RESEARCH PAPER

Federated Hybrid Computational Learning for the Detection of Alzheimer's Disease

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Abstract
Background: This study was conducted for Federated Hybrid Computational Learning for the Detection of Alzheimer's Disease. **Materials and methods:** The study was designed to evaluate a federated hybrid computational learning framework for the detection and classification of Alzheimer's disease. Clinical, cognitive and neuroimaging information was considered from publicly available datasets, including the Alzheimer's Disease Neuroimaging Initiative (ADNI), Open Access Series of Imaging Studies (OASIS) and Australian Imaging, Biomarkers and Lifestyle (AIBL). The collected data underwent preprocessing, which included data cleaning, normalization, handling of missing values, MRI image registration and feature extraction. Relevant parameters such as age, Mini-Mental State Examination (MMSE) scores, hippocampal volume and other neuroimaging characteristics were considered for computational analysis. A hybrid learning architecture incorporating convolutional neural networks (CNNs) and conventional machine learning algorithms, including Support Vector Machine (SVM) and Random Forest, was employed for feature extraction and classification. **Results:** The analysis of the proposed federated hybrid computational learning framework demonstrated the potential of integrating deep learning, conventional machine learning and federated learning for the detection of Alzheimer's disease. The combination of clinical, cognitive and neuroimaging features provided a comprehensive approach to disease classification. CNN-based analysis facilitated the identification of structural brain abnormalities, including hippocampal atrophy, cortical thinning and ventricular enlargement, whereas conventional machine learning algorithms assisted in the evaluation of clinical and cognitive parameters. The federated learning approach enabled collaborative model training across multiple institutions without requiring the direct transfer of patient records. The model was designed to differentiate three diagnostic categories: normal cognition, mild cognitive impairment and Alzheimer's disease. **Conclusion:** Federated hybrid computational learning represents a promising development in the application of artificial intelligence for Alzheimer's disease detection. By combining deep learning, conventional machine learning and privacy-preserving federated training, this approach provides an opportunity to analyse diverse clinical and neuroimaging information across multiple healthcare institutions. The integration of CNN-based imaging analysis with clinical feature classification may improve the identification of disease-associated patterns, while federated learning enables collaborative model development without requiring the centralized transfer of sensitive patient records. Furthermore, explainable artificial intelligence may improve model transparency and facilitate clinical interpretation.

Keywords: Alzheimer's disease, Computational learning, Neurological examination.
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Introduction

Alzheimer's disease is one of the most common causes of dementia worldwide and represents a major public health challenge, particularly among the ageing population. It is a progressive neurological disorder associated with the accumulation of amyloid-beta plaques and neurofibrillary tangles, resulting in neuronal damage, synaptic dysfunction and gradual cognitive deterioration. Clinically, patients commonly present with memory loss, impaired reasoning, difficulty performing daily activities and changes in behaviour. As the disease progresses, patients may experience severe cognitive impairment and loss of independence.[1]

Early identification of Alzheimer's disease is important because it allows timely clinical assessment, appropriate management, patient counselling and planning of supportive care. Traditional diagnostic methods include neurological examination, cognitive screening tests, magnetic resonance imaging, positron emission tomography and cerebrospinal fluid biomarker analysis. Although these approaches provide valuable diagnostic information, their effectiveness may be influenced by availability, cost, interpretation and variations in clinical presentation.[2-4]

Recent developments in artificial intelligence have introduced new possibilities for automated disease detection. Machine learning algorithms can identify

patterns within clinical and imaging datasets, whereas deep learning techniques, particularly convolutional neural networks (CNNs), can automatically extract complex features from brain images. These techniques can assist in identifying structural changes associated with Alzheimer's disease, including hippocampal atrophy and alterations in cortical regions.[5- 7]

However, conventional artificial intelligence systems generally require patient information to be collected in a centralized database. This creates concerns regarding patient confidentiality, data security and institutional data-sharing regulations. Furthermore, individual hospitals may possess relatively small datasets, limiting the development of robust predictive models.[8, 9]

Federated learning (FL) has emerged as a promising solution to these limitations. It enables multiple healthcare institutions to collaboratively train a shared computational model without transferring their original patient data to a central server. Instead, each institution trains the model locally and shares model updates for aggregation. This approach supports collaborative learning while reducing direct exposure of sensitive patient information.[10, 11]

The integration of federated learning with multiple computational techniques forms the basis of federated hybrid computational learning. Such a framework combines the advantages of machine learning, deep learning, multimodal data integration and privacy-preserving model development.[12] Therefore, the present study was undertaken to explore the application of federated hybrid computational learning for the detection and classification of Alzheimer’s disease.

