compiled and redistributed back to the clients, and accuracy improves with every round of training.

WORKFLOW

The framework offers a method that uses federated learning to classify brain tumors. It integrates the latest deep learning architectures with training that safeguards data privacy. The process commences with data acquisition, using MRI images from various hospitals or local datasets. Instead of gathering sensitive data in one place, local clients train their models while keeping their data safe. The pipeline starts with image input, which undergoes preprocessing to improve quality, reduce noise, and normalize dimensions. Then, image thresholding is applied to highlight key areas, allowing for effective segmentation of tumor-affected regions. After segmentation, feature extraction identifies important characteristics of tumor structures. Features extracted from the data are fed into deep learning architectures such as VGG16 and DenseNet for processing, leading to efficient classification and meaningful feature learning. These models are trained locally at different institutions, and the final weight updates are sent to a federated server. The server combines these updates using the FedAvg algorithm, creating a global model trained without exchanging raw data. The global model takes advantage of the distributed data from many clients, enhancing both generalizability and accuracy.

The final phase of the system involves staging and classifying tumors. It can detect several forms of tumors, such as glioma, pituitary, and meningioma, while simultaneously detecting instances exhibiting no tumor. The system predicts the stage of each detected tumor, which is essential for planning the right treatments. This system offers an effective and high-performance framework for medical imaging analysis that combines federated learning with advanced deep learning architectures.

$$w_{global} = \sum_{i=1}^{K} \frac{n_i}{n} w_i \tag{1}$$

The equation illustrates the FedAvg process, which combines the local model updates from multiple clients into a unified global model. In this expression, $w$global represents the global model weights, while wi denotes the weights learned by the ith client. The term ni refers to the size of the training dataset at client i, while n denotes the total number of samples from all participating clients. By calculating a weighted average, clients with larger datasets have a bigger impact on the global model. Within this project, the equation ensures effective collaboration among five clients, enabling accurate brain tumor detection while safeguarding patient privacy.

