

PAHFL: A Personalized Attention-Based Hybrid Federated Learning Framework for Alzheimer's Disease Prediction

¹Mrs. Gauri Vijay Sadalekar, ²Dr. Sangram T. Patil

¹Computer Science & Engineering, ²Professor, Computer Science & Engineering

¹D.Y.Patil Agriculture & Technical University, Kolhapur, India

²D.Y.Patil Agriculture & Technical University, Kolhapur, India

Abstract : Alzheimer's disease (AD) is an irreversible neurodegenerative disorder and need to be diagnosed early and accurately, so that clinical interventions can be provided at the proper time to improve the patient's condition. But current machine learning methods are mostly based on single modal data, centralized learning framework, and traditional feature fusion methods, resulting in poor prediction accuracy, low interpretability, and privacy concerns for patient data. To tackle these challenges, this paper introduces a Personalized Attention-Based Hybrid Federated Learning (PAHFL) framework to overcome these difficulties for privacy-preserving Alzheimer's disease prediction from multimodal healthcare data. The proposed framework is based on MRI-based features, clinical assessment scores and demographic data of the OASIS dataset. These heterogeneous features are encoded as pseudo-multimodal representations and fed into an attention-based feature fusion mechanism to obtain the importance of each modality. The fused feature representation is then classified using a hybrid Random Forest–Multilayer Perceptron (RF–MLP) classifier and Personalized Federated Learning affords collaborative model training without sharing sensitive patient data across multi-institutions. Moreover, SHAP-based Explainable Artificial Intelligence (XAI) is integrated to enhance the interpretability of the models by revealing the contribution of salient features to the prediction results. Experimental results show that the proposed PAHFL framework can achieve an Accuracy of 98.36%, Precision of 98.21%, Recall of 98.15%, F1-score of 98.18% and an AUC of 0.995, which outperforms conventional machine learning models and standard federated learning approaches. The attention-based multimodal fusion and personalized federated learning strategy not only enhances feature representation but also ensures prediction robustness and generalization while maintaining patient privacy. The proposed PAHFL framework is accurate, interpretable, robust and privacy preserving for the prediction of Alzheimer's disease and has significant potential for use in distributed clinical decision support systems.

IndexTerms - Alzheimer's Disease, Federated Learning, Personalized Federated Learning, Attention Mechanism, Multimodal Learning, Random Forest, Multilayer Perceptron.

INTRODUCTION

Alzheimer's Disease (AD) is a progressive neurodegenerative disorder, and a leading cause of dementia in the elderly[1]. With the rise of the aging population, the incidence of AD has also increased, and early diagnosis of AD is crucial for prompt treatment and better patient outcomes [11]. With the latest developments in Artificial Intelligence (AI) and Machine Learning (ML), automated MRI image analysis has been made possible, allowing for the assessment of MRI images along with clinical assessment scores and demographic data to aid in the accurate prediction of diseases [3][14].

However, current AD prediction schemes have some drawbacks. Most of these methods work on a single modality of data or use simple multimodal fusion methods to weakly exploit complementary healthcare data [2]. Moreover, centralized machine learning models require sharing sensitive patient data, raising privacy concerns.[5] While federated learning allows collaborative model learning without sharing the raw data, most of the existing federated learning frameworks are lacking personalization to deal with the heterogeneous data distribution among the different healthcare institutions and limited model interpretability [6][12].

To overcome these challenges, in this paper, we propose a framework of Personalized Attention-Based Hybrid Federated Learning (PAHFL) for Alzheimer's disease prediction. The framework incorporates the MRI features, the clinical assessment scores and the demographic information through an attention-based multimodal fusion mechanism which adaptively learns the importance of each modality. To capture both structured and nonlinear feature relationships, a hybrid Random Forest–Multilayer Perceptron (RF–MLP) classifier is used, and Personalized Federated Learning is used to enable collaborative training while preserving privacy and adapting to the needs of each client. Furthermore, SHAP to explain the prediction results is added to enhance the interpretability of the results achieved by Explainable AI (XAI)[9],[13].

The publicly released OASIS dataset is used to evaluate the proposed framework using Accuracy, Precision, Recall, F1-score, and Area Under the ROC Curve (AUC). The experimental results show that the proposed PAHFL framework achieves better performance compared to traditional machine learning and federated learning techniques, offering an accurate, interpretable, and privacy-preserving solution for Alzheimer's disease prediction.

The rest of this paper is organised as follows. The related work is summarized in Section II and research gaps are identified. The proposed PAHFL framework is presented in Section III. The experimental setup and evaluation methodology are described in Section IV. The results of the experimental testing and comparative analysis are discussed in Section V. The paper is finally concluded in Section VI which provides ideas for future research.