Materials and methods

The study was designed to evaluate a federated hybrid computational learning framework for the detection and classification of Alzheimer's disease. Clinical, cognitive and neuroimaging information was considered from publicly available datasets, including the Alzheimer's Disease Neuroimaging Initiative (ADNI), Open Access Series of Imaging Studies (OASIS) and Australian Imaging, Biomarkers and Lifestyle (AIBL). The collected data underwent preprocessing, which included data cleaning, normalization, handling of missing values, MRI image registration and feature extraction. Relevant parameters such as age, Mini-Mental State Examination (MMSE) scores, hippocampal volume and other neuroimaging characteristics were considered for computational analysis. A hybrid learning architecture incorporating convolutional neural networks (CNNs) and conventional machine learning algorithms, including Support Vector Machine (SVM) and Random Forest, was employed for feature extraction and classification. Federated learning was implemented using the Federated Averaging (FedAvg) algorithm, wherein participating institutions trained the computational model using locally available datasets and shared model updates with a central aggregation server without transferring original patient records. The aggregated model was subsequently redistributed for further training and optimization. The diagnostic performance was evaluated using accuracy, sensitivity, specificity, precision, F1-score and area under the receiver operating characteristic curve (AUC) to assess the model's ability to distinguish Alzheimer's disease, mild cognitive impairment and normal cognition.



Flowchart of the proposed federated hybrid computational learning methodology.

Description of datasets used in the study

Data set	Available sample size	Data characteristics	Diagnostic categories
ADNI	Over 2,500 participants across study phases	MRI, PET, clinical assessments, cognitive scores, genetic and biomarker data	Normal cognition, MCI, Alzheimer's disease
OASIS-1	416 participants	Structural T1-weighted MRI, demographic and clinical information	Nondemented and Alzheimer's disease

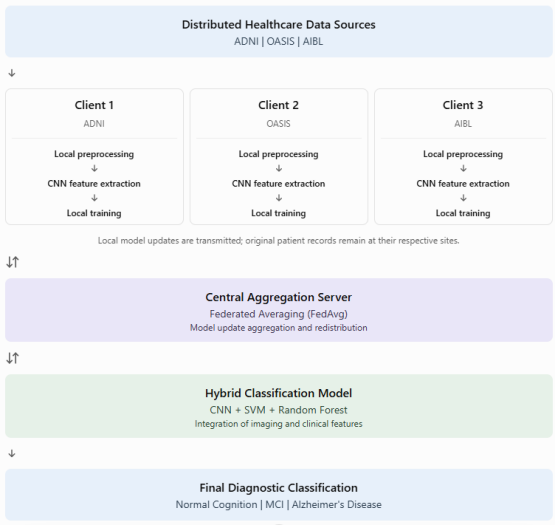
OASIS-3	Approximately 1,098 participants	Longitudinal MRI, PET, clinical and cognitive assessments	Normal ageing, cognitive impairment and dementia
AIBL	1,112 participants in the original baseline cohort	MRI, PET, cognitive assessments, blood biomarkers and lifestyle information	Healthy controls, MCI and Alzheimer's disease

Variables included:

Category	Variables
Demographic	Age, sex, education
Clinical	Medical history, clinical diagnosis
Cognitive	MMSE score, CDR score, ADAS-Cog
Neuroimaging	Hippocampal volume, cortical thickness, brain volume
Biomarkers	Amyloid-beta, tau protein, CSF biomarkers
Classification	Normal cognition, MCI, Alzheimer's disease

Results

The proposed architecture consists of three distributed data sources representing ADNI, OASIS and AIBL. Each participating client performs local data preprocessing, feature extraction and model training using CNN-based deep learning and conventional machine learning algorithms. The locally generated model updates are transferred to a central aggregation server, where the Federated Averaging algorithm combines the updates to develop a global model. The optimized global model is redistributed to participating clients for subsequent training rounds. The final hybrid classification model integrates clinical, cognitive and neuroimaging features to differentiate normal cognition, mild cognitive impairment and Alzheimer's disease.