FedAvg Model

$$w_{global} = \sum_{i=1}^{K} \frac{n_i}{n} w_i$$

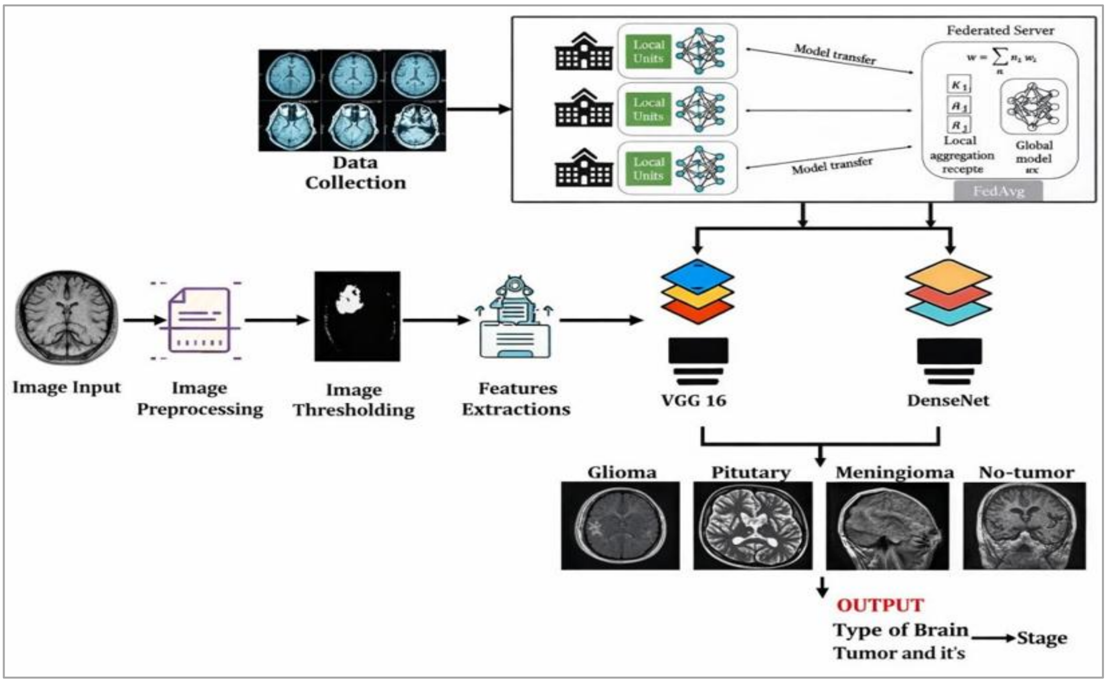

Figure 1: Workflow

RESULTS AND DISCUSSIONS

The federated learning system employed VGG16 and DenseNet models with the FedAvg algorithm. Five clients learned locally from their datasets and fed back to the global model via parameter aggregation. Such a distributed approach retained sensitive MRI data locally at each institution, mitigating privacy issues in healthcare. The results show that VGG16 and DenseNet performed well in classifying brain tumors. DenseNet achieved accuracies of 0.9039, 0.8908, 0.8515, 0.9345, and 0.9301, while VGG16 had 0.8952, 0.8865, 0.8734, 0.9214, and 0.9039 from all five clients, respectively. This indicates DenseNet generally outperformed VGG16 in average accuracy due to its dense connectivity. Nevertheless, VGG16 also showed competitive results, proving effective in medical image classification with federated learning.

These results are confirmed in the training history graphs. Constant improvements in validation and training accuracy were observed for both clients, with the highest validation accuracy for Client 4. Training and validation loss also steadily decreased, implying a smooth optimization procedure. Small fluctuations in loss and accuracy indicate data heterogeneity issues typical in federated learning.

These findings ratify federated learning as feasible for medical images, achieving high classification performance while ensuring privacy. It enables cooperation among institutions and robustness through varied data sources. Improvements for the future could involve tackling non-IID data, incorporating differential privacy, and scaling to more comprehensive datasets to improve use in a clinical setting.