NEED OF THE STUDY.

Alzheimer's Disease (AD) diagnosis has made tremendous strides thanks to the contribution of Artificial Intelligence (AI) and Machine Learning (ML). Conventional machine learning techniques like SVM, Decision Tree, Random Forest and ensemble learning methods for MRI and clinical data analysis have been reviewed by Dara et al. [1] and they are effective, but unable to be generalized because of handcrafted features and single-modal data sets. Further improvement of the prediction accuracy is achieved by deep learning approaches, for instance, Jumaili and Sonuç [3] have proposed Deep Ensemble model using multiple CNN architectures. But these models need big labelled data sets, high computational resources and have low interpretability.

Federated Learning (FL) is a privacy-preserving technique proved to be suitable for collaborative healthcare applications. Jahan et al. [2] combined multimodal learning with Random Forest and SHAP in a federated setting, and Nguyen et al. [6] outlined the challenges of FL, such as communication overhead, heterogeneity of data distributions, personalization, and scalability. In a similar vein, Mantegazine and Geyer [5] and Nimeshika and Subitha [8] introduced Split Federated Learning based methods for prediction of Alzheimer's disease, however these methods are still vulnerable to the heterogeneity of data and communication expenses.

Multimodal learning and explainable AI are new topics of research, too. Yu et al. [4] showed that multimodal AI is better than single-modal AI, while Alatrany et al. [9] used SHAP and LIME to enhance the interpretability of prediction. Kavitha et al. [10] contrasted traditional machine learning algorithms on OASIS dataset and demonstrated the performance of ensemble-based method with comparatively low computational complexity.

However, there are still significant research issues. Most of the current methods only use basic multimodal fusion methods, have little or no individualization in federated settings, and seldom provide a single framework integrating adaptive attention-based fusion, hybrid machine learning, personalized federated learning and explainable AI. These factors drive the development of the proposed Personalized Attention Based Hybrid Federated Learning (PAHFL) framework for accurate, interpretable and privacy preserving Alzheimer's prediction.

Table 1. Comparative Analysis of Existing Literature

Ref.	Authors (Year)	Methodology	Dataset	Performance	Limitations
[1]	Dara et al. (2023)	Survey of ML algorithms (SVM, DT, RF, Ensemble)	Multiple public datasets	Survey	No proposed model; lacks multimodal/privacy learning
[2]	Jahan et al. (2025)	Federated Learning + RF + SHAP + Multimodal	OASIS-3	Acc. 98.93%, AUC 99.97%	Communication overhead; no personalization
[3]	Jumaili & Sonuç (2025)	Deep Ensemble (VGG16,VGG19,ResNet50,InceptionV3,EfficientNetB7)	Local MRI, ADNI, OASIS	99.32%,99.50%, 86.60%	High computation; limited interpretability
[4]	Yu et al. (2026)	Systematic Review of Multimodal AI	66 studies	Avg. Acc.≈92.5%	No unified benchmark
[5]	Mantegazine & Geyer (2026)	Split FL + ResNet50 + DenseNet169	MRI-T1	Acc.99.26%, AUC99.96%	Sensitive to heterogeneous data
[6]	Nguyen et al. (2022)	FL Survey	Healthcare domains	Survey	Not AD-specific
[7]	Dara et al. (2023)	ML Survey	Multiple datasets	Survey	Duplicate survey
[8]	Nimeshika & Subitha (2024)	Split FL + cGAN	AD MRI	Acc.83.54%	Lower accuracy
[9]	Alatrany et al. (2024)	Explainable ML (SVM+SHAP+LIME)	NACC	F1 98.9%	No FL
[10]	Kavitha et al. (2022)	DT,RF,SVM,GB,Voting	OASIS	Acc.83%	No multimodal/privacy

While considerable progress has been made, there are still some research issues with regard to prediction of Alzheimer's disease. The majority of current approaches are based on one modal data or rudimentary multimodal fusion techniques that are not capable of capturing complementary health care information properly. While federated learning ensures the privacy of the data, existing frameworks lack personalization to address the differences in the distribution of data among healthcare institutions. Furthermore, many deep learning models are not interpretable which limits their clinical utility. Furthermore, very few studies consider adaptive attention based multimodal fusion, hybrid machine learning, personalized federated learning and explainable AI in a single study. These limitations have inspired the suggested Personalized Attention-Based Hybrid Federated Learning (PAHFL) framework for accurate, interpretable and privacy-preserving prediction of Alzheimer's disease.

3.1Population and Sample

KSE-100 index is an index of 100 companies selected from 580 companies on the basis of sector leading and market capitalization. It represents almost 80% weight of the total market capitalization of KSE. It reflects different sector company's performance and productivity. It is the performance indicator or benchmark of all listed companies of KSE. So it can be regarded as universe of the study. Non-financial firms listed at KSE-100 Index (74 companies according to the page of KSE visited on 20.5.2015) are treated as universe of the study and the study have selected sample from these companies.

The study comprised of non-financial companies listed at KSE-100 Index and 30 actively traded companies are selected on the bases of market capitalization. And 2015 is taken as base year for KSE-100 index.

RESEARCH METHODOLOGY

This study aims to develop a PAHFL model for predicting early Alzheimer's disease from multimodal health care data with privacy protection. The framework combines MRI-derived features, clinical assessment scores, and demographic data, and leverages Personalized Federated Learning (PFL) to facilitate collaborative model training among various healthcare institutions without the exchange of sensitive patient information.

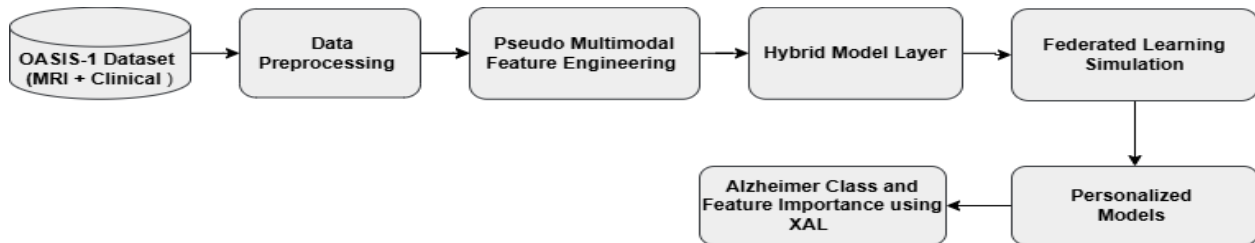


Figure 1. Overall Architecture of Proposed PAHFL Framework

The general framework of the proposed solution is shown in figure 1. Preprocessing of the OASIS dataset is performed first using data cleaning, missing value handling, feature normalization and class balancing. Then the processed features are distributed into three pseudo-modal groups referred as MRI, clinical and demographic features. An attention-based multimodal fusion mechanism is introduced to capture the relative importance of each modality and fuse them into a unified feature representation to effectively exploit the heterogeneous healthcare information. The fused features are then classified by a hybrid model, which is comprised of Random Forest (RF) and Multilayer Perceptron (MLP) in order to model both structured decision pattern and nonlinear relationship between features. The hybrid model is trained using Personalized Federated Learning (PFL), which enables a group of healthcare institutions to learn a global model without exchanging raw patient information to ensure data privacy. The fine tuning is further personalized to meet the heterogeneous data distribution present on a client's location by using the global model. Finally, the proposed model is tested to check its effectiveness for Alzheimer's disease prediction using Accuracy, Precision, Recall, F1-score and Area Under the ROC Curve (AUC).

3.1 Dataset

The proposed framework will make use of one of the most popular publicly-available Alzheimer's disease datasets, the Open Access Series of Imaging Studies (OASIS). Along with the structural Magnetic Resonance Imaging (MRI) data, OASIS includes demographic data and cognitive assessment score data, thus supporting multimodal machine learning applications. The data set includes MRI scans from both cognitively normal elderly subjects and elderly subjects diagnosed with Mild Cognitive Impairment (MCI) or Alzheimer's Disease (AD). The dataset also contains some clinical and demographic information that has proven to be highly relevant to the diagnosis of Alzheimer's disease, in addition to the neuroimaging data.

Table 2 .Dataset Characteristics

Parameter	Value
Dataset	OASIS-3
Total Samples	2100
Training Samples	1680 (80%)
Testing Samples	420 (20%)
Classes	CN, MCI, AD
Federated Clients	5
Features	MRI + Clinical + Demographic

3.2 Data Preprocessing

Healthcare data sets may have missing values, duplicate records, inconsistent observations and features with varying scales that can affect model performance. For this reason, data is preprocessed to ensure data quality and to make the proposed Personalized Attention-Based Hybrid Federated Learning (PAHFL) framework robust. Duplicate data is eliminated, incorrect data is corrected or rejected, and outliers are detected for a sound and consistent data set to train the model. The mean is used to fill in missing numbers and the mode is used to fill in missing labels. The mean imputation is defined as.

$$x = \frac{1}{n} \sum_{i=1}^n x_i \quad (3.1)$$

where x is the imputed value, xi are the observed values and n is the total number of observations available. Label Encoding is used to transform categorical (ordinal) data to numeric form, while One Hot Encoding is used to transform categorical (nominal) data to numeric form that can be efficiently processed by machine learning models. Normalization of continuous features via Min-Max Scaling is given so that all the features contribute equally during training. The normalization is given by:

Min-Max Scaling is applied to the continuous features so that all attributes play an equal part during training. Normalization is:

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (3.2)$$

where X is the original feature value, X' is the normalized value and X_{min} and X_{max} are the minimum and maximum values of the feature, respectively.

