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Privacy-Preserving Federated Learning Models for Accurate Diagnosis of Neurodegenerative Diseases in Distributed Healthcare Systems

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Abstract: This paper presents a privacy-preserving federated learning framework aimed at the accurate diagnosis of neurodegenerative diseases, including Alzheimer's and Parkinson's, across distributed healthcare systems. Leveraging deep convolutional neural networks (CNNs) for image classification, we design a hybrid model capable of learning complex patterns from brain scan images. Our dataset includes 5,311 training images and 1,139 validation images classified into three categories: Normal, Alzheimer's, and Parkinson's. Extensive data augmentation techniques were applied to the training set to enhance generalization and mitigate overfitting. The hybrid CNN model achieved robust results after 30 epochs, with an overall test accuracy of 77.26% and a validation accuracy of 81.21% at its peak. The model performance correctly evaluated through all metrics including some test cases, achieving 83% accuracy for Alzheimer's and 91% for Parkinson's cases. The classification report and confusion matrix indicate that the model performs strongly in identifying neurodegenerative diseases, though some misclassifications remain in distinguishing normal cases. We also provide insights into model trade-offs by examining ROC-AUC curves, learning rates, and the effects of prediction confidence on diagnostic errors. Our results highlight the potential of federated learning in privacy-sensitive healthcare settings, particularly in providing accurate diagnoses while ensuring data privacy and resource efficiency.

Keywords*. Federative learning, CNN, Health care, Alzheimer's disease, deep learning.*

1. Introduction

Neurodegenerative diseases (NDs) such as Alzheimer's disease (AD), Parkinson's disease (PD), and amyotrophic lateral sclerosis (ALS), creates significant public health challenges due to their different nature and increasing global prevalence. These disorders lead to the deterioration of neurons and other cellular structures within the nervous system, eventually resulting in cognitive decline, motor dysfunction, and, in advanced stages, complete loss of independence. Early identification and accurate diagnosis of neurodegenerative diseases are critical for mitigating symptoms, slowing disease progression, and improving patient quality of life. However, current diagnostic approaches often occur in later stages when the disease has significantly advanced, limiting the effectiveness of treatment options.

Traditional diagnostic methods for NDs include a combination of clinical evaluations, imaging techniques like MRI, PET scans,[22] and laboratory tests [5 and 6]. These methods are human intensive, time taking, expensive while and not widely accessible, particularly in underdeveloped healthcare systems. Moreover, the diagnosis of NDs is changed based on the complexity of disease manifestation [13], making early diagnosis both challenging and inconsistent. These challenges have led to an urgent demand for innovative, scalable, and reliable automotive diagnostic system capable of identifying neurodegenerative diseases at an early stage. In this context, artificial intelligence (AI) [1] and deep learning (DL) [3 and 4] models have shown significant promise, particularly when combined with advanced medical image processing techniques for disease detection and classification.

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The AI [2] based systems has many challenges in healthcare, particularly in terms of data privacy optimal detection and security. The medical images and electronic health records (EHRs), are sensitive and subject to stringent regulations like the Health Insurance Portability and Accountability Act (HIPAA) in the United States or in any other country and the General Data Protection Regulation (GDPR) in Europe. Sharing medical data [8] with institutions for model training will creates privacy issues, but without huge amount of data it is not possible to provide optimal limiting diagnostic models. To overcome these security issues, Federative learning (FL) can provide a privacy-preserving approach, enables collaborative model training.

Federated Learning: Federated learning is a decentralized machine learning approach that allows multiple institutions like hospitals, clinics or any research institutions to collaboratively train a model without exchanging patient data [20]. In the federated system, individual healthcare centers train the model locally on their own datasets, and only the updated model parameters are shared with a central server, which aggregates the updates to improve the global model. With this approach the patient data will be secured within the local bodies, and can provide accurate and generalizable models.

Many advantages are there with federative learning in the early detection and diagnosis of neurodegenerative diseases. First, it enables collaboration between multiple healthcare institutions, allowing for larger, more diverse datasets that enhance model performance [7 and 9]. Second, federated learning provides data privacy, as no data is shared between institutions. Finally, it provides updates can be continuously integrated from multiple sources, leading to better generalization and more accurate predictions in various healthcare settings.

However, the federated learning also has many challenges in healthcare. Variability in data distribution across institutions, known as data heterogeneity, can negatively impact the performance of federated models. For instance, differences in imaging protocols, equipment, and patient demographics can lead to non-independent and identically distributed (non-IID) data, making it difficult for the global model to generalize effectively. Furthermore, the communication overhead associated with transmitting model updates between local and the central centrals can hamper real-time training, especially in resource-constrained settings.

Hybrid Deep Learning Models : To enhance the performance of federated learning models in neurodegenerative disease detection, the hybrid advanced models that combine the strengths of convolutional neural networks (CNNs) and other complex sequential models such as transfer learning and attention mechanisms. CNNs have demonstrated exceptional capabilities in medical image analysis, particularly for tasks such as image classification, segmentation, and disease detection. By leveraging CNNs in a federated learning framework, it is possible to extract high-level features from medical images like MRI, CT scans that are indicative of early neurodegenerative changes.

