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Alzheimer’s Disease Detection Using Deep Learning and Federated Learning

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Abstract:

Appropriate and precise diagnosis of brain diseases is crucial, as many forms of Alzheimer’s disease display similar indications in their initial stages. Most automatic detection or classification systems based on deep learning present confidentiality concerns due to their use of integrated computing and local storage data requirements for training. The goal of this paper is to defend sensitive patient data by proposing a deep learning algorithm that utilizes Federated learning techniques in an IoT-based edge computing framework. It is demonstrated that the confidentiality of patient data can be maintained while preserving accuracy and efficiency. This method provides a secure edge data protection model that eliminates the requirement for centralized storage. This paper discusses the strategy and implementation of the federated structure, taking into account the number of devices in the network, memory, and processing capabilities. The success and accuracy of the proposed algorithm, which comes to 98.6%, are also established with empirically defined metrics such as accuracy and defined thresholds.

Keywords: *IoT, Alzheimer’s Classification, Federated Learning, Deep Learning.*

I. INTRODUCTION

Transfer learning [1] leverages prior knowledge to address new, related challenges more effectively, using data from adjacent fields. Computational intelligence has enhanced this process through network-based, Bayes, fuzzy, and intelligence-based transfer learning [2].

Classification of Alzheimer's with a focus on protecting privacy and managing data heterogeneity amongst institutions. One noteworthy study tackles the issues of unbalanced medical datasets and patient privacy by combining conditional generative adversarial networks (cGANs) with split federated learning (SFL). While cGANs create synthetic samples to enhance classification performance on minority classes, this method allows decentralized agents to cooperatively train models without sharing raw data. The system demonstrated the viability of federated learning frameworks in practical medical scenarios while maintaining privacy by achieving an accuracy of roughly 83.54 percent on Alzheimer's classification tasks [3]

Alzheimer's is a neurodegenerative disorder that damages brain cells and impairs brain function, changing memory and making life unstable for people [4]. The two primary factors thought to contribute to the pathophysiology of AD are the over-production of amyloid-ß (Aß) and the hyperphosphorylation of aberrant proteins. Cell death and compromised memory and learning result from the accumulation of tau neurofibrillary entanglements and A-plaques, which also change nucleo-cellular cytoplasmic transfer between neurons [5]. It is impossible to overestimate the importance of accurate and timely disease identification and detection. Economic growth, the development of IT, and the introduction of clinical information processing technologies have made this necessary. Early detection plays a critical role in this process and is not only a medical necessity but also a social concern.

In Figure 1, the complex framework used in this study is demonstrated by the illustrations of the integrated IoT key enabling technologies. Cloud computing is essential to this framework because it uses shared computing resources to aggregate models and produce a comprehensive universal model.

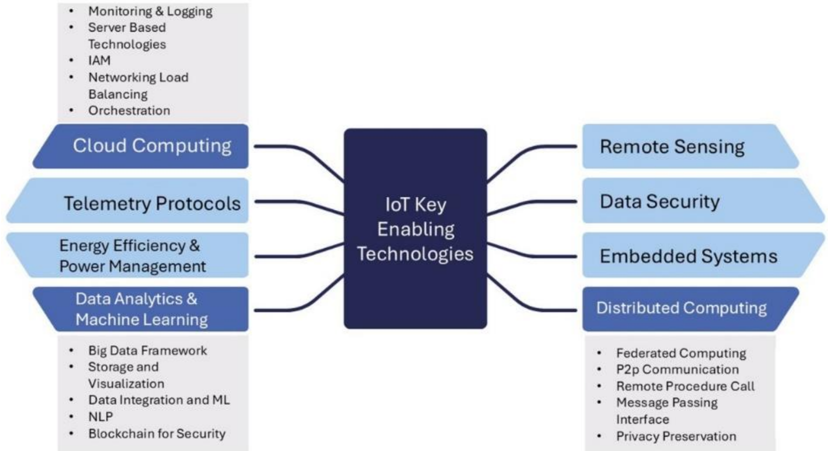


Figure 1. IoT Essential Supporting Technologies.