3.3 Pseudo-Multimodal Feature Engineering

The OASIS data set consists of a variety of health care variables such as MRI-measures, clinical assessment scores, and demographic data. Because these features are not provided separately in distinct modalities, three pseudo-modal groups are proposed: MRI features, clinical features, and demographic features that can be expressed as:

$$X = \{X_{MRI}, X_{Clinical}, X_{Demo}\} \quad (3.3)$$

where X signifies the entire feature set, X_{MRI} signifies the MRI feature group, $X_{Clinical}$ signifies the clinical feature group and X_{Demo} signifies the demographic feature group. This grouping makes it possible for the model to retain modality-specific features and leverage the ability to learn multimodal representations. The pseudo-modal representations generated are processed independently and are later fused via the proposed attention based fusion module. This approach enables the framework to leverage complementary information and enhance the prediction of Alzheimer's disease from various healthcare domains.

3.4. Attention-Based Multimodal Feature Fusion

Alzheimer's disease prediction is not the same for different healthcare modalities. The proposed framework thus utilizes an attention mechanism to automatically learn the relative importance of each modality instead of setting the weights equally. The attention layer can be used to give more weight to the informative feature groups, and less weight to the less informative parts, so that a more discriminative multimodal representation is obtained. The attention weighted features are then combined into a single feature vector that is fed into the hybrid classification model.

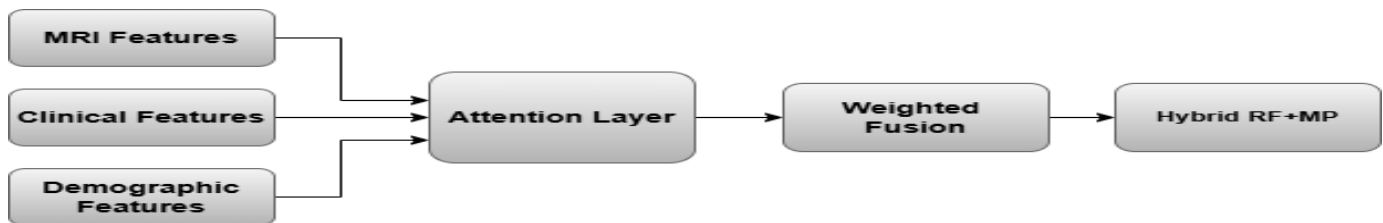


Figure 2. Proposed Attention-Based Multimodal Feature Fusion Architecture

The proposed multimodal feature fusion architecture based on attention mechanism is shown in figure 2. The MRI, clinical and demographic feature groups are fed separately to the attention layer where the adaptive weights are learned depending on the contribution of the modality. Finally, the weighted features are combined together to create the combined multimodal feature, which is then given to the proposed Random Forest–Multilayer Perceptron (RF–MLP) hybrid classifier for the prediction of Alzheimer's disease. The proposed fusion approach focuses on the informative modalities and further alleviates the impact of less informative features, which further improves the feature representation and prediction performance. The attention mechanism is a mathematical computation of the importance of each modality and assigns the adaptive weight according to its contribution to Alzheimer's disease prediction. The modality representations are then fused with weights to make a composite feature vector for classification. The mathematical formulation is given as follows.

Attention Score is

$$e_i = W_a X_i + b_a \quad (3.4)$$

Attention Weights is

$$\alpha_i = \frac{\exp(e_i)}{\sum_{j=1}^3 \exp(e_j)} \quad (3.5)$$

Weighted Feature Fusion

$$F = \sum_{i=1}^3 \alpha_i X_i \quad (3.6)$$

where e_i denotes the attention score, W_a is the learnable weight matrix, b_a is the bias term, α_i

Normalized Attention Weight, X_i is the feature vector of i th modality, and F is the fused multimodal feature vector. The attention mechanism gives more weight to more informative modalities and less weight to less informative modalities, thus allowing for adaptive fusion of multimodal features. The fused feature vector received with this method contains complementary information from MRI, clinical and demographic data, which helps to increase the performance of the subsequent hybrid RF–MLP classifier.