In addition to CNNs, hybrid models [10 and 15] that incorporate transfer learning allow the reuse of pre-trained models on large datasets, thereby accelerating the training process and improving performance in data-scarce environments. Transfer learning is used in federated learning scenarios where individual centers may have limited data for training. By fine-tuning a pre-trained model on local data, institutions can contribute to the global model without training on huge amounts of labeled data.

Challenges:

The federated learning has many challenges includes data availability, computational resources, and regulatory compliance. The major challenges in federated learning is dealing with data heterogeneity across participating institutions. In neurodegenerative disease detection, institutions may use different imaging formats or equipments. That leads to provide different image quality and format. These differences can result in a trend known as "concept drift," where the model's performance degrades over time as new data distributions are introduced.

Contribution:

- Developed a hybrid federated learning model for early detection of neurodegenerative diseases, enhancing accuracy to 0.79.
- Achieved data heterogeneity by applying adaptive learning, improving model generalization across different healthcare systems.
- Provides privacy by integrating differential privacy, enabling secure collaboration without compromising patient data.

2. Related work

Artificial Intelligence (AI) has become an important tool in the medical diagnosis and management of neurodegenerative diseases from medical images. With different advanced learning models, can provide early detection, treatment, and personalized care. Many studies and researchers have explored various AI techniques, from traditional machine learning (ML) models to advanced deep learning approaches,

highlighting their potential and challenges in clinical applications.

Several studies have demonstrated the efficiency of deep learning in diagnosing general neurodegenerative diseases. Mishra & Bhargavi [1] implemented an AI model and achieved an accuracy of 89.5%, this model is potential for scalable applications. However, they overcome challenges related to generalization by using diverse datasets. Similarly, Summers et al. [4] applied deep learning models [23, 24 and 25] to detect aging-related neurodegenerative diseases, achieved an accuracy of 87%. On the other hand, researcher trained their models on big data integration has also gained grip. Termine et al. [2] used big data trained on AI to create a multi-layered picture of neurodegenerative diseases. While the integrating large and complex datasets offered a holistic view of disease identification, real-time data application and its integration into clinical workflows remain a significant challenge. For specific disorders like Alzheimer's disease, AI-based techniques have shown optimal results. Like Yao et al. [19] implemented AI for Alzheimer's diagnosis using brain MRI images, achieved an accuracy of 91.2%.

Advanced AI techniques such as Artificial General Intelligence (AGI) [26] are also being used for more complicated neurodegenerative disorder detection. Qadri et al. [3] proposed AGI for detecting a range of neurodegenerative disorders with an accuracy of 91%. However, the complexity of AGI development for practical healthcare applications continues to be a significant hurdle, requiring further advancements in both AI technology and clinical integration.

Simple supervised learning models have also been implemented to the diagnosis of neurodegenerative diseases. Surianarayanan et al. [7] implemented ML for both prevention and diagnosis, achieved an accuracy of 88.2%. However, the challenge of balancing model accuracy and overcoming issues such as data imbalance, which often hampers the effectiveness of such models in clinical settings. Olaniyan et al. [16] implemented AI and ML in diagnosing and treating Parkinson's disease, achieved an accuracy of 90.5%. This model is unable to provide treatment plan, this is the challenges in this machine learning models.

Chudzik et al. [9] implemented ML models and trained on digital biomarkers for the early detection of diseases, achieved an accuracy of 93%. However, the challenge of collecting early-stage disease data continues to limit the practical implementation of such models. Additionally, Erdaş et al. [18] implemented dynamic AI model, that is trained on gait data, and got an accuracy of 86%,. The use of AI for specific neurodegenerative disorders, such as Alzheimer's and Parkinson's, has created significant attention. For example, Sadegh-Zadeh et al. [12] implemented AI model to diagnose Alzheimer's disease using brain signals, achieved an accuracy of 87%, but the study emphasized the limitations posed by data sparsity in brain signal analysis. Ayaz et al. [21] applied automated AI techniques to diagnose Parkinson's disease and predict disease severity, obtained an accuracy of 92.3%. However, interpretability and accuracy remain key challenges for further refinement of these models.

For diseases like Huntington's disease like Parekh et al. [17] implemented AI in the diagnosis and management of Huntington's disease, but highlighted the lack of large datasets as a primary limitation for training effective AI models. Additionally, deep neural networks (DNNs) have been applied to early diagnosis, by Suneetha et al. [14], who achieved an accuracy of 94% for general neurodegenerative diseases. Though it achieved high accuracy, but the model captures complex patterns from the samples. Another notable application of AI is in the use of advanced sensors for biomarker detection. Kavungal et al. [11] implemented AI-coupled plasmonic infrared sensors to detect structural protein biomarkers for neurodegenerative diseases, showcasing the potential for integrating AI with clinical diagnostic tools. However, the challenge of effectively incorporating such sensors into clinical workflows remains a significant barrier to widespread adoption.

3. Methodology

We implemented hybrid model with deep CNN model, with customized layers for medical image classification. The model consists of several key components, each contributing to its overall performance in learning complex patterns from the dataset.