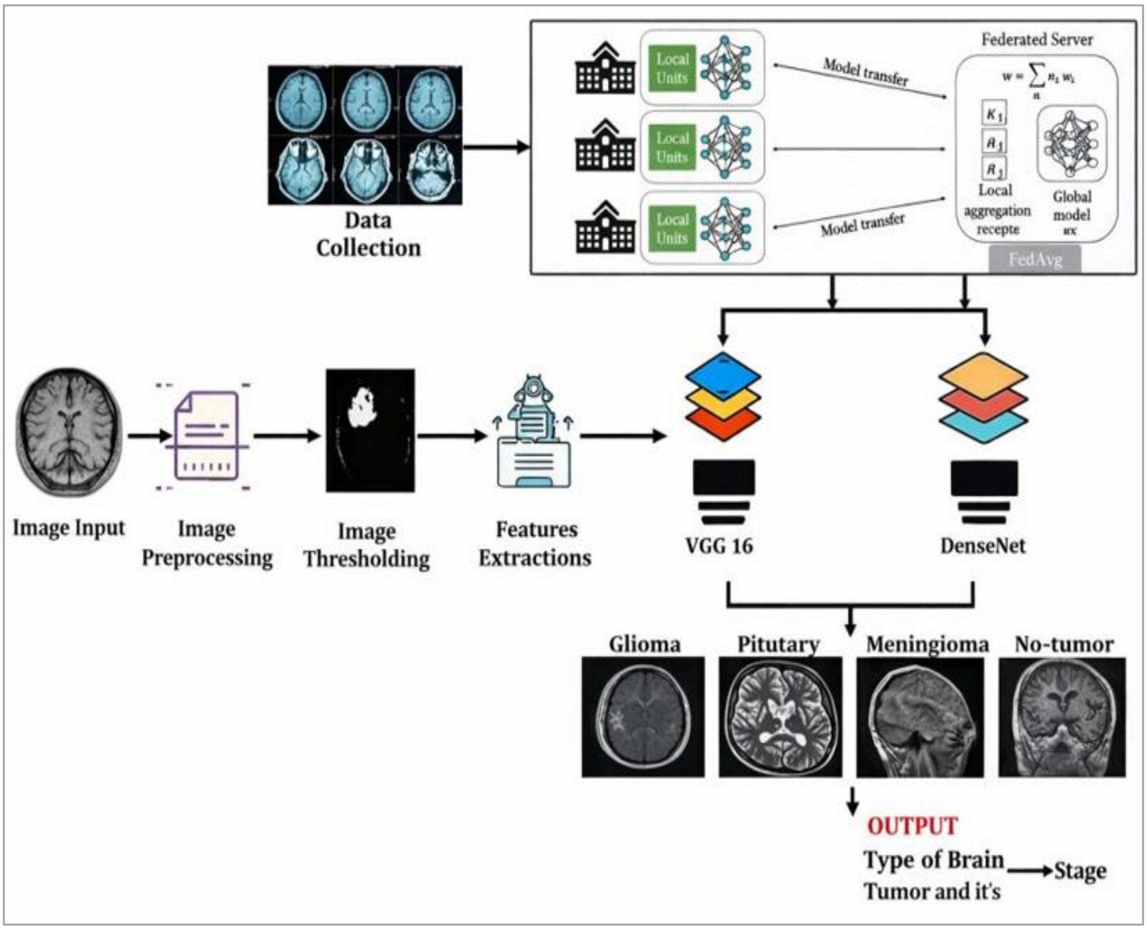

Figure 2: Accuracy

The Figure 2 shows how five clients performed during training and validation in the federated learning of brain tumor classification. The Training Accuracy chart (upper-left) displays a steady upward trend for all clients. They all reach an accuracy above 0.85 after a few epochs, indicating successful local learning. Similarly, the Validation Accuracy chart (upper-right) shows stable performance among the clients, with most of them achieving above 0.80. Small fluctuations, particularly in Client 3, highlight challenges stemming from non-IID data distributions, which are common in federated environments.

The Training Loss plot (bottom-left) indicates a gradual decrease in error in all clients, converging to low loss values, which is an indication of stability in the training procedure. The Validation Loss graph (bottom-right) also indicates a downward trend, albeit with higher heterogeneity across clients. For example, Clients 2 and

***Corresponding Author:** Nithin Kumar B

4 show higher variations than others, again a pointer toward dataset heterogeneity.

Overall, it is seen that Federated Averaging (FedAvg) was successful in averaging per-client updates to a robust global model. Despite minor variations among clients, the whole system attained good training along with validation performance, which, in turn, substantiates the stability of federated learning in categorizing brain tumors while ensuring data confidentiality.

Table 1

Model	C1	C2	C3	C4	C5	Mean
DenseNet121	0.9039	0.8908	0.8515	0.9345	0.9301	0.9022
VGG16	0.8952	0.8865	0.8734	0.9214	0.9039	0.8961

DenseNet121 achieved a higher mean federated accuracy (0.9022) compared to VGG16 (0.8961).

Table 2

Model	Federated Accuracy	Centralized Accuracy
DenseNet121	0.9022	0.9187
VGG16	0.8961	0.9123

The results indicate that both DenseNet121 and VGG16 achieve higher accuracy under centralized training compared to federated learning. DenseNet121 records 0.9187 in centralized training versus 0.9022 in federated settings, while VGG16 shows 0.9123 centrally compared to 0.8961 in the distributed setup. The small performance gap (~1.5–1.6%) demonstrates that the federated approach maintains competitive accuracy while preserving data privacy without pooling raw MRI data.