II. Literature Review

Alzheimer's disease (AD) causes significant cognitive impairment and functional deterioration in sufferers, although the specific etiology is unclear. Early detection of Alzheimer's disease is critical to enabling prompt therapies that can reduce its development. This study addresses the complexity and unpredictability of Alzheimer's disease using a multimodal approach that includes medical imaging and demographic data. Accurate diagnosis requires local storage for data training and involves centralized computing and federated learning [6]. The majority of current automated classification techniques that use machine learning or deep learning raise privacy concerns. Alzheimer's disease [7] is a dangerous condition that is common in human societies and, regrettably, is becoming more common every day. The number of patients is increasing, but there are fewer physical doctors available, and their schedules are full. The field of AD digital healthcare is extremely complex and uses a variety of technologies, such as deep learning algorithms, cloud computing, and fog computing. Nevertheless, the high computational time required for AD detection procedures has presented difficulties for the deployment of these fog, cloud, and deep learning technologies [8].
In a study author established a hardware acceleration framework for an FL model to expedite both training and testing phases. The hardware-accelerator was constructed with an Altera 10 GX FPGA and programmed in VHDL. Experimental results demonstrate that the proposed techniques provide a marked improvement over other algorithms considered 'best-in-class' for training time while achieving 89% accuracy and 87% sensitivity for the early discovery of Alzheimer's [9]. Another suggested method makes use of two crucial tactics: boosting computation per client in the interim between rounds and boosting parallelism by using more clients in every communication round. Additionally, the effects of extreme quantity distribution skew are investigated. The effectiveness of each of these configurations is assessed using a convolutional neural network [10].

Building strong models for medical data has been thought to be possible with data-driven deep learning, which frequently needs a lot of different data to be effective. However, the current medical datasets are dispersed and small in size due to the high cost of collection and privacy restrictions. A data-private collaborative learning method called FL via model extraction allows the model to use all available data without direct sharing. The multi-site average prediction scores on the public dataset are used to distill the data knowledge and share it. However, because of the data domain shift in MRI data brought on by acquisition protocols, recruitment criteria, etc., the average consensus is not optimal for each client. In this study, the Author suggests federated conditional mutual learning (FedCM) to enhance performance by considering both client similarity and local performance [11].
In [12] author proposed a CNN that receives pre-processed MRI images and creates a prediction file. After that, this prediction file is distributed to clients for local training along with demographic information. Training data is integrated using a belief rule base (BRB), multiple data sources into a singular diagnostic model. Even though a wealth

of data is available in medical facilities, the open-sourcing of such information is restricted due to laws focused on protecting sensitive patient data. As such, Federated Learning (FL) offers the perfect solution because it avoids these issues. To test the model, the author first deployed it using the centralized training approach to test the two aggregation frameworks they propose, FedAvg and Secure-Arpeggiation. Through the simulation of heterogeneous environments, they analyze the impacts of demographic disparities (age, gender, diagnosis) and unbalanced data distribution on Federated learning models. The ability to simulate heterogeneous environments makes it easy to examine the differences in statistical data and ML models trained with FL, illustrating the need to explore these factors when developing ML models for AD detection [13].

Another study uses federated learning on T1-weighted MRI data to classify AD while maintaining privacy. It suggests ways to reduce communication overhead by increasing local computation and involving more clients per communication round in order to increase parallelism. The method was evaluated using a range of data distributions, including skewed and non-identical datasets that reflected the heterogeneity of the real world. With a maximum accuracy of 84.75%, precision, and recall of about 85%, the federated learning model demonstrated that federated learning can manage diverse medical datasets with high classification performance [10].

In [14] author proposed the LeNet5 model with Adam and SGD optimizers to study cross-silo federated learning for brain disease classification, including Alzheimer's disease detection. According to this study, moderate or better performance requires at least 20% client participation, highlighting the difficulties associated with client participation rates in federated settings. For the classification of Alzheimer's disease, the model's average accuracy, precision, recall, and F1 score came to roughly 95%. This shows that federated learning can outperform centralized models while maintaining data privacy across several institutions.

III. METHODOLOGIES AND TECHNIQUES

The proposed system is built around three main components that work together as part of a federated framework: the shared federated learning system, the edge devices that we have taken, and the central federated server. The goal of the approach is to improve data confidentiality and security by addressing the limitations of traditional, centralized classification models and replacing them with a more secure, decentralized solution. This work provides a thorough assessment of the efficacy of the proposed FL algorithm called Inception v3 when combined with edge computing. The classification accuracy of several centralized classification algorithms is compared to that of the suggested federated method. The suggested technique aims to accurately identify the tumor while also preserving patient data

Accurate image categorization requires an extensive amount of data, especially when it comes to contrast and color deviations and contrast. The Model Architectural Flow employed a 70/15/15 data split, which included training, validation, and testing. Model contains 05 nodes for communicating edge IOT devices

A. Training Dataset Refinement: Augmentation and Selection

Data augmentation can be used to improve/refine the dataset for better results. In order to enable more efficient model training, Image augmentation can enhance visual quality or expand the dataset [15]. Pre-processing algorithms must be applied to the acquired dataset if it is not suitable for training; this creates a more complete dataset with extra features that could make the training process easier. The Alzheimer dataset, which was used in this study, is accessible on Kaggle [18]. Figure 2 provides an instance of a range of image types. The Alzheimer dataset also includes four classes, e.g., dementia: mild, moderate, non-demented, and very mild.

Data augmentation is carried out using the pipeline TensorFlow’s Keras API. It generates a sequential model named 'data_augmentation' with two layers. The first layer, 'RandomFlip', is set up to conduct horizontal flipping on incoming visuals using a predetermined seed value of 42 to assure consistency. The second layer, 'RandomRotation', rotates images randomly within a 10% range (i.e., ±10% of 360 degrees), while maintaining deterministic behavior with the same seed. This augmentation process may be used to train pictures, increasing data variety while ensuring consistent results across runs.

The extremely high accuracy (98.6%) may indicate that the model is learning effectively on previously unseen data, particularly during validation. This risk rises if the dataset is short, uneven, or lacks sufficient validation. Without strong cross-validation or regularization, the quoted performance may be deceptive.

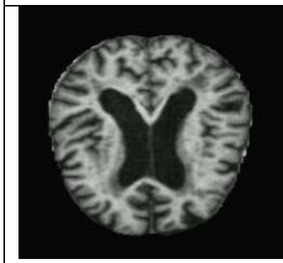
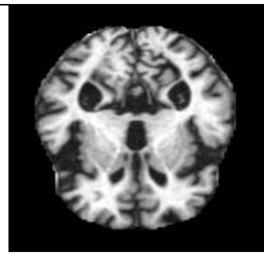
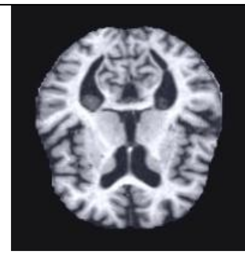
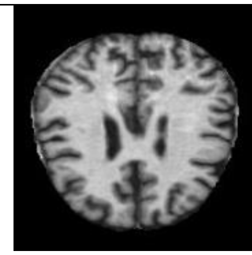
Mild Demented	Moderate Demented	Non Demented	Very Mild Demented
			

Figure. 2. Dataset InceptionV3

InceptionV3 is the base model chosen for the suggested Federated Learning scenario, as shown in Figure 3. It is a pre-trained CNN classifier with deep learning that was created especially for image classification. It is extensively used for a wide range of computer vision-related tasks.

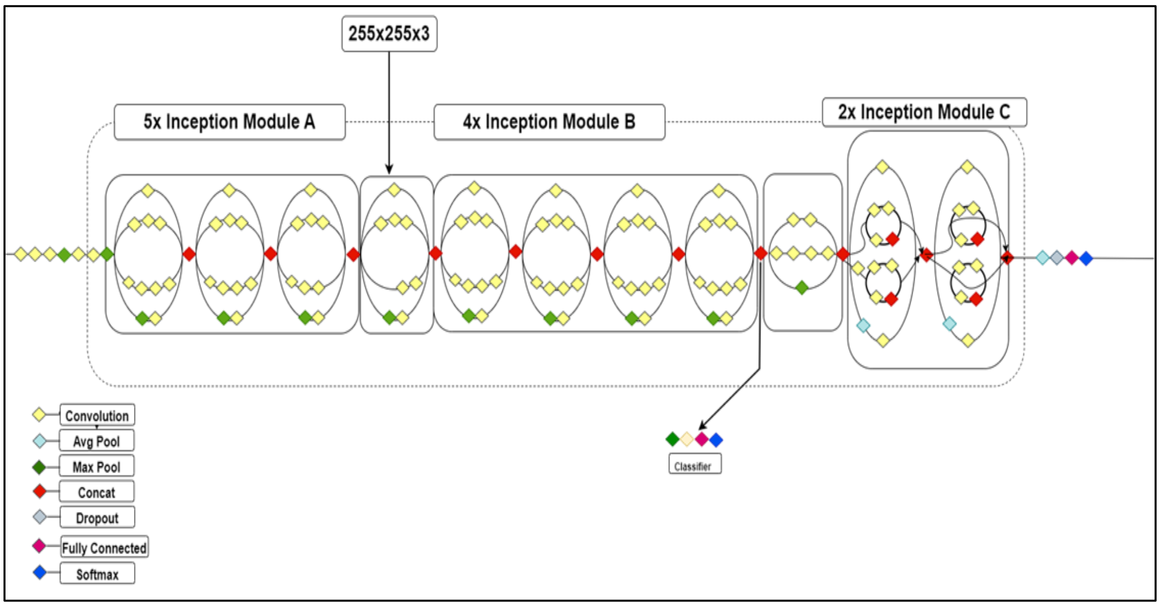


Figure 3. InceptionV3 Model [17]

Several convolutional layers make up InceptionV3, which aids in feature extraction from input images. It requires 299 x 299 pixel images with three RGB color channels. The network is prepared to learn more intricate patterns in the deeper layers by using various filters in the early layers to identify fundamental features like edges. To capture a range of feature details, each Inception module uses convolutions with varying kernel sizes, such as 1×1, 3×3, and 5×5. To increase the network's efficiency, the output from these convolutions is then either concatenated or shrunk in size.

B. Secure Aggregation and Federated Averaging Implementation.

Fast responses in real-time mobile computing applications, particularly those running over low-latency networks, are supported by the suggested framework. Every network edge device has a camera or image sensor that can take pictures in real time and classify them. They can train models directly on the data they gather because these devices also serve as local training nodes. The edge devices start training on their datasets after the base model is deployed to them, modifying it to better capture the distinctive Image structures of their respective environments. Inception v3 model training is carried out locally to account for the hardware variations among edge devices, such as storage and processing power. Following training, the modified model weights are transmitted back to a central federated server, where they are integrated to enhance the global model's overall performance.

Equation 1 illustrates the cross-entropy loss function, where (yi) is the true label (0,1) for input xi, f φ (xi) is the predicted probability of the positive class for input xi, N is the total number of training samples, and φ stands for the base model parameters.
This function is usually calculated using the forward propagation process through the various neural network layers provided in equation (02). With the help of the activation function, predetermined weights, and biases, each layer of the network transforms the input data. Each layer's output is produced by running it through the activation function while adding up all of the input data that has gone through the function. This iteration process keeps going until the network reaches the last layer that produces the intended output.

$$\mathbf{L_{CE}(\varphi) = -\frac{1}{N}\sum_{i=1}^{N} y_i \log\left(f_\varphi(x_i)\right) + (1 - y_i)\log\left(1 - f_\varphi(x_i)\right)} \quad (1)$$

$$\boldsymbol{f_\varphi x_i = f_L(f_{L-1}(\cdots f_1(x_i;\varphi_1)\cdots;\varphi_{L-1});\varphi_L)} \quad (02)$$

This paper presents a comprehensive evaluation of the efficacy of the proposed FL algorithm in conjunction with edge computing. The classification accuracy of various centralized classification algorithms is contrasted with that of the proposed federated approach. Accurately identifying tumors and safely protecting patient data are the two objectives of the proposed approach. In this case, the federated algorithm's use is warranted since it makes decentralized training possible, a feature that is essential for maintaining patient privacy. The scalability of the federated approach may become problematic and may lead to latency or communication delays if there are substantially more nodes than intended. As the number of edge nodes increases, the network must be able to accommodate them and assess if they work well with different network configurations.
Assessing the FL algorithm's capability to produce a globally effective model while taking into account its efficiency and speed of convergence was a crucial component of this study. TensorFlow and other tools for orchestration and model creation are used in the Python framework itself. We have used the Kaggle [18] dataset, which covers a different range of photos depicting 04 distinct Brain conditions. In order to guarantee that every image had a uniform format across the network's edge devices, preprocessing was essential to the deep learning workflow. In order to make the dataset cleaner and more consistent for model training, this step helped standardize image resolution and eliminate any undesired artifacts.
Figure 4 shows the accuracy trajectory of the Global model. Figure 4 (left) offers a thorough representation of the federated learning procedure over several historical periods. The training epochs are plotted along the x-axis, and accuracy metrics are displayed on the y-axis. The model's loops and accuracy graph on the training process is vividly displayed by the training accuracy curve, which also shows a steady improvement trend throughout subsequent epochs. In addition, the validation accuracy curve confirms the model's strong performance across a range of input images by demonstrating its capacity to generalize to fresh validation data. The global model's loss patterns across all FL loops and cycles are depicted in Figure 4 (right). At the same time, the validation loss curve is an essential tool for tracking how well the model performs on validation data and efficiently identifying any possible over-fitting or under-fitting problems. A successful model training process that balances model complexity and generalization ability is indicated by the convergence of the loss curves. The model's promising potential is highlighted by the reported accuracy of 98.6% in 14 epochs. In order to tackle these factors, our research incorporates a heterogeneous dataset and prioritizes thorough testing under a range of circumstances to improve the model's resilience and suitability. Whereas, Figure 5 contains the accuracy and loss of each of the 4 node that took part in the training procedure.

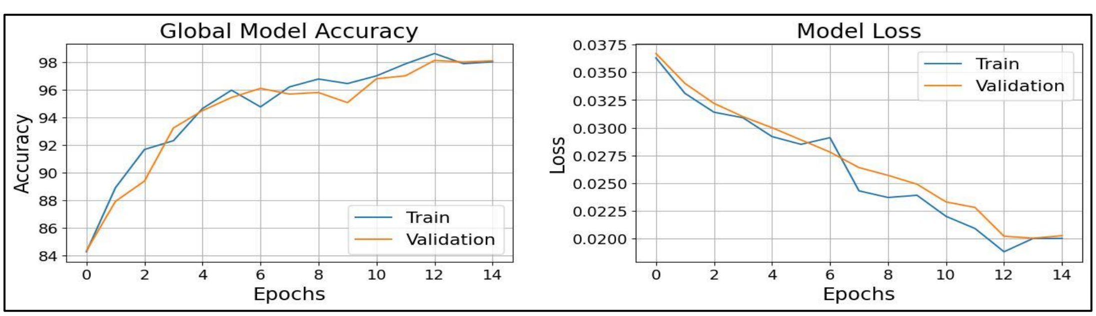


Figure 4. (Left) Global Model Accuracy**; (Right)** Global Model Loss

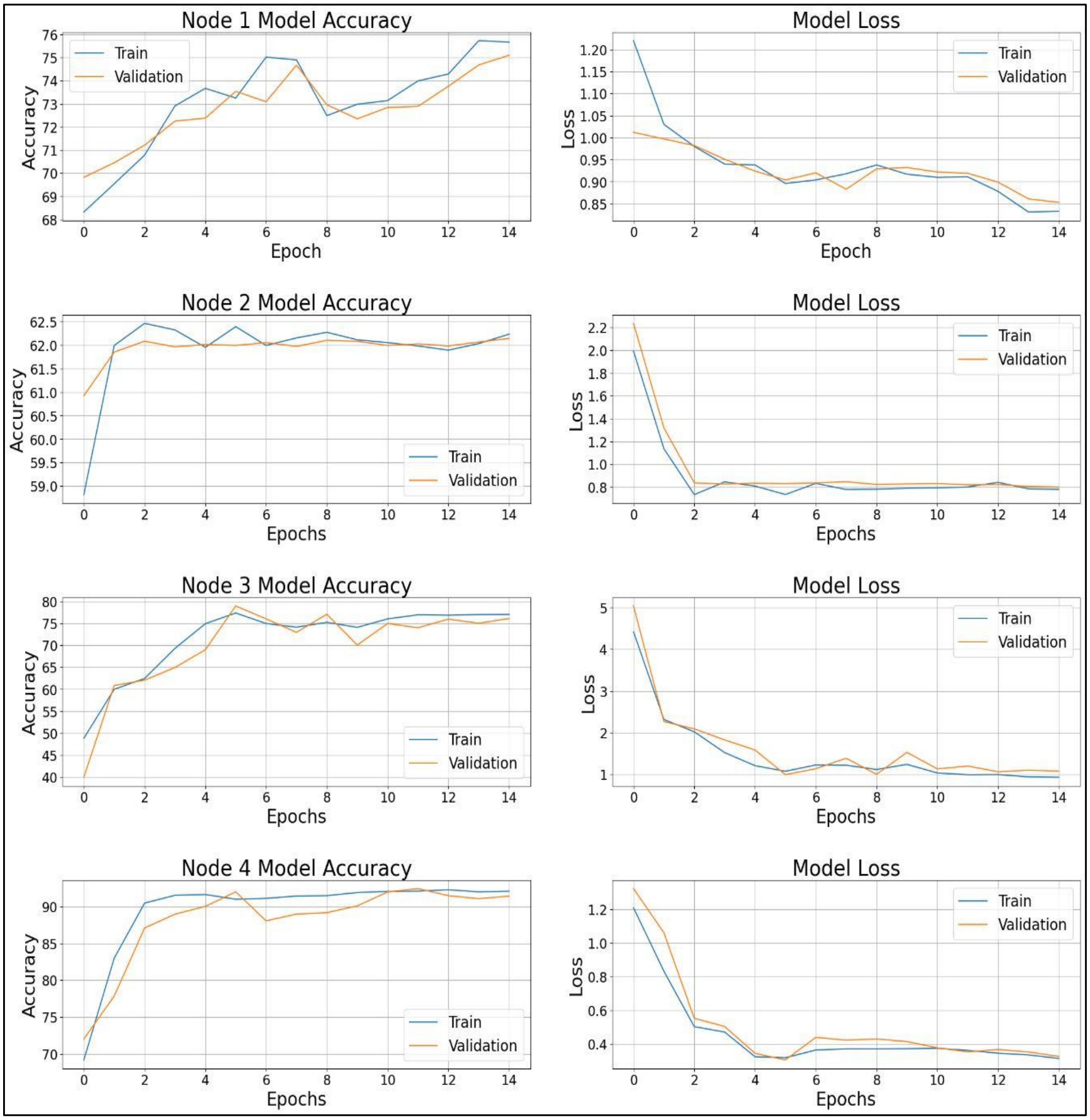


Figure 5. Individual Nodes' Accuracy and Loss Curves

Figure 05 depicts training and validation accuracy and loss trends across 15 epochs for four distinct federated learning nodes. Node 1 exhibits a constant improvement in both training and validation accuracy, reaching around 76%, with a steady decrease in loss, suggesting good convergence. Node 2 achieves a lower accuracy plateau of roughly 62% with minimal over-fitting as the training and validation curves remain close; the loss rapidly decreases and stabilizes. Node 3 shows quick early improvement, attaining approximately 80% accuracy with occasional variations and a significant initial loss reduction, indicating strong generalization. Node 4 outperforms the others, reaching over 90% accuracy with extremely precise training and validation curves and little loss at epoch 4, indicating a robust model fit with no evident overfitting. Overall, all nodes display successful training behavior, but performance varies, most likely because of data heterogeneity across nodes.

IV. CONCLUSION AND RECOMMENDATIONS

We have presented a framework designed to precisely classify Alzheimer's disorder while protecting patient privacy. The approach integrates FL with other IoT support devices. This framework not only ensures the security of sensitive patient data but also delivers fast and reliable classification results. Unlike traditional centralized systems, which collect data on a central server for training, this framework uses a decentralized approach where training occurs directly on edge devices within the network. After thorough testing, the suggested algorithm succeeded in scoring an impressive accuracy of 98.6%, outperforming several centralized learning models. FL in this setup taps into the collective intelligence of all participating edge devices, each working with its local dataset. These devices send their trained model updates to a central federated server, where the results are merged to continually improve the global model with each iteration.

REFERENCES

[1] A. Raza, S. Musa, A. Shahrafidz Bin Khalid, M. Mansoor Alam, M. Mohd Su'ud, and F. Noor, "Enhancing Medical Image Classification Through PSO-Optimized Dual Deterministic Approach and Robust Transfer Learning," IEEE Access, vol. 12, pp. 177144–177159, 2024, doi: 10.1109/ACCESS.2024.3504266.

[2] A. A. Siddique, A. Raza, M. S. Alshehri, N. Alasbali, and S. F. Abbasi, "Optimizing Tumor Classification Through Transfer Learning and Particle Swarm Optimization-Driven Feature Extraction," IEEE Access, vol. 12, pp. 85929–85939, 2024, doi: 10.1109/ACCESS.2024.3412412.

[3] G. N. Nimeshika and S. D, "Enhancing Alzheimer's disease classification through split federated learning and GANs for imbalanced datasets," PeerJ Comput. Sci., vol. 10, p. e2459, Nov. 2024, doi: 10.7717/peerj-cs.2459.

[4] G. M. Shankar and D. M. Walsh, "Alzheimer's disease: synaptic dysfunction and Aβ," Mol. Neurodegener., vol. 4, no. 1, Art. no. 1, Dec. 2009, doi: 10.1186/1750-1326-4-48.

[5] F. Ramzan et al., "A Deep Learning Approach for Automated Diagnosis and Multi-Class Classification of Alzheimer's Disease Stages Using Resting-State fMRI and Residual Neural Networks," J. Med. Syst., vol. 44, no. 2, Art. no. 2, Feb. 2020, doi: 10.1007/s10916-019-1475-2.

[6] N. Alasbali et al., "Privacy-enhanced skin disease classification: integrating federated learning in an IoT-enabled edge computing," Front. Comput. Sci., vol. 7, p. 1550677, Apr. 2025, doi: 10.3389/fcomp.2025.1550677.