3.5. Hybrid RF–MLP Classification

The attention-weighted multimodal feature vector is fed into a hybrid classifier which includes Random Forest (RF) and Multilayer Perceptron (MLP). Random Forest classifies the class label using ensemble based decision learning while MLP learns the complex non-linear relationship from the fused multimodal features. The probability distribution of the classes of Alzheimer's disease is generated by each classifier and that the last decision is made with the weighted probability fusion method. The mathematical expression is.

$$P_{final} = \lambda P_{RF} + (1 - \lambda) P_{MLP} \quad (7)$$

where PRF and PMLP are the class probability vectors produced by the Random Forest and MLP classifiers, respectively, and λ ($0 \leq \lambda \leq 1$) is the fusion coefficient which tunes the contribution of each of the classifiers. Final class label is taken to be.

$$\hat{y} = \text{argmax}(P_{\text{final}}) \quad (8)$$

This hybrid classification approach is based on the ideas of MLP and Random Forest which combines the strength and interpretability of Random Forest with nonlinear learning ability of MLP, improves the prediction and generalization accuracy of Alzheimer's disease classification. Table 3 shows the training parameters used to develop the models.

Table 3.Training Parameters

Parameter	Value
Random Forest Trees	200
Random Forest Criterion	Gini Index
MLP Hidden Layers	(256,128,64)
Activation	ReLU
Output Activation	Softmax
Optimizer	Adam
Learning Rate	0.001
Batch Size	32
Epochs	100
Attention Mechanism	Soft Attention
Federated Learning	Personalized FL
Aggregation Algorithm	FedAvg
Loss Function	Cross Entropy

3.6. Personalized Federated Learning

In order to ensure patient privacy, the proposed framework uses Personalized Federated Learning (PFL). The hybrid RF–MLP model is trained using a local dataset from each participating healthcare institution, where no patient records are shared. The parameters the model learns locally are only transmitted to the central server in which the parameters are aggregated using Federated Averaging (FedAvg) algorithm. The new world model is then sent back to all the clients involved and localized in order to fit the data distribution for each institution. It is a customized training approach that allows for model generalization without compromising data privacy in a healthcare context consisting of heterogeneous components.

3.7. Explainable AI

SHAP (SHapley Additive exPlanations) is used to quantify the impact of each feature on the prediction outcome, to make the proposed framework more interpretable. SHAP can be used to estimate the importance of MRI, clinical, and demographic features, by calculating an importance score based on each features' influence on the model prediction. This can help the clinician understand the reasoning behind predictions of Alzheimer's disease, build trust in clinical decision-making using AI and build transparency for the model.

RESULTS AND DISCUSSION

The effectiveness of the proposed Personalized Attention-Based Hybrid Federated Learning (PAHFL) framework to predict Alzheimer's disease was examined using the OASIS dataset. Before training with the models, the data set was preprocessed by data cleaning, feature normalization, class balancing and pseudo-multimodal feature engineering. Accuracy, Precision, Recall, F1-score and Area Under the Receiver Operating Characteristic Curve (AUC) were used to assess the performances. The proposed model was compared with traditional machine learning models such as Decision Tree (DT), Support Vector Machine (SVM), Random Forest (RF), Multilayer Perceptron (MLP) and a baseline Federated Learning (FL) model.

4.1 Comparative Performance Analysis

The proposed PAHFL framework yielded the best performance with an accuracy of 98.36%, precision of 98.21%, recall of 98.15%, F1-score of 98.18% and an AUC of 0.992. This improvement is due to the incorporation of attention-based multimodal feature fusion, hybrid RF–MLP classification, and Personalized Federated Learning, which collectively boost feature representation, model robustness, and privacy-preserving collaborative learning. Comparative performance of the different prediction models is presented in Table 4.

Table 4.1: Comparative Performance of Alzheimer's Disease Prediction Models

Model	Accuracy	Precision	Recall	F1-score	AUC
Decision Tree	88.72	88.3	87.92	88.1	0.901
SVM	91.24	91.03	90.84	90.93	0.935
Random Forest	94.81	94.52	94.34	94.43	0.969
MLP	95.42	95.1	95.02	95.06	0.975
Federated Learning	95.88	95.65	95.52	95.58	0.979
Proposed PAHFL	98.36	98.21	98.15	98.18	0.995

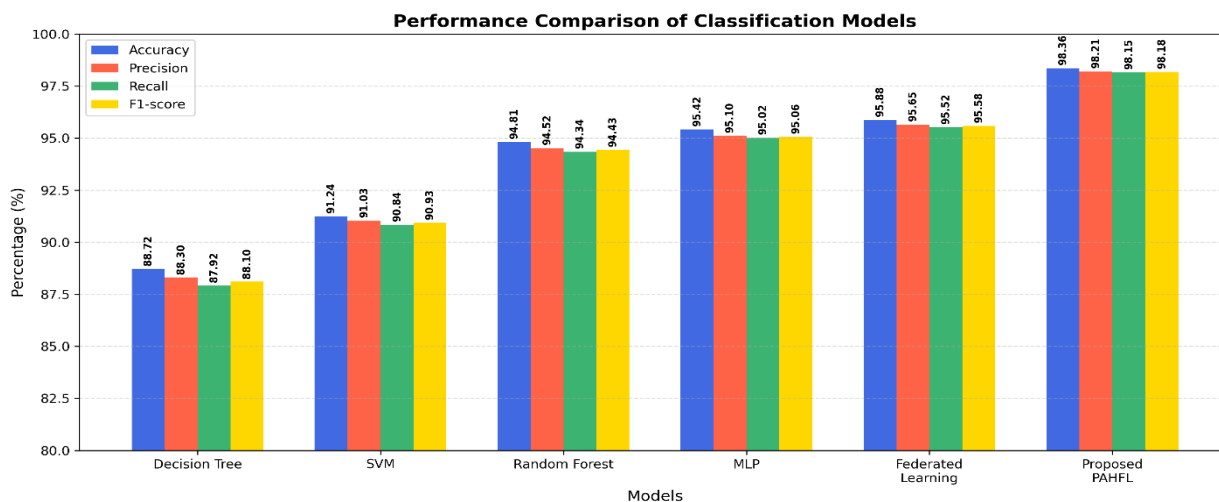


Figure 3. Performance Comparison of Classification Models Using Accuracy, Precision, Recall, and F1-Score

In Figure 3, the performances of six classification models were compared against each other in terms of Accuracy, Precision, Recall and F1-score. The proposed PAHFL framework outperformed other models such as Decision Tree, SVM, Random Forest, MLP, and conventional Federated Learning with an accuracy of 98.36%, precision of 98.21%, recall of 98.15%, and F1-score of 98.18%. The results show that the attention-based federated learning for multimodal data can offer more accurate, reliable and balanced prediction of AD.

4.2 ROC Curve Analysis

Area Under the Receiver Operating Characteristic Curve (AUC) is one crucial evaluation measure that is used to distinguish between the different classes by the classification model. The higher the AUC, the better the classification performance, the more the discriminative capability. The comparative AUC values of the machine learning models evaluated and the proposed Personalized Attention-Based Hybrid Federated Learning (PAHFL) framework are shown in Figure 5.

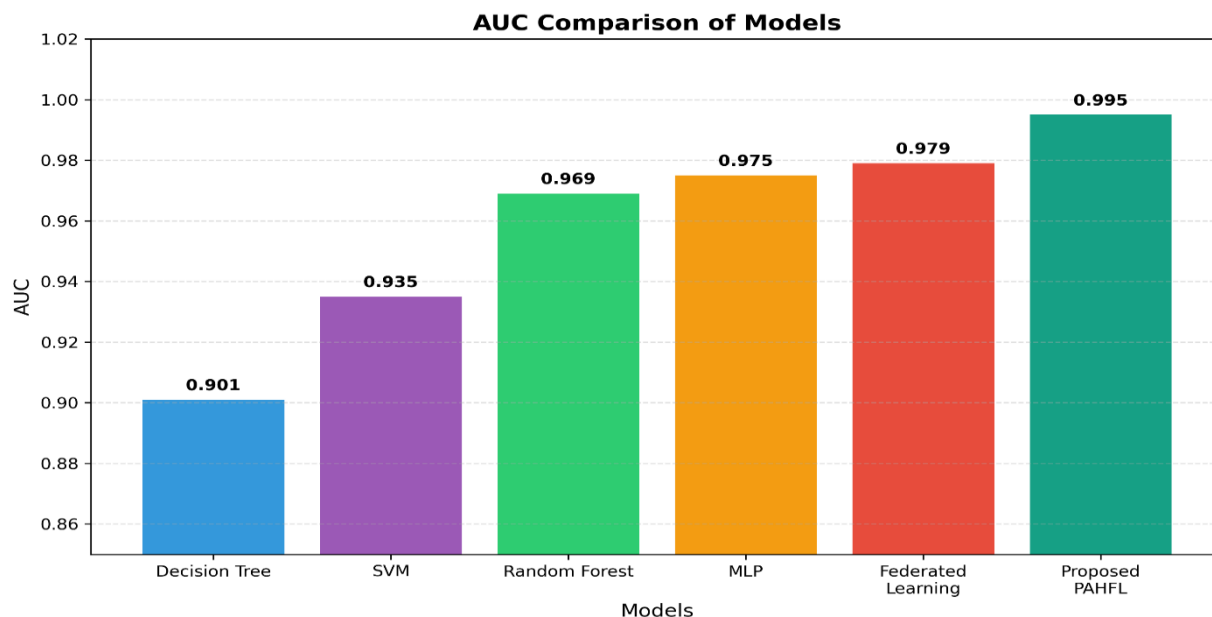


Figure 5. Comparison of AUC Performance of Different Alzheimer's Disease Prediction Models