CONFUSION MATRIX

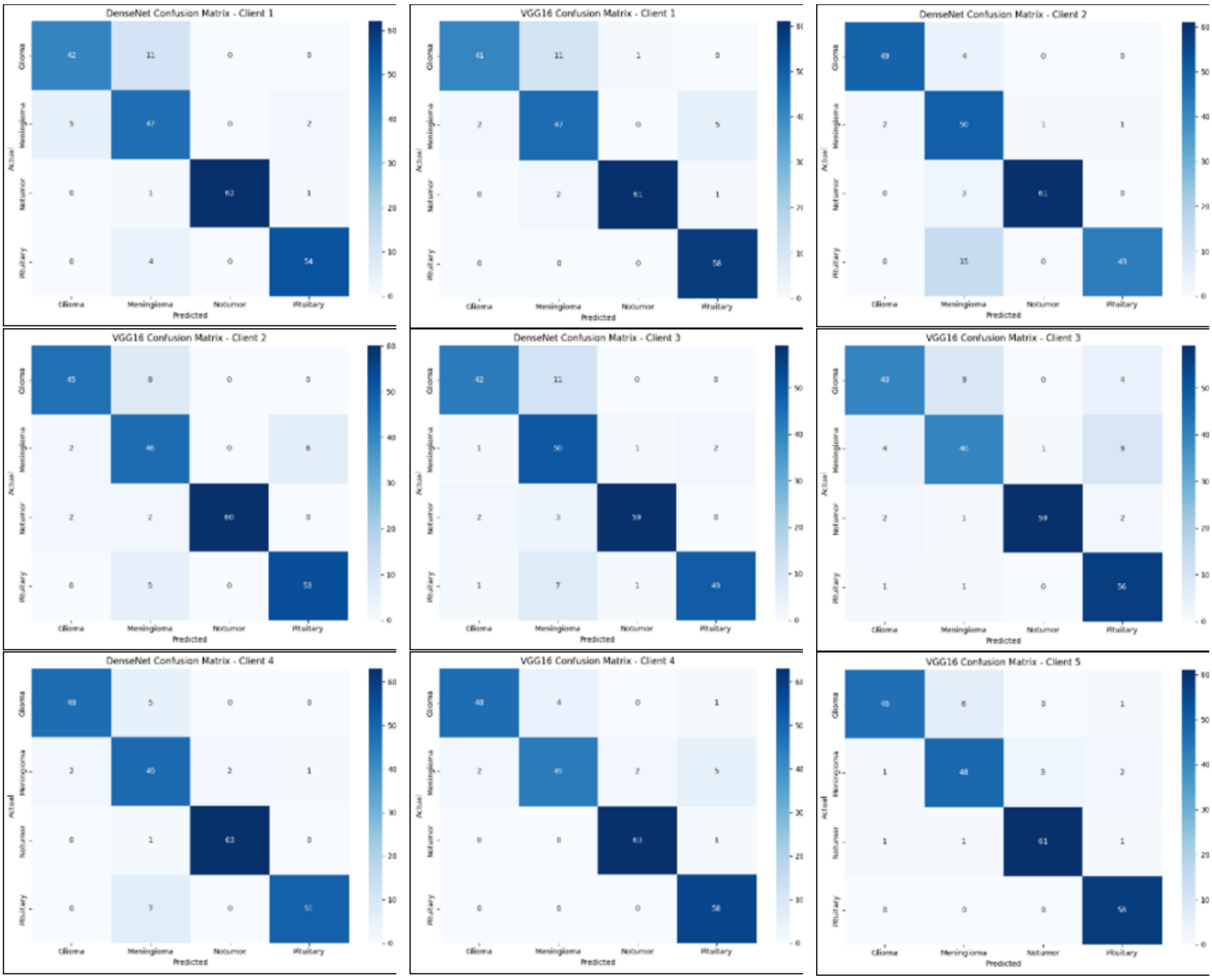

Figure 3: Confusion Matrix

The confusion matrices in Figure 3 also show the results of the classification of glioma, meningioma, no-tumor, and pituitary across five clients using DenseNet and VGG16. In Client 1, DenseNet performed robustly in no-tumor (62) and pituitary (54) classification, while glioma (42) and meningioma (41) had a few misclassifications,

***Corresponding Author:** Nithin Kumar B

primarily with pituitary. VGG16 for the same client behaved similarly in the no-tumor (61) and pituitary (52) classes, though it showed more errors in glioma and meningioma classification. DenseNet did exceptionally well in glioma (44) and no-tumor (63) in Client 2, with minimal misclassifications in meningioma (39) across glioma and pituitary. VGG16 was more even in its results, performing well in meningioma (40) and pituitary (53), showing better generalizability in this client's data. DenseNet excelled in glioma (42), no-tumor (59), and pituitary (43) in Client 3, while meningioma (39) was still relatively harder to predict. VGG16 was consistent in no-tumor (59) and pituitary (56), but confusion was greater in the glioma and meningioma classes, and so on for Client 4 and Client 5.

Overall, the results indicate that DenseNet consistently benefits from feature reuse and gradient flow, making its predictions more stable, while VGG16 occasionally outperforms it in meningioma classification. The misclassifications highlight the difficulty of distinguishing tumors with similar visual structures, emphasizing the significance of refining class-level accuracy in federated medical imaging tasks.

TUMOR DETECTION VISUALIZATION (OUTPUT)

The Figure 4 depicts the output of the pipeline for brain tumor detection for Client 3, with the ground truth being meningioma. The system begins with the raw input MRI image (top-left), depicting the original image sent from the client database. The image is converted into grayscale form (top-middle), where the information is compressed by reducing the number of colour channels while maintaining the structural detail for the purpose of brain tumor identification.

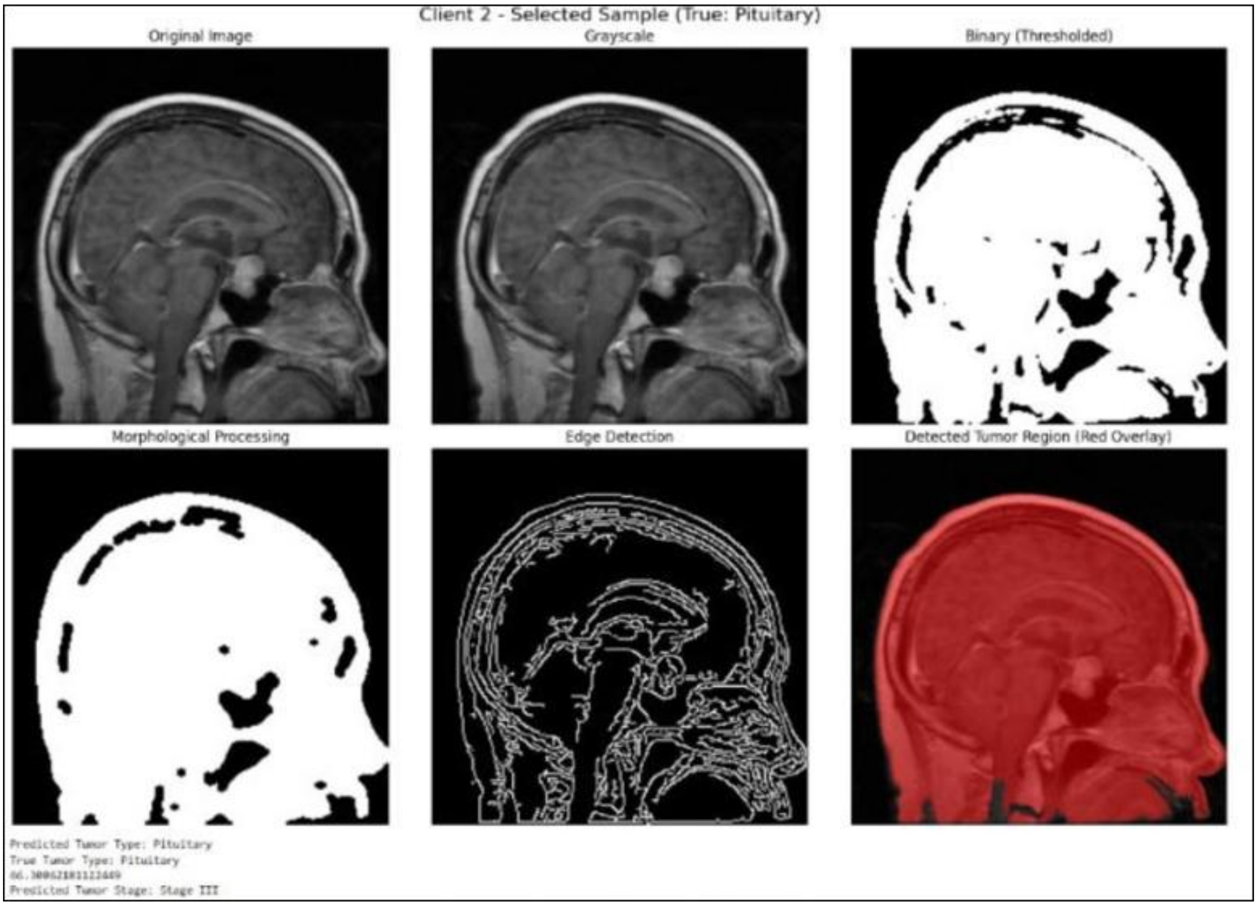

Figure 4: Output

Next, a binary thresholding step (top-right) is used to distinguish the tumor region from surrounding tissues, producing a high-contrast image where potential tumor areas appear in white. To improve the segmented area, morphological processing is performed in the bottom-left section. This step removes small noise and sharpens the form of the identified tumor. Following this, edge detection (bottom-middle) highlights the structural boundaries within the MRI, offering clear contours that assist in localizing the tumor more precisely.

Lastly, the identified tumor region is displayed as a red overlay (bottom-right) on the original scan. Such visualization offers clinicians an interpretable indication of the tumor position and extent that facilitates diagnosis and preparation for treatment. The output for Client 3 affirms that the federated framework can duly process and emphasize tumor regions while preserving patient data secrecy.

***Corresponding Author:** Nithin Kumar B

CONCLUSION

The current work shows the power of Federated Learning (FL) and deep learning-based approaches for brain tumor identification from MRI data. By using VGG16, DenseNet, and the Federated Averaging (FedAvg) algorithm, this study highlights the benefits of privacy-focused collaborative learning, which protects sensitive patient information at individual hospitals. In this framework, five clients were involved in federated training. Each client trained models locally and only shared parameters for aggregation. This approach maintained privacy while improving model strength. The results revealed that both DenseNet and VGG16 performed well. DenseNet achieved a mean accuracy of 0.9022, while VGG16 reached **0.8961** among the clients. DenseNet's dense connectivity structure allowed better gradient flow and feature reuse. Both models proved effective in a federated setting without needing centralized data. This work reinforces FL's potential in medicine by enabling collaboration without risking patient privacy. Some areas for future enhancement include handling non-IID data distributions, applying differential privacy for better security, and scaling the model for larger, more diverse datasets. These improvements could make this a viable solution for real-world medical diagnosis.