[7] S. Orenay-Boyacioglu, O. Boyacioglu, and A. Dondu, "Alzheimer's Disease and Epigenetics," in Handbook of the Biology and Pathology of Mental Disorders, C. R. Martin, V. R. Preedy, V. B. Patel, and R. Rajendram, Eds., Cham: Springer Nature Switzerland, 2024, pp. 1–28. doi: 10.1007/978-3-031-32035-4_172-1.

[8] A. Lakhan, T.-M. Grønli, G. Muhammad, and P. Tiwari, "EDCNNS: Federated learning enabled evolutionary deep convolutional neural network for Alzheimer disease detection," Appl. Soft Comput., vol. 147, p. 110804, Nov. 2023, doi: 10.1016/j.asoc.2023.110804.

[9] K. Khalil et al., "A Federated Learning Model Based on Hardware Acceleration for the Early Detection of Alzheimer's Disease," Sensors, vol. 23, no. 19, Art. no. 19, Jan. 2023, doi: 10.3390/s23198272.

[10] M. A. Sahid, M. P. Uddin, H. Saha, and M. R. Islam, "Towards privacy-preserving Alzheimer's disease classification: Federated learning on T1-weighted magnetic resonance imaging data," Digit. Health, Nov. 2024, doi: 10.1177/20552076241295577.

[11] Y.-L. Huang, H.-C. Yang, and C.-C. Lee, "Federated Learning via Conditional Mutual Learning for Alzheimer's Disease Classification on T1w MRI," in 2021 43rd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC), Mexico: IEEE, Nov. 2021, pp. 2427–2432. doi: 10.1109/EMBC46164.2021.9630382.

[12] N. Basnin, T. Mahmud, R. U. Islam, and K. Andersson, "An Evolutionary Federated Learning Approach to Diagnose Alzheimer's Disease Under Uncertainty," Diagnostics, vol. 15, no. 1, p. 80, Jan. 2025, doi: 10.3390/diagnostics15010080.

[13] A. Mitrovska, P. Safari, K. Ritter, B. Shariati, and J. K. Fischer, “Secure federated learning for Alzheimer’s disease detection,” Front. Aging Neurosci., vol. 16, p. 1324032, Mar. 2024, doi: 10.3389/fnagi.2024.1324032.

[14] M. A. Sahid, H. Saha, M. R. Islam, and M. P. Uddin, “Enhancing Parallelism in Cross-silo Federated Learning for Brain Disease Classification,” 2024 IEEE Int. Conf. Comput. Appl. Syst. COMPAS, 2024, Accessed: May 04, 2025. [Online]. Available: https://www.semanticscholar.org/paper/Enhancing-Parallelism-in-Cross-silo-Federated-for-Sahid-Saha/4de71a3ffc22f2947fdc081b966c802cd435855b

[15] “A Survey of Machine Learning Techniques Leveraging Brightness Indicators for Image Analysis in Biomedical Applications.” Accessed: Apr. 21, 2025. [Online]. Available: https://ieeexplore.ieee.org/abstract/document/10930941

[16] S. I. Ali Meerza, Z. Li, L. Liu, J. Zhang, and J. Liu, “Fair and Privacy-Preserving Alzheimer’s Disease Diagnosis Based on Spontaneous Speech Analysis via Federated Learning,” in 2022 44th Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC), Glasgow, Scotland, United Kingdom: IEEE, Jul. 2022, pp. 1362–1365. doi: 10.1109/EMBC48229.2022.9871204.

[17] A. Raza, M. S. Alshehri, S. Almakdi, A. A. Siddique, M. Alsulami, and M. Alhaisoni, “Enhancing brain tumor classification with transfer learning: Leveraging DenseNet121 for accurate and efficient detection,” Int. J. Imaging Syst. Technol., Aug. 2023, doi: 10.1002/ima.22957.

[18] “Alzheimer’s Disease Dataset.” Accessed: May 03, 2025. [Online]. Available: https://www.kaggle.com/datasets/rabieelkharoua/alzheimers-disease-dataset