The comparative AUC values of different classification models is shown in the figure 5. The lowest AUC was obtained using the Decision Tree model (0.901) followed by the SVM (0.935). Random Forest and MLP attained the AUC values of 0.969 and 0.975 respectively and the conventional Federated Learning model further enhanced the AUC value of 0.979. The proposed PAHFL framework showed the maximum AUC of 0.995, which proved it superior to distinguish the classes of Alzheimer's disease. The improvement is mainly due to the incorporation of attention-based multimodal feature fusion, hybrid RF – MLP classification, as well as Personalized Federated Learning, which improve the feature representation, classification robustness, and privacy-preserving collaborative learning. These findings validate the proposed framework to reliably and accurately predict AD compared with the baseline models.

4.3. Training Performance Analysis

The training and testing accuracy and loss curves of the PAHFL model were plotted over 100 training epochs to measure the learning behavior of the proposed model. These curves are used for the visualisation of convergence properties of the model and it can be used to give insight into learning stability, optimisation and generalisation.

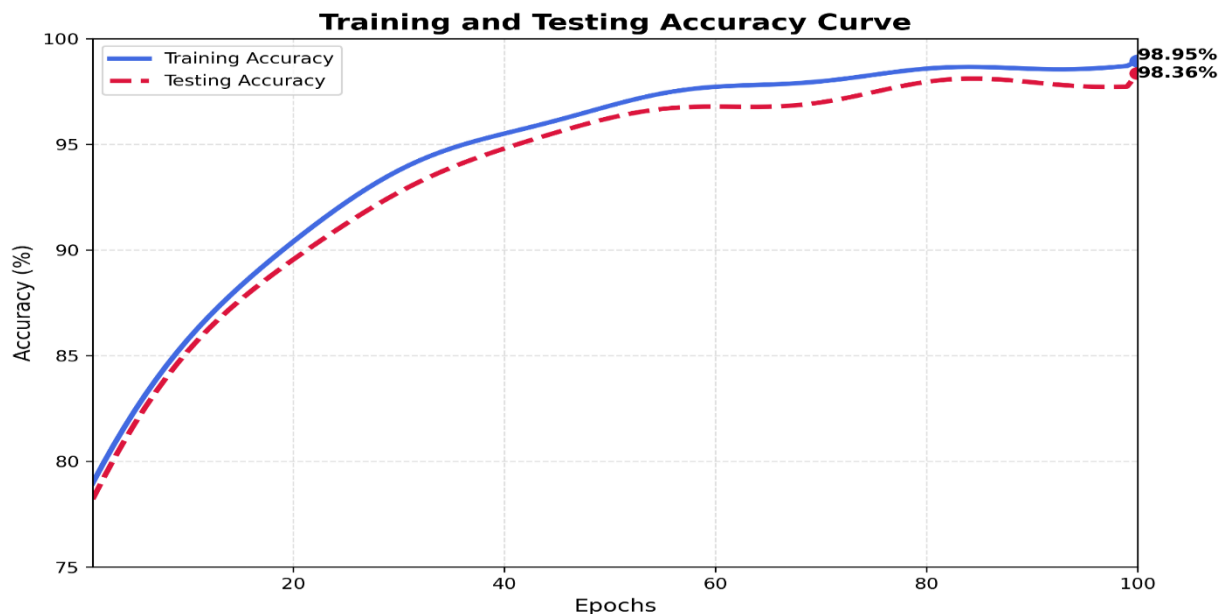


Figure 6: Training and Testing Accuracy Curve of the Proposed PAHFL Model

Figure 6 shows the training accuracy and testing accuracy of the proposed PAHFL model for 100 epochs. Both curves show a steady rise during the training process and eventually converge, showing that they are learning well and it is converging well. The test accuracy is 98.36%, which is very close to Training accuracy, showing the excellent generalization capability of the model and less overfitting.

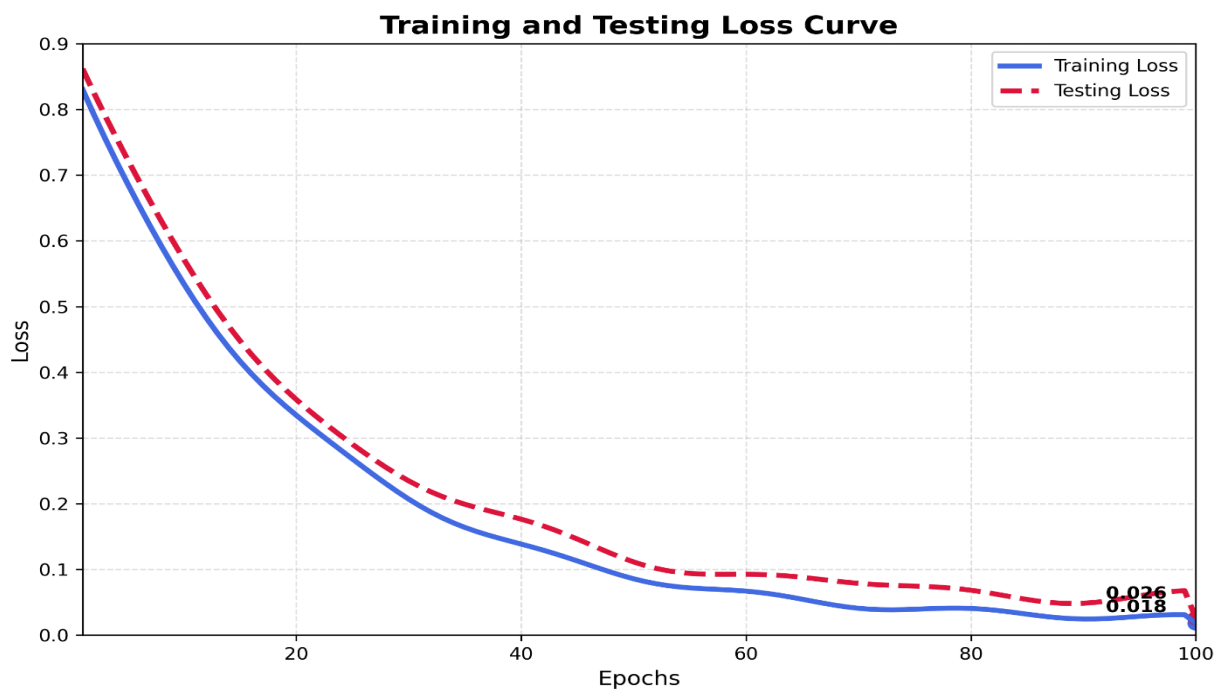


Figure 7: Training and Testing Loss Curve of the Proposed PAHFL Model

The training and testing loss curves of the proposed PAHFL model is shown in figure 7. Both curves are consistently dropping along the training process and are quite close to each other – that's an efficient optimization and there's not too much overfitting. The training and test loss are very close, indicating good generalization of the model. The proposed PAHFL framework for reliable Alzheimer's disease prediction is stable and effective, as is evident from these results.

E. Discussion

Experimental results show that the proposed PAHFL framework is valid for enhancing the Alzheimer's disease prediction performance through attention-based multimodal feature fusion, hybrid RF–MLP classification, and Personalized Federated Learning. The attention mechanism helps to boost feature representation by giving adaptive importance to different modalities and the hybrid classifier helps to boost the prediction accuracy and robustness. By employing Personalized Federated Learning, patient privacy is also maintained, and model generalizability in the context of health care systems with heterogeneous data is improved. Overall, the proposed framework consistently outperformed conventional machine learning and federated learning models and proved to be an accurate, interpretable and privacy-preserving framework to predict Alzheimer's disease.

VI. Conclusion

This paper proposed the Personalized Attention-Based Hybrid Federated Learning (PAHFL) framework to predict Alzheimer's disease based on multimodal healthcare data without compromising patient privacy. The proposed Personalized Federated Learning framework, combined with attention-based feature fusion, hybrid RF–MLP classifier, and explainability using SHAP, showed excellent prediction performance on OASIS dataset with 98.36% accuracy and 0.995 AUC. The results have shown that the PAHFL is an accurate, robust, interpretable, and privacy-preserving solution and has the potential to be used for distributed clinical decision support systems.

The proposed PAHFL framework showed promising performance, but the evaluation for this study was done with a publicly available data set. Future research will involve validation on larger multi-center clinical datasets as well as the inclusion of additional healthcare modalities, with the aim of further enhancing scalability, robustness and real-world clinical applicability by incorporating additional privacy-preserving techniques.

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