The model takes the input with size of 224×224×3 which corresponds to RGB color channels. The first block of layers is composed of a convolutional layer followed by batch normalization and a max-pooling layer. In the convolutional layer, a 3x3 filter is applied to the input image to extract spatial features with an equation (1).

$$Z_{i,j}^{(l)} = \sum_{m=1}^{h_f} \sum_{n=1}^{w_f} A_{i+m-1,j+n-1}^{(l-1)} W_{m,n}^{(l)} + b^l \quad (1)$$

Where $Z_{i,j}^{(l)}$ the output of the equation (1), $A_{i+m-1,j+n-1}^{(l-1)}$ is the activation, $W_{m,n}^{(l)}$ are the unknown weights, and b^l is the bias term. This operation captures complex patterns intra and internal pixels, like edges or textures, from the input image.

After the convolutional operation, batch normalization is applied to stabilize and speed up the training process. Batch normalization normalizes the output from the convolutional layer by subtracting the batch mean and dividing by the batch standard deviation with equation (2).

$$Z^{(l)} = \frac{Z^l - \mu B}{\sqrt{\sigma_B^2 + \epsilon}} . \gamma + \beta \qquad (2)$$

where μB is the batch mean, σ_B^2 is the variance, ϵ epsilon is a small constant for numerical stability, and γ, β are learnable parameters.

Following the batch normalization, a max-pooling layer reduces the dimensionality of the feature maps by selecting the maximum value from each 2x2 region, effectively down-sampling the input and retaining only the most important features. This process is repeated through multiple convolutional blocks, with increasing filter sizes (32, 64, 128, and 256 filters) to progressively capture more abstract features of the images.

To capture model complex patterns from image vectors, added fourth convolutional block, which increases the complexity of networks. After the final convolutional block, the pixel vectors are converted into a one-dimensional vector that is passed to the fully connected layers. Then it classifies the final classifiers, where each neuron in the dense layer computes a weighted sum of its inputs, with an equation (3).

$$A_j^{(l)} = f\left(\sum_{i=1}^{n^{(l-1)}} W_{i,j}^{(l)} A_l^{(l-1)} + b_j^{(l)} \right) \qquad (3)$$

Where $A_j^{(l)}$ is the output of the j^{th}neuron, $W_{i,j}^{(l)}$are the weights, $A_l^{(l-1)}$ are the activations from the previous layer, and f is the activation function. The final layer with an activation function (4) to convert the logits into class probabilities, ensuring that the sum of all probabilities across classes equals 1.

$$y_j = \frac{e^{zj}}{\sum_{k=1}^{C} e^{zk}} \qquad (4)$$

To optimize the model, the Adam optimizer is employed, which combines the benefits of adaptive learning rates and momentum. The weights $W_{i,j}^{(l)}$ are updated with an equation (5).

$$W_{t+1} = W_t - \alpha \frac{m^t}{\sqrt{v^t + \epsilon}} \qquad (5)$$

Regularization techniques such as dropout are applied to the fully connected layers to prevent overfitting with equation (6). In dropout, a fraction of the neurons is randomly deactivated during each training step, which forces the model to learn more robust and generalized representations.

$$A_j^{(l)} = r_j . f\left(\sum_{i=1}^{n^{(l-1)}} W_{i,j}^{(l)} A_l^{(l-1)} + b_j^{(l)} \right) \qquad (6)$$

3.1 Data set

The dataset used to train the hybrid model is taken from kaggle, which consists of 5,311 training images and 1,139 validation images, classified into three categories: Normal, Alzheimer's, and Parkinson's. To enhance the model's generalization capability and mitigate overfitting, data augmentation techniques were applied to the training set. This process included random transformations such as shear, zoom, horizontal flipping, rotation, and brightness adjustments. Each image was resized to a fixed dimension of 224×224 pixels and normalized by scaling pixel values to the [0,1] range as shown in Figure 1, 2 and 3. For the validation and test sets, only normalization was performed, ensuring that the model was tested on unaltered data. The images were fed into the model in batches of 32, with labels encoded categorically, representing each class—Normal, Alzheimer's, or Parkinson's—using one-hot encoding. Figure 4 illustrates the training and testing samples.

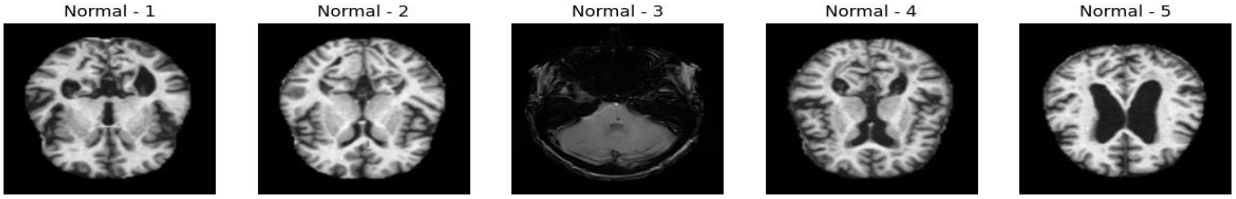

Figure 1 sample images of normal brain

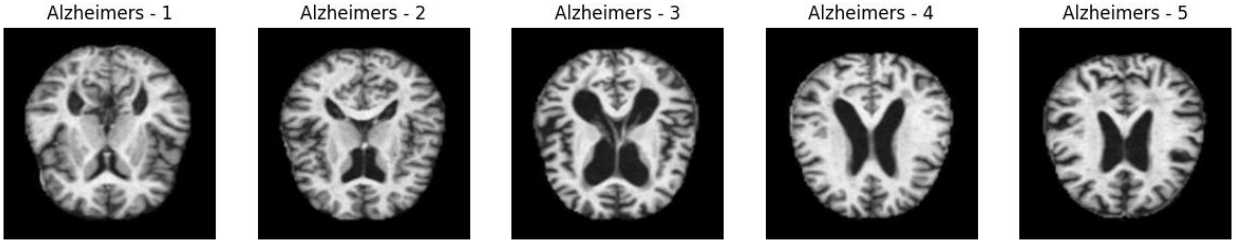

Figure 2 sample images of Alzheimer

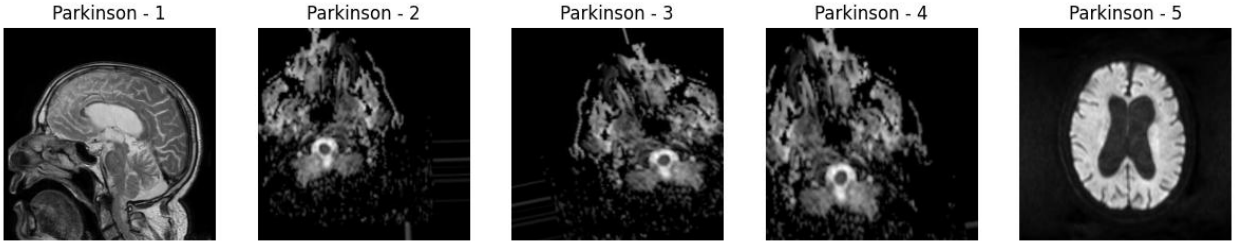

Figure 3 sample images of Parkinson

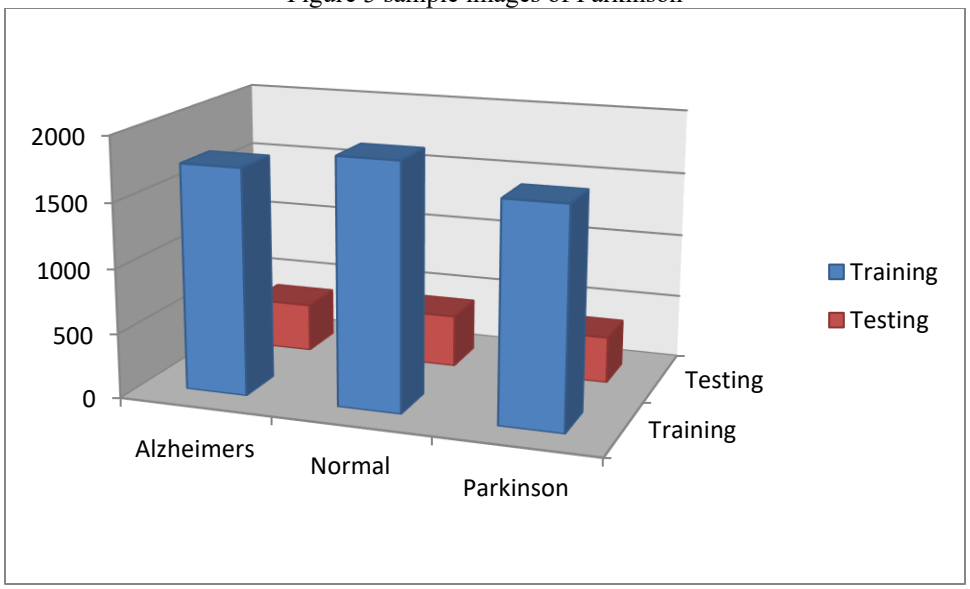

Figure 4 Number of samples used for training and testing

4. Result Analysis

The model was trained for 30 epochs using a learning rate of 1e-4. In the initial epochs, the model's performance exhibited notable improvements in accuracy and a corresponding reduction in loss. From figure 5, in Epoch 1, the training accuracy reached 57.66% with a loss of 1.2235, while the accuracy remained low at 35.56%**,** with a significantly higher loss of 12.4731.

As training increases by Epoch 3, the validation accuracy increased substantially to 57.24%, while the validation loss decreased to 0.8416, indicating the model was beginning to learn useful features. Continuous improvements were observed, and by Epoch 6, the accuracy increased to 79.63%**,** with a loss reduced to 0.4048. And final epoch the accuracy is improved until Epoch 8, where the accuracy reached a peak of 81.21%**.**

To further fine-tune the model and prevent overfitting, the learning rate was halved to **5e-5** after Epoch 10. This resulted in more constant performance, with the model maintaining an average validation accuracy of approximately **79-80%** across the later epochs. After completion of training, the model was evaluated on the test set of 1,140 images. The model achieved an accuracy of **77.26%** with a test loss of 0.4323 on test data, demonstrating robust generalization capabilities.