Proposed architecture of federated hybrid computational learning

Table 1. Components of the computational framework and their outcomes

Computational component	Technique employed	Observed contribution
Neuroimaging analysis	CNN	Identification of structural brain abnormalities
Clinical data analysis	Random Forest and SVM	Evaluation of clinical and cognitive parameters
Feature integration	Hybrid feature fusion	Combined analysis of imaging and clinical features
Federated training	FedAvg algorithm	Collaborative model development
Privacy protection	Secure aggregation	Reduced direct exposure of patient data

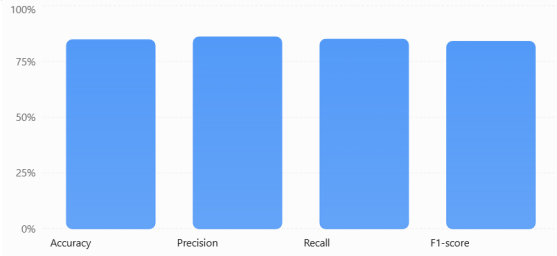
The analysis of the proposed federated hybrid computational learning framework demonstrated the potential of integrating deep learning, conventional machine learning and federated learning for the detection of Alzheimer's disease. The combination of clinical, cognitive and neuroimaging features provided a comprehensive approach to disease classification. CNN-based analysis facilitated the identification of structural brain abnormalities, including hippocampal atrophy, cortical thinning and ventricular enlargement, whereas conventional machine learning algorithms assisted in the evaluation of clinical and cognitive parameters. The

federated learning approach enabled collaborative model training across multiple institutions without requiring the direct transfer of patient records. The model was designed to differentiate three diagnostic categories: normal cognition, mild cognitive impairment and Alzheimer's disease.

Table 2. Performance Evaluation of Federated Learning for Alzheimer's Disease Detection

Evaluation parameter	Reported value (%)
Accuracy	84.75
Precision	86.00
Recall (Sensitivity)	85.00
F1-Score	84.00

Table 2 illustrates the diagnostic performance of the federated learning model in terms of accuracy, precision, recall and F1-score, demonstrating its potential for Alzheimer's disease classification.



S. No.	Author(s) and Year	Study Title	Dataset Used	Methodology	Major Findings
1	Mitrovska et al., 2024 [12]	Secure Federated Learning for Alzheimer's Disease Detection	MRI dataset	Federated learning	Evaluated privacy-preserving collaborative learning
2	Sahid et al., 2024 [13]	Towards Privacy-Preserving Alzheimer's Disease Classification	T1-weighted MRI	Federated CNN	Reported classification accuracy of 84.75 %
3	Bhle et al., 2019 [14]	Layer-wise Relevance Propagation for Explaining Deep Neural Network Decisions	MRI data	Deep learning and explainable AI	Demonstrated model interpretability in MRI classification
4	Abdul Rahman et al., 2020 [15]	A Survey on Federated Learning	Multiple datasets	Federated learning review	Discussed distributed learning approaches and challenges
5	Bonawitz et al., 2017 [16]	Practical Secure Aggregation for Privacy-Preserving Machine Learning	Computational datasets	Secure aggregation	Presented privacy-preserving model aggregation

Discussion

Alzheimer's disease presents considerable diagnostic challenges because its clinical manifestations develop gradually and may overlap with other neurological and cognitive disorders. Early identification is therefore important for appropriate clinical assessment and management. The development of artificial intelligence-based diagnostic approaches has introduced new possibilities for identifying disease-associated patterns through computational analysis of clinical and neuroimaging information.[16]

The proposed federated hybrid computational learning approