2024 2nd International Conference on Information and Communication Technology (ICICT)
October 21-22, Dhaka, Bangladesh

Optimizing Privacy and Efficiency in Brain Tumor Classification through Advanced Non-IID Federated Deep Learning

1st Md Samsuzzaman
Faculty of Computer Sc. and Engr.
Patuakhali Sc. and Tech. University
Patuakhali, Bangladesh
sobuz@pstu.ac.bd

2nd Rakibul Hasan Sezan
Faculty of Computer Sc. and Engr.
Patuakhali Sc. and Tech. University
Patuakhali, Bangladesh
sejan16@cse.pstu.ac.bd

3rd Arjon Golder
Faculty of Computer Sc. and Engr.
Patuakhali Sc. and Tech. University
Patuakhali, Bangladesh
arjonnill07@gmail.com

4th Md. Abdul Masud
Faculty of Computer Sc. and Engr.
Patuakhali Sc. and Tech. University
Patuakhali, Bangladesh
masud@pstu.ac.bd

5th Golam Md. Muradul Bashir
Faculty of Computer Sc. and Engr.
Patuakhali Sc. and Tech. University
Patuakhali, Bangladesh
murad@pstu.ac.bd

***Abstract*—Recent advancements in Artificial Intelligence (AI) have significantly transformed various fields, especially medical diagnostics. However, centralized deep learning models face significant challenges due to the increasing data volumes from edge devices, including issues related to data privacy and heterogeneity. In this study, a federated deep learning model for brain tumor classification using MRI data is presented. The model enhances the MobileNetV3 architecture with Squeeze-and-Excitation (SE) and Convolutional Block Attention Module (CBAM) blocks. A novel non-IID (non-Independent and Identically Distributed) data partitioning strategy, proposed in this study, ensures robust data distribution across clients. Utilizing the Flower framework and the FedOpt algorithm, the model achieved a notable accuracy of 97.40% in eight training rounds, operating efficiently on 15GB of RAM and 10GB of GPU memory. This research underscores the potential of Federated Learning (FL) to address data privacy and resource constraints, demonstrating its efficacy in accurate brain tumor classification. These findings pave the way for future scalable and secure medical AI applications.**

***Index Terms*—Federated Learning, MobileNetV3, Squeeze-and-Excitation (SE), Convolutional Block Attention Module (CBAM), Non-IID Data, Data Privacy, FedOpt Algorithm.**

I. INTRODUCTION

The latest breakthroughs in AI have led to transformative capabilities across various fields, particularly in medical diagnostics [1]. The increasing volume of data generated by edge devices, such as medical imaging equipment, presents significant challenges for deploying centralized deep learning models [2], [3]. FL addresses data scarcity by enabling collaborative model training without sharing raw data, thus safeguarding patient privacy [4]. However, privacy regulations, such as HIPAA and GDPR, restrict data sharing, further complicating access to brain tumor MRI data [5]. While existing research on both centralized and federated deep learning has shown potential in enhancing brain tumor diagnosis, a significant gap remains in addressing the resource limitations of edge devices used in FL [4], [6], [7]. This study introduces an innovative federated deep learning model for brain tumor classification using MRI data. The MobileNetV3 architecture [8] was customized and enhanced with SE [9] and CBAM blocks [10] through transfer learning. Furthermore, a novel non-IID dataset partitioning algorithm was developed to evaluate the model's robustness across multiple clients. Performance optimization was conducted using the Flower framework [11] and the FedOpt algorithm [12], leading to significant advancements. The key contributions of this study are as follows:

- Efficiently managing non-IID data in medical imaging.
- Enhancing accuracy through advanced attention mechanisms.
- Developing a non-IID dataset partitioning algorithm.
- Optimizing performance in resource-constrained environments.

The remainder of this article is organized as follows:Section II reviews related work, Section III covers the dataset and methodology, Section IV presents the results and discussion, and Section V concludes the paper.

II. RELATED WORK

FL Initially introduced with the Federated Averaging (FedAvg) algorithm [13], enables model training directly on user devices without sharing raw data, ensuring data privacy. Studies have shown that FL can achieve accuracy in brain tumor segmentation and classification comparable to centralized models, while addressing key challenges such as privacy, security, and data heterogeneity. For example, one study reported 80.17% accuracy [14], while another achieved Dice scores of 90.67%, 86.23%, and 78.90% [15]. Additional research demonstrated 82% accuracy on the BT-small-2c dataset and 96% on the BT-large-3c dataset [16]. FL has also achieved 98.69% classification accuracy on IID data and over 93% on non-IID data [17], with 91.05% accuracy reported in brain tumor identification using CNN ensemble architectures [18].

While FL shows promising accuracy in brain tumor classification, its evaluation on non-IID datasets remains limited, which is crucial for testing its robustness and generalizability in real-world scenarios with non-uniform data distribution. Further research is needed to assess the resource efficiency and feasibility of deploying these models on mobile and edge computing platforms [4] [7].

III. Methodology

A. Dataset Preparation

In this study, a publicly available brain tumor MRI dataset from Kaggle [19], which combines Br35H, Figshare and SARTAJ datasets, was used. The dataset comprises 7023

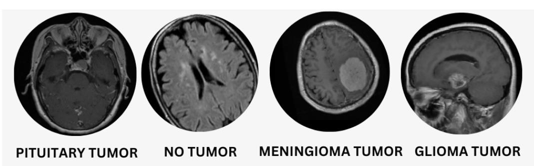

Fig. 1: Sample images of brain tumors

images, categorized into four classes: glioma (1714 images), meningioma (1858 images), no tumor (2297 images), and pituitary (1857 images). The dataset was split into training and testing sets, with the training set further partitioned using the proposed balanced non-IID strategy (Algorithm 1) to maintain data heterogeneity across clients. To enhance model generalization, the images were resized to 224x224 pixels to ensure consistency in model training and performance evaluation.Additionally, random rotations within ±10 degrees were applied to improve robustness. Pixel values were normalized to the [0, 1] range to standardize intensity values across the dataset.

B. Proposed Custom Model Architecture

The custom model architecture utilized in this study, depicted in Figure 2(c), is based on MobileNetV3 Large [8], integrated with transfer learning to leverage its pre-trained weights. This approach is chosen for its efficiency and accuracy, making it ideal for federated deep learning and enhancing performance for our specific task. Key modifications include integrating SE [9] and CBAM blocks [10] depicted in Figure 2(a) and 2(b). SE blocks are added to layers 3 and 6 to recalibrate channel-wise features using convolutional layers with ReLU and sigmoid activations. CBAM blocks, added to layers 9 and 12, refine feature representations by focusing on relevant spatial and channel information through sequential channel and spatial attention mechanisms. Additionally, the classifier is modified with dropout layers (50% rates) before and after ReLU activations to prevent overfitting. This combination of SE and CBAM blocks, within the lightweight MobileNetV3 framework and enhanced by transfer learning, significantly improves the network's ability to accurately classify complex medical images, such as MRIs, by focusing on crucial features and maintaining generalization capabilities.

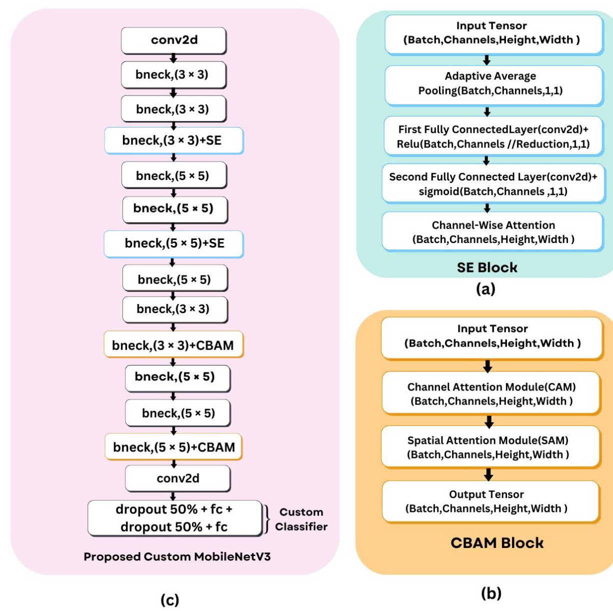

Fig. 2: Proposed model architecture with (a) SE, (b) CBAM, (c) custom MobileNetV3 and custom classifier layer

C. Data Partitioning

A balanced non-IID partitioning strategy was proposed to distribute data among clients, ensuring diverse and representative data subsets for effective training in FL setup. This custom partitioning process was developed to meet the specific requirements of our FL approach. To mitigate ordering bias, data indices were shuffled and then assigned to clients in a round-robin manner, ensuring that each client received a mix of samples from different classes. The balanced distribution was verified by ensuring that the minimum size of the data subsets allocated to each client was not less than the batch size. Data loaders for each client were subsequently created using the partitioned data, configured to shuffle the data with a specified batch size and number of worker processes for efficient data loading during training.

This partitioning strategy is crucial in FL, as it ensures that each client's local model is trained on diverse data, thus improving the robustness and generalization capabilities of the global model. The algorithm for the proposed balanced non-IID partitioning is as follows:

Algorithm 1 Proposed Balanced Non-IID Partitioning of Dataset

Require: Dataset D with C classes, number of clients N, batch size B
Ensure: A list of client indices $client\_indices$ with balanced non-IID partitions
  Initialize a dictionary $class\_indices$ with C empty lists
  for each $(index, label)$ in D **do**
    Append $index$ to $class\_indices[label]$
  end for
  for each list in $class\_indices$ **do**
    Shuffle the list
  end for
  Initialize a list $client\_indices$ with N empty lists
  for each $(class\_idx, indices)$ in $class\_indices$ **do**
    for each i, idx in $indices$ **do**
      Append idx to $client\_indices[i\%N]$
    end for
  end for
  $min\_size \leftarrow$ minimum size of lists in $client\_indices$
  if $min\_size < B$ **then**
    Handle insufficient batch size case, e.g., adjust parameters or data
  end if
  return $client\_indices$

D. Training Process

The training process and the implementation of the models were meticulously designed to ensure optimal performance and stability. The hyperparameters were carefully tuned to balance training stability and model convergence. The resources utilized during training included 15GB of system RAM and 10GB of GPU memory, ensuring efficient processing of the data and model parameters depicted in Table I.

TABLE I: Training parameters and resource usage

Parameter / Resource	Value / Usage
Learning Rate	0.0005
Batch Size	20
Number of Epochs	5
Number of Clients	8
Number of Rounds	8
Training Hardware	Google Colab TPU
System RAM	15GB
Memory	10GB

E. Proposed Federated Deep Learning Approach

The proposed horizontal FL framework leverages the Ray [20] platform to achieve efficient and scalable communication between clients and the central server as shown in Fig. 3. Clients perform local model training while preserving data privacy by retaining raw data on-device. Only model weights are shared with the server, where the FedOpt algorithm aggregates them to enhance the global model. The global model is iteratively updated and broadcast back to clients, ensuring continuous model refinement while maintaining privacy. To optimize system performance, Key system configurations include a 50% client participation rate with a minimum of four clients for training and evaluation, ensuring robustness across heterogeneous environments.

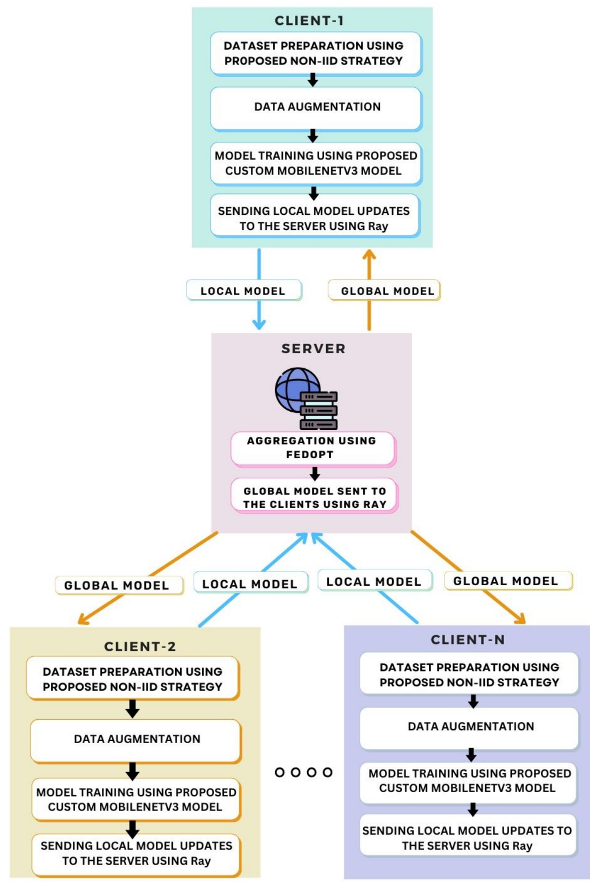

Fig. 3: Proposed federated deep learning approach with FedOpt strategy

The novel integration of SE, CBAM Blocks and FedOpt along with proposed Non-IID partitioning strategy uniquely positions the proposed approach as a highly efficient solution for decentralized medical image classification tasks, distinguishing it from existing FL models.

IV. RESULTS AND DISCUSSION

A. The Performance of the Model

The proposed federated deep learning framework was evaluated by tracking model accuracy and loss over multiple

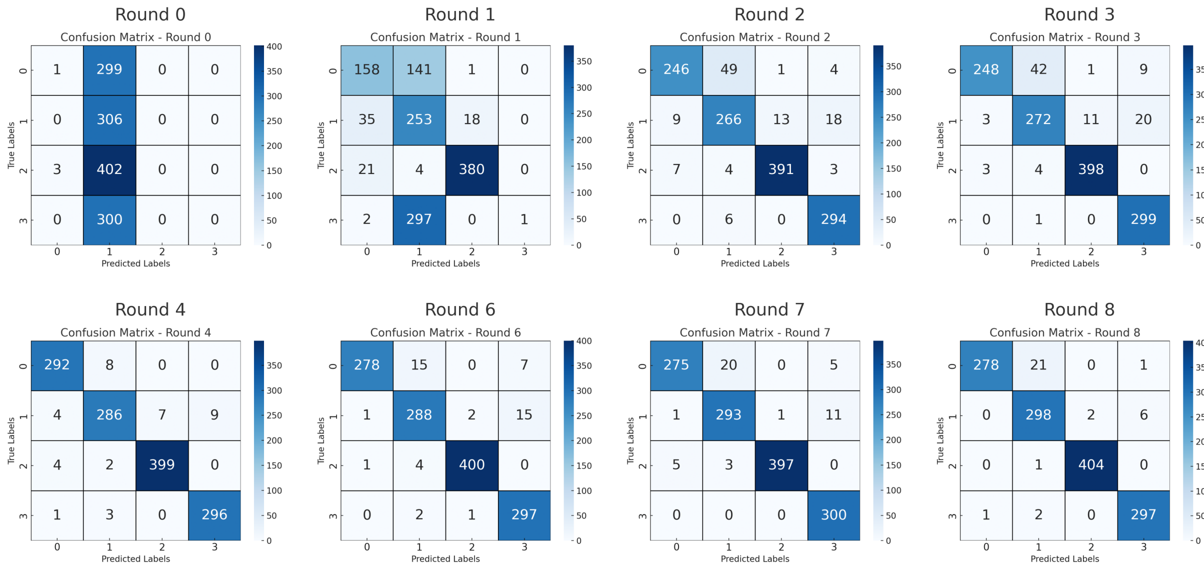

Fig. 4: Confusion matrices over multiple rounds

training rounds. As shown in Fig. 5 accuracy improved from approximately 23% in the initial round to more than 97% in the eighth round, demonstrating the effectiveness of the learning process. Model loss declined steeply from around 7.0 in the first round to below 0.5 by the final round, indicating efficient convergence and reduced error rates.

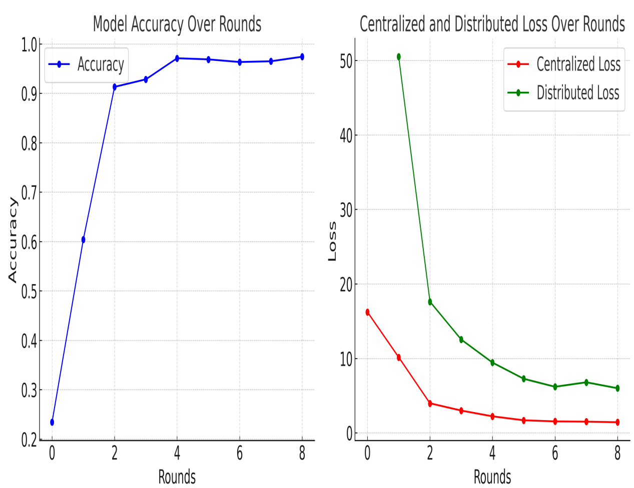

Fig. 5: Model accuracy and loss over rounds

The confusion matrices in Fig. 4 detail the model classification performance in training rounds. Initially, significant misclassifications were observed, which diminished markedly as training progressed. In the second round, substantial improvement was evident, which continued into subsequent rounds. The final confusion matrix for round eight shows high precision and recall with minimal misclassifications, demonstrating the improved ability of the model to classify brain tumor images into glioma, meningioma, pituitary tumor and without tumor categories.

The key performance metrics showed remarkable improvement. Precision increased from 12.10% in the initial round to 97.35% by the final round. Recall values increased from 25.08% to 97.20%, indicating improved identification of true positives. The F1 score, which represents the harmonic mean of precision and recall, improved from 9.65% to 97.23%, reflecting the overall enhancement in classification ability according to Table II.

TABLE II: Evaluation metrics over training rounds

Round	Precision	Recall	F1-Score	Accuracy	Centralized Loss	Distributed Loss
0	0.1210	0.2508	0.0965	0.2342	16.2259	-
1	0.7619	0.5738	0.5175	0.6041	10.1542	50.4968
2	0.9111	0.9087	0.9085	0.9130	3.9745	17.6162
3	0.9278	0.9237	0.9237	0.9283	2.9952	12.5328
4	0.9699	0.9699	0.9699	0.9710	2.2214	9.4365
5	0.9673	0.9679	0.9676	0.9687	1.6925	7.2630
6	0.9621	0.9614	0.9612	0.9634	1.5429	6.1898
7	0.9632	0.9636	0.9629	0.9649	1.5034	6.7928
8	0.9735	0.9720	0.9723	0.9741	1.4309	5.9924

B. The Performance Comparison and Discussion

The proposed federated deep learning model, a custom MobileNetV3 Large enhanced with SE and CBAM blocks, achieves performance comparable to traditional machine learning methods and existing federated learning approaches in brain tumor classification, as shown in Table III. Unlike centralized models, which struggle with data privacy and generalization, and much of the existing FL research that lacks sufficient testing on heterogeneous data and resource-constrained environments, this approach effectively addresses these challenges.

TABLE III: Comparison of different models for brain tumor classification

Study	Accuracy	Technique
Srinivasan and Saravanan [21]	93.81%	Hybrid Deep CNN Model
Lisang Zhou [14]	80.17%	EfficientNetB0 with FedAvg
Moinul Islam, [17]	91.05%	Federated learning and base ensemble model on Non-IID data Partitioning
Proposed Model	**97.40%**	**Customised MobileNetV3 with SE and CBAM block, FedOpt algorithm, and Non-IID data partitioning**

By utilizing the Flower framework and FedOpt algorithm, the proposed federated deep learning model ensures data privacy through decentralized data management. A balanced non-IID partitioning strategy enhances the model's robustness across diverse data subsets. The integration of MobileNetV3 Large, with SE and CBAM blocks, further improves feature extraction, achieving 97.40% accuracy after just eight training rounds. Moreover, the model efficiently operates with 15GB RAM and 10GB GPU memory, demonstrating its effectiveness in maintaining privacy and delivering high performance in resource-constrained environments for medical image classification.

V. Conclusion

The research presents an advanced federated deep learning model for brain tumor classification using MRI data. The MobileNetV3 architecture has been enhanced with SE and CBAM blocks through transfer learning, and a custom non-IID partitioning algorithm was proposed. This allowed the model to be trained on multiple clients, demonstrating robustness and generalizability. Utilizing the Flower framework and the FedOpt algorithm, a notable 97.40% accuracy was achieved within eight training rounds, operating with just 15GB of RAM and 10GB of GPU memory. Although significant advances have been made, more research is needed to scale the FL framework for larger datasets and implement real-time clinical systems. This study underscores the crucial role of federated learning in medical imaging, highlighting its potential to develop secure, efficient, and decentralized medical AI applications.

References

[1] D. Miller and E. Brown, "Artificial intelligence in medical practice: The question to the answer?," *The American journal of medicine*, vol. 131, no. 2, pp. 129–133, 2017.

[2] A. Lundervold and A. Lundervold, "An overview of deep learning in medical imaging focusing on mri," *Zeitschrift fur medizinische Physik*, vol. 29, no. 2, pp. 102–127, 2018.

[3] S. K. Zhou, H. Greenspan, C. Davatzikos, J. Duncan, B. Ginneken, A. Madabhushi, J. L. Prince, D. Rueckert, and R. Summers, "A review of deep learning in medical imaging: Imaging traits, technology trends, case studies with progress highlights, and future promises," *Proceedings of the IEEE*, vol. 109, pp. 820–838, 2020.

[4] M. J. Sheller, G. A. Reina, B. Edwards, J. Martin, and S. Bakas, "Multi-institutional deep learning modeling without sharing patient data: A feasibility study on brain tumor segmentation," *Brainlesion : glioma, multiple sclerosis, stroke and traumatic brain injuries*, vol. 11383, pp. 92–104, 2018.

[5] Y.-B. Choi, K. E. Capitan, J. S. Krause, and M. M. Streeper, "Challenges associated with privacy in health care industry: Implementation of hipaa and the security rules," *Journal of Medical Systems*, vol. 30, pp. 57–64, 2006.

[6] W. Li, F. Milletarì, D. Xu, N. Rieke, J. Hancox, W. Zhu, M. Baust, Y. Cheng, S. Ourselin, M. Cardoso, and A. Feng, "Privacy-preserving federated brain tumour segmentation," pp. 133–141, 2019.

[7] M. S. Ali, M. M. Ahsan, L. Tasnim, S. Afrin, K. Biswas, M. M. Hossain, M. M. Ahmed, R. Hashan, M. K. Islam, and S. Raman, "Federated learning in healthcare: Model misconducts, security, challenges, applications, and future research directions–a systematic review," *arXiv preprint arXiv:2405.13832*, 2024.

[8] A. Mabrouk, A. Dahou, M. A. Elaziz, R. P. Díaz Redondo, and M. Kayed, "Medical image classification using transfer learning and chaos game optimization on the internet of medical things," *Computational Intelligence and Neuroscience*, vol. 2022, no. 1, p. 9112634, 2022.

[9] J. Hu, L. Shen, S. Albanie, G. Sun, and E. Wu, "Squeeze-and-excitation networks," *2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 7132–7141, 2017.

[10] H. Arabian, F. A. Dalla, N. A. Jalal, T. A. Alshirbaji, and K. Moeller, "Attention networks for improving surgical tool classification in laparoscopic videos," *Current Directions in Biomedical Engineering*, vol. 8, pp. 676–679, 2022.

[11] Y. Liu, J.-J. Peng, J. Kang, A. M. Iliyasu, D. Niyato, and A. El-latif, "A secure federated learning framework for 5g networks," *IEEE Wireless Communications*, vol. 27, pp. 24–31, 2020.

[12] M. Asad, A. Moustafa, and T. Ito, "Fedopt: Towards communication efficiency and privacy preservation in federated learning," *Applied Sciences*, 2020.

[13] B. McMahan, E. Moore, D. Ramage, S. Hampson, and B. A. y Arcas, "Communication-efficient learning of deep networks from decentralized data," in *Artificial intelligence and statistics*, pp. 1273–1282, PMLR, 2017.

[14] L. Zhou, M. Wang, and N. Zhou, "Distributed federated learning-based deep learning model for privacy mri brain tumor detection," *arXiv preprint arXiv:2404.10026*, 2024.

[15] M. David, "Efficient federated tumor segmentation via normalized tensor aggregation and client pruning," *Lecture Notes in Computer Science*, 2022.

[16] D. H. Mahlool and M. H. Abed, "Distributed brain tumor diagnosis using a federated learning environment," *Bulletin of Electrical Engineering and Informatics*, 2022.

[17] 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*, 2022.

[18] E. Albalawi, T. Mahesh, A. Thakur, V. V. Kumar, M. Gupta, S. Bhatia Khan, and A. Almusharraf, "Integrated approach of federated learning with transfer learning for classification and diagnosis of brain tumor," *BMC Medical Imaging*, vol. 24, no. 1, p. 110, 2024.

[19] M. Nickparvar, "Brain tumor mri dataset." https://www.kaggle.com/datasets/masoudnickparvar/brain-tumor-mri-dataset.

[20] P. Moritz, R. Nishihara, S. Wang, A. Tumanov, R. Liaw, E. Liang, W. Paul, M. I. Jordan, and I. Stoica, "Ray: A distributed framework for emerging ai applications," *ArXiv*, vol. abs/1712.05889, 2017.

[21] S. Srinivasan, D. Francis, S. K. Mathivanan, H. Rajadurai, B. D. Shivahare, and M. A. Shah, "A hybrid deep cnn model for brain tumor image multi-classification," *BMC Medical Imaging*, vol. 24, no. 1, p. 21, 2024.