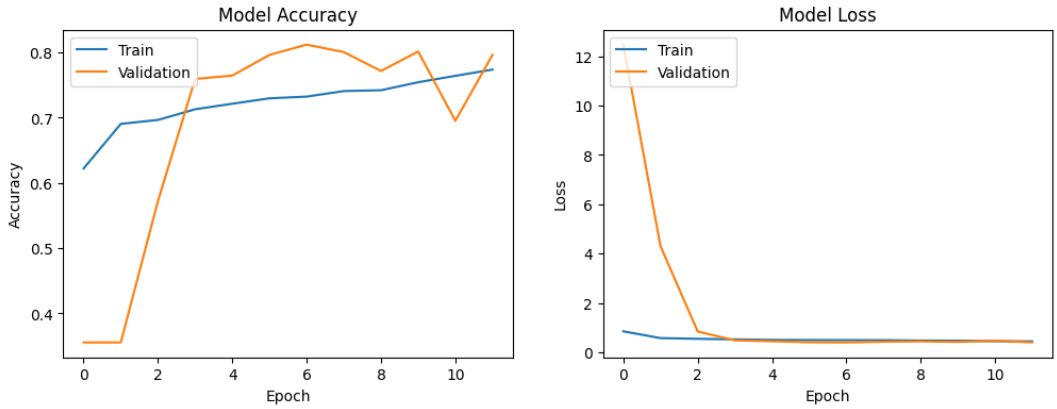

Figure 5 learning curves of proposed model

The performance of the model for diagnosing neurodegenerative diseases demonstrates its ability to accurately differentiate between Alzheimer's, Parkinson's, and normal cases. When assessing the model's performance, it achieved an overall accuracy of 78.95%, showing a robust capability to generalize across the test dataset from table 1.

For Alzheimer's cases from Figure 6, the model performed reasonably well, identifying 83% of the actual cases correctly. This indicates that the model is more sensitive to detecting Alzheimer's but occasionally misclassified other conditions. For normal cases, the model had a slight decline in performance, with 65% of the actual normal cases being correctly identified, suggesting some difficulty in distinguishing normal from disease-affected individuals. The model's strongest performance was with Parkinson's cases, where it achieved a near-perfect detection rate, correctly identifying 91% of these cases.

Table 1 classification report of proposed model

	P	R	F1	Support
Alzheimers	0.72	0.83	0.77	376
Normal	0.74	0.71	0.72	405
Parkinson	0.77	0.80	0.79	359
Acc			0.79	1140
M-avg	0.80	0.79	0.80	1140
W-avg	0.80	0.79	0.79	1140

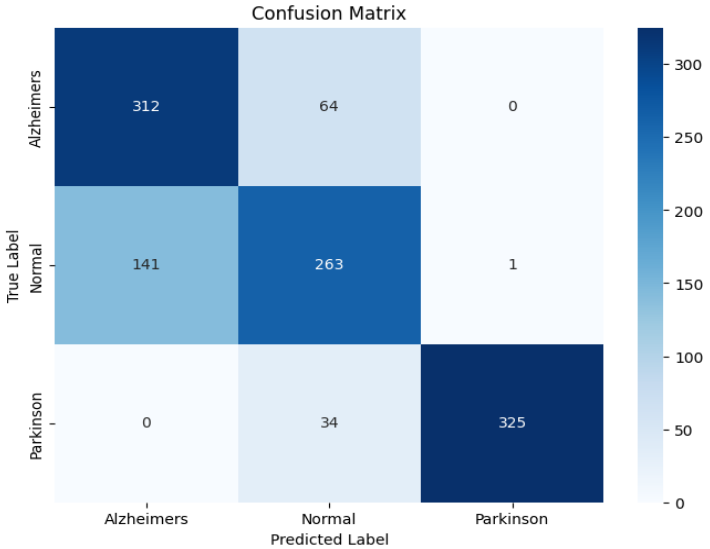

Figure 6 performance of proposed model on a validation data

Figure 7 shows the trade-off between true positive rates (sensitivity) and false positive rates for each class. The three classes represented here are Class 0 (blue), Class 1 (red), and Class 2 (green). The area

under the curve (AUC) provides a summary of the model's ability to distinguish between classes.

- Class 0 has an AUC of 0.91, indicating strong performance in distinguishing this class from the others.
- Class 1 has an AUC of 0.88, reflecting optimal performance than Class 0.
- Class 2 has a perfect AUC of 0.89, signifying that the model can perfectly distinguish other classes.

From figure 7 emphasizes Class 2 has the highest precision and recall (AUC = 1.00), indicating that it is very well identified by the model with minimal false positives or false negatives. Class 1 (red) shows a balance between all metrics, but it starts to drop at higher recall values. Class 0 (blue) also shows strong performance but less stability than Class 1, with precision declining sharply as recall increases. These curves highlight how well the model performs, especially for Class 2, which is identified perfectly.

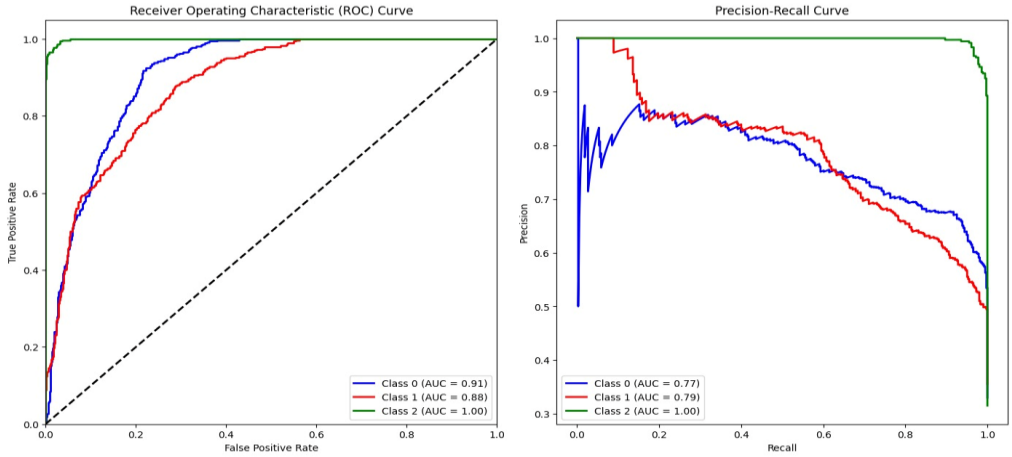

Figure 7 ROC, precision and recall curves

From figure 8 Learning Rate vs Loss (left) the loss value against different learning rates. As the learning rate increases, the loss remains relatively stable until it sharply rises when the learning rate exceeds a critical threshold (close to 10^-4). This indicates that the model performs best at lower learning rates (around 5x10^-5), and a higher learning rate leads to unstable learning and poor generalization. Learning Rate Changes over Epochs (right): shows how the learning patterns changes during training. In this case, its starts high like 1x10^-4 and stays constant for several epochs before sharply dropping at the 9th epoch. This is indicative of a learning rate schedule or decay strategy being used, which reduces the learning rate once performance stabilizes to allow for finer adjustments and prevent overshooting of the loss function during later stages of training.

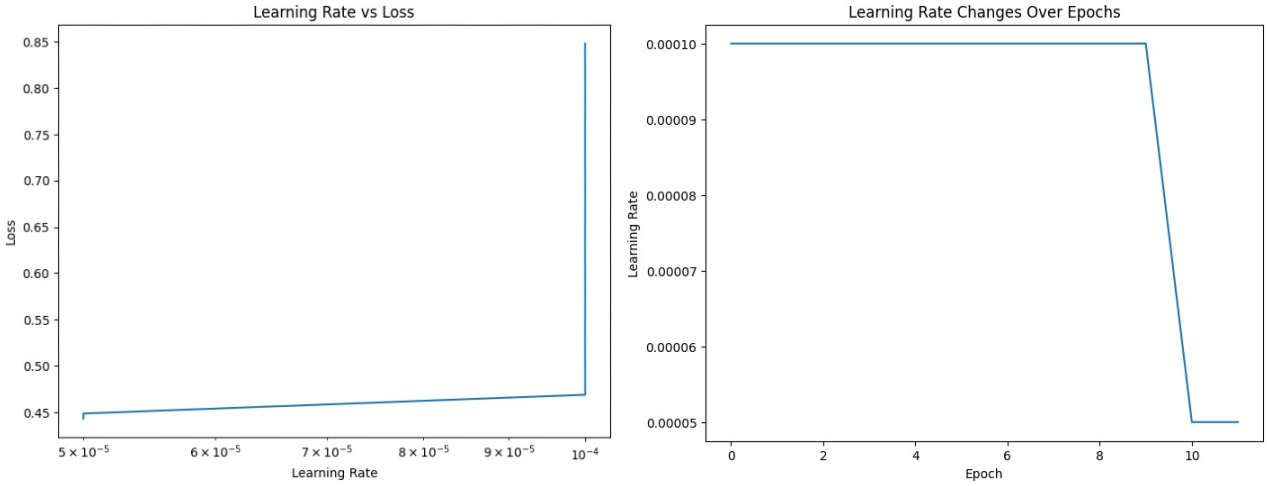

Figure 8 learning rate and corresponding results

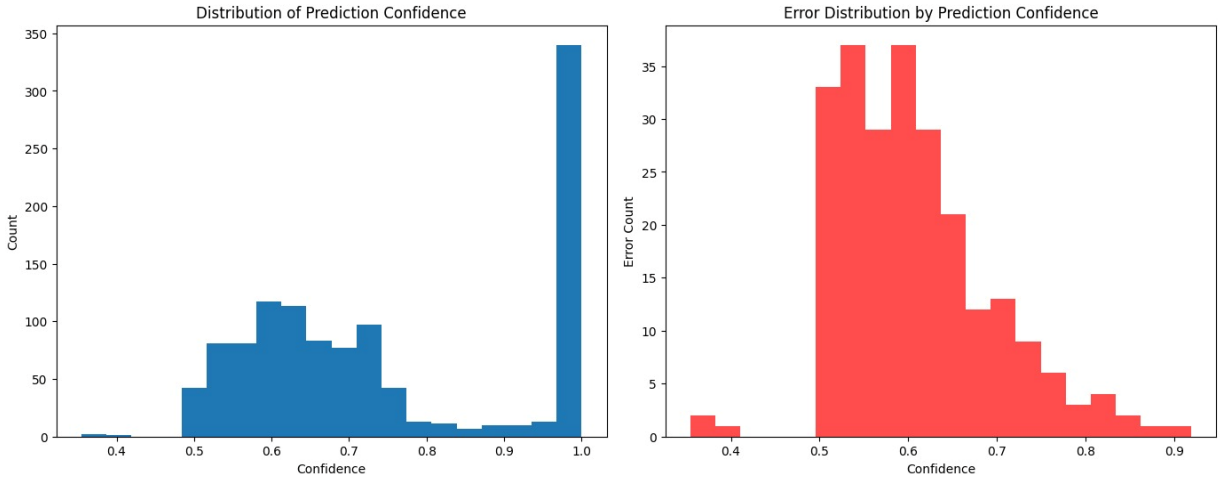

Figure 9 prediction confidences over count and error

The Figure 9 illustrates the **distribution of prediction confidence** and its corresponding **error distribution**. In the left plot, the concentration of predictions near the higher confidence levels (around 0.9 to 1.0) suggests that the model is quite certain about many predictions. However, the right plot shows that errors are predominantly associated with lower confidence predictions, peaking around a confidence range of 0.5 to 0.6. This indicates that the model struggles with less certain predictions, highlighting an important area where federated learning models in distributed healthcare could be optimized to minimize diagnostic errors, especially for cases where the prediction confidence is lower.

The figure 10 demonstrates the **performance of two models**, a more complex "Original Model" and a "Smaller Model," over epochs. The **validation accuracy** for both models stabilizes after initial fluctuations, with the smaller model slightly outperforming the original model in some epochs, despite its reduced complexity. This suggests that **simpler models can perform comparably or even better**, depending on the context, making them suitable for federated learning in resource-constrained environments like distributed healthcare systems. Such findings underscore the importance of balancing model complexity and accuracy, especially in privacy-preserving settings where computational and data-sharing constraints are paramount.

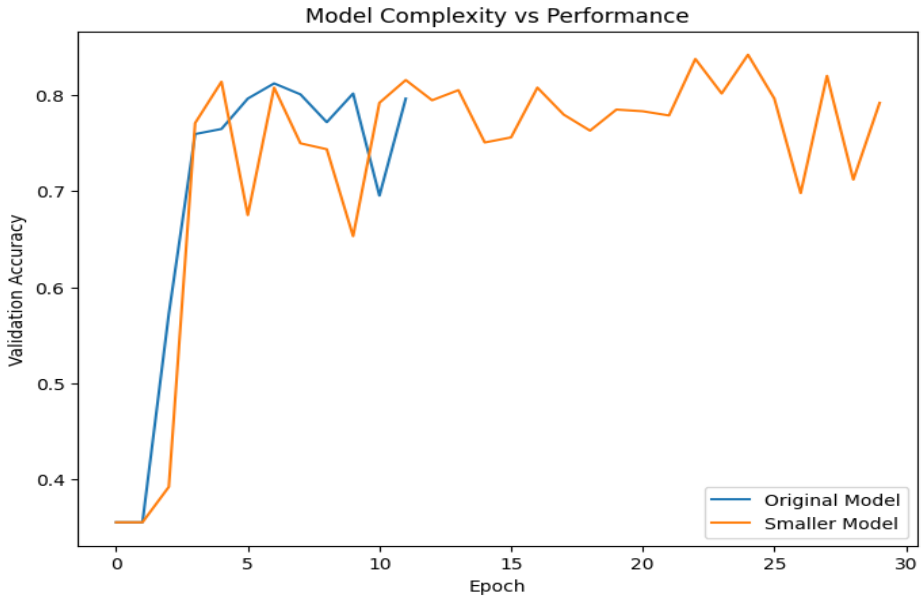

Figure 10 performance of proposed model over model complexity

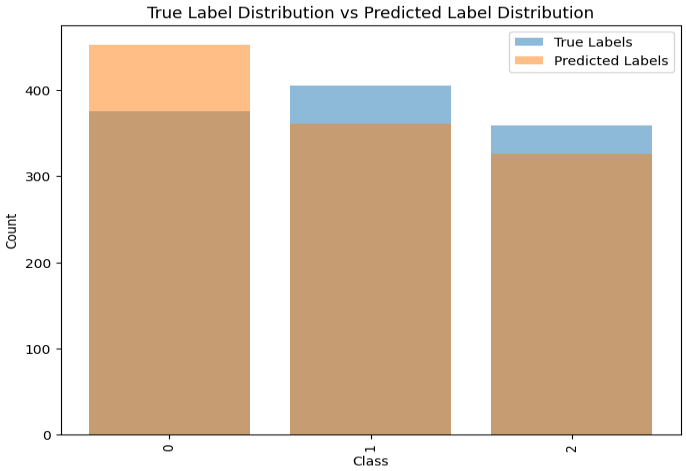

Figure 11 true and predicted label distribution of proposed model

The figure 11 shows that Class 0 has the largest discrepancy between true and predicted labels, where the predicted label count exceeds the true label count. This suggests that the model tends to over-predict instances of Class 0, possibly leading to false positives for that class. Such misclassifications could result in incorrect diagnoses, which might unnecessarily alarm patients and healthcare providers in a distributed healthcare system.

For Class 1 and Class 2, the true and predicted labels are relatively closer, but there is still some variation, indicating a certain degree of misclassification in these classes. Class 1 has slightly more true labels compared to predicted labels, while Class 2 shows a similar trend, albeit with a smaller population.