REFERENCES

1. Sheller, M. J., Edwards, B., Reina, G. A., Martin, J., Pati, S., Kotrotsou, A., Milchenko, M., et al. (2020). Federated learning in medicine: Facilitating multi-institutional collaborations without sharing patient data. *Scientific Reports, 10*(1), 12598. https://doi.org/10.1038/s41598-020-69250-1
2. Xu, J., Glicksberg, B. S., Su, C., Walker, P., Bian, J., & Wang, F. (2021). Federated learning for healthcare informatics. *Journal of Healthcare Informatics Research, 5*(1), 1–19. https://doi.org/10.1007/s41666-020-00082-4
3. Khan, M. I., et al. (2021). Adaptive weight aggregation in federated learning for brain tumor segmentation. In *International MICCAI Brainlesion Workshop* (pp. 455–469). Springer. https://doi.org/10.1007/978-3-030-87240-3_42
4. Mahlool, D. H., & Abed, M. H. (2022). Optimize weight sharing for aggregation model in federated learning environment of brain tumor classification. *Journal of Al-Qadisiyah for Computer Science and Mathematics, 14*(3), 76.
5. Islam, M., Reza, M. T., Kaosar, M., & Parvez, M. Z. (2023). Effectiveness of federated learning and CNN ensemble architectures for identifying brain tumors using MRI images. *Neural Processing Letters, 55*(4), 3779–3809. https://doi.org/10.1007/s11063-023-11125-0
6. Joshi, M., Pal, A., & Sankarasubbu, M. (2022). Federated learning for healthcare domain—Pipeline, applications and challenges. *ACM Transactions on Computing for Healthcare, 3*(4), 1–36. https://doi.org/10.1145/3533709
7. Viet, K. L. D., Ha, K. L., Quoc, T. N., & Hoang, V. T. (2023). MRI brain tumor classification based on federated deep learning. In *2023 Zooming Innovation in Consumer Technologies Conference (ZINC)* (pp. 131–135). IEEE. https://doi.org/10.1109/ZINC58345.2023
8. Ullah, F., Nadeem, M., Abrar, M., Amin, F., Salam, A., & Khan, S. (2023). Enhancing brain tumor segmentation accuracy through scalable federated learning with advanced data privacy and security measures. *Mathematics, 11*(19), 4189. https://doi.org/10.3390/math11194189
9. Oladimeji, O. O., & Ibitoye, A. O. J. (2023). Brain tumor classification using ResNet50-convolutional block attention module. *Applied Computing and Informatics*. https://doi.org/10.1108/ACI-08-2022-0062
10. Zhang, C., Meng, X., Liu, Q., Wu, S., Wang, L., & Ning, H. (2023). FedBrain: A robust multi-site brain network analysis framework based on federated learning for brain disease diagnosis. *Neurocomputing, 559*, 126791. https://doi.org/10.1016/j.neucom.2023.126791
11. Kalpana, V., Chowdary, J. S., Sravya, T. N. V. L., Reddy, A. A., Pravallika, P., & Gnanasri, V. (2023). Implemented global model for brain tumor detection using federated learning. In *2023 7th International Conference on Electronics, Materials Engineering & Nano-Technology (IEMENTech)* (pp. 1–5). IEEE. https://doi.org/10.1109/IEMENTech60402.2023.10445659
12. Trivedi, N. K., Shukla, S., Agarwal, A. K., Tiwari, R. G., & Gautam, V. (2023). Brain tumour diagnosis with lightweight federated learning using identically distributed images. In *2023 International Conference on Artificial Intelligence for Innovations in Healthcare Industries (ICAIIHI)* (Vol. 1, pp. 1–5). IEEE.
13. Bhadauriya, S., Merothiya, T., Yadav, S. C., & ChandraPrabha, M. (2023). Detection of brain tumour using CNN in federated machine learning. In *2023 5th International Conference on Advances in Computing, Communication Control and Networking (ICAC3N)* (pp. 653–658). IEEE. https://doi.org/10.1109/ICAC3N60023.2023.10390290
14. Nandan, U., Sai, C., Sai, N., & Viswanadapalli, A. (2024). Enhanced brain tumor detection and privacy preserving using federated learning. *International Journal of Scientific Research in Science and Technology, 11*(6), 131–144.
15. Ahmed, A. S., Feng, J., Ferzund, J., Yaqub, M., Ali, M. U., Manan, M. A., & Raheem, A. (2025). FAME: A federated adversarial learning framework for privacy-preserving MRI reconstruction. *Applied Magnetic Resonance, 56*(6), 681–722. https://doi.org/10.1007/s00723-025-01692-0

***Corresponding Author:** Nithin Kumar B

16. Onaizah, A. N., Xia, Y., & Hussain, K. (2025). FL-SiCNN: An improved brain tumor diagnosis using siamese convolutional neural network in a peer-to-peer federated learning approach. *Alexandria Engineering Journal, 114*, 1–11. https://doi.org/10.1016/j.aej.2025.01.032
17. Albalawi, E., Alshammari, M. T. R., Thakur, A., Kumar, V. V., Gupta, M., Khan, S. B., & Almusharraf, A. (2024). Integrated approach of federated learning with transfer learning for classification and diagnosis of brain tumor. *BMC Medical Imaging, 24*(1), 110. https://doi.org/10.1186/s12880-024-01208-2
18. Ma, Y. (2025). Federated learning for brain tumor diagnosis: Methods, challenges and future prospects. In *ITM Web of Conferences* (Vol. 70, Article 03028). EDP Sciences. https://doi.org/10.1051/itmconf/20257003028
19. Appasami, G., & Savarimuthu, N. (2025). Federated learning for secure medical MRI brain tumor image classification. *The European Physical Journal Special Topics*. https://doi.org/10.1140/epjs/s11734-025-01547-5
20. Ravali, P., Reddy, P. C. S., & Praveen, P. (2024). Brain tumor classification and diagnosis using federated learning with transfer learning. In *2024 4th International Conference on Mobile Networks and Wireless Communications (ICMNWC)* (pp. 1–5). IEEE.