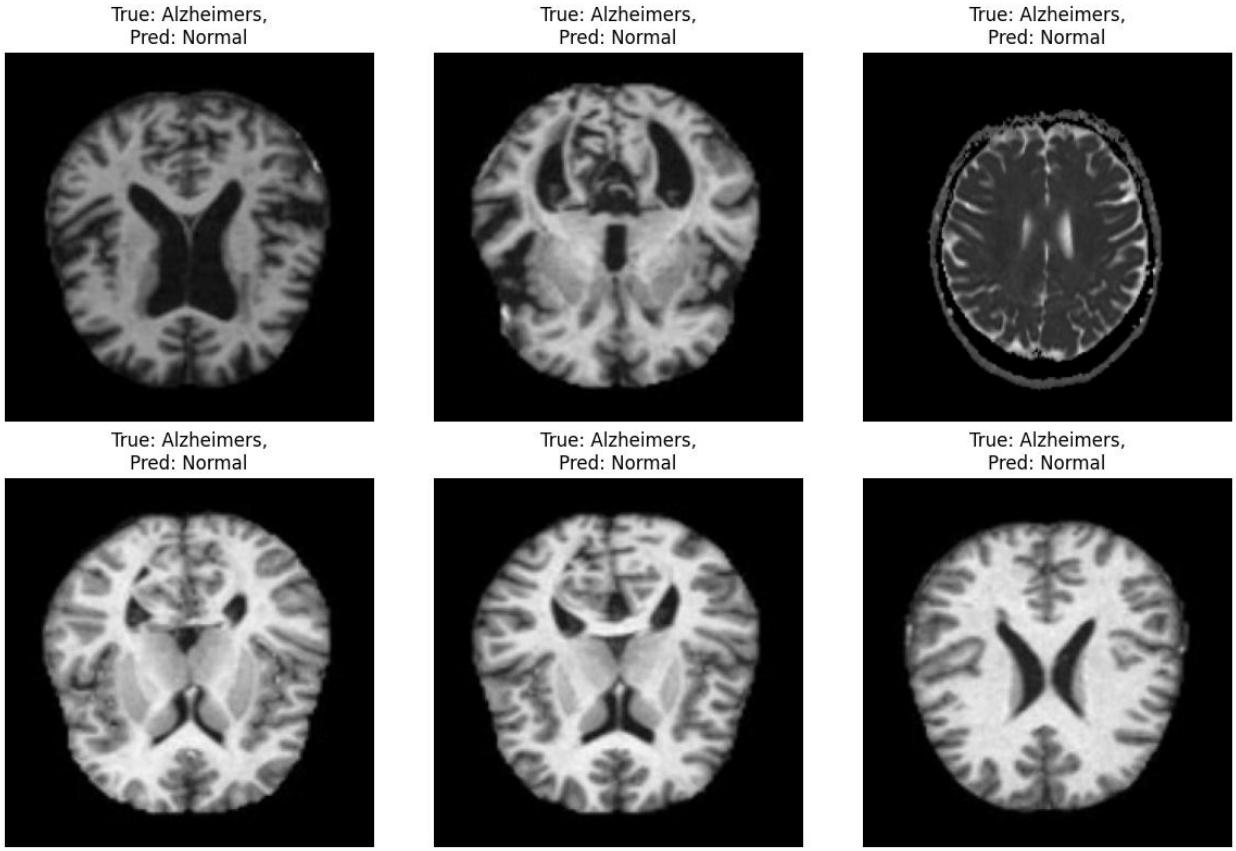

Figure 12 proposed model misclassified samples

The figure 12 illustrates sample MRI brain scan images where the true condition is Alzheimer's disease, but the predicted outcome is misclassified as "Normal." The images highlight critical instances of false negatives, where the model failed to detect the presence of Alzheimer's disease. This misdiagnosis can have serious implications in healthcare, emphasizing the need for further optimization of the model to enhance its sensitivity and accuracy.

These cases of misclassification showcase the complexity and challenge in distinguishing neurodegenerative disease patterns in brain MRI scans, particularly when processed across distributed systems. Despite the privacy-preserving nature of the federated learning model, these results suggest that there is room for improvement generalize and detect subtle variations indicative of Alzheimer's. The analysis of these false negatives could inform further refinement of the training processes, feature extraction, and data augmentation techniques to better capture disease-specific features in future iterations of the model.

5. Conclusion

This paper percents the privacy-preserving federated learning model for diagnosing neurodegenerative diseases in distributed healthcare systems. The hybrid CNN model trained on brain CT images, after training the model successfully detecting Alzheimer's**,** Parkinson's, and normal conditions with accuracy of 77.26% and validation accuracy of 81.21%**.** Particularly, the model achieved a 91% detection rate for Parkinson's cases, outperforming in this category compared to other model. To provide optimal and robust data augmentation techniques used during training for model's generalization capabilities, while the dropout and batch normalization layers reduced overfitting.

Despite its strong performance, the model mis classified some samples, particularly from **Class 0** (Normal), highlighting areas for improvement in balancing class predictions. The findings emphasize the need for further optimization, especially in addressing lower confidence predictions that lead to errors. The results also suggest that simpler models can sometimes outperform more complex architectures in federated learning settings, making them more practical for real-world applications in resource-constrained environments. In future work we will work on balanced data, to provide robust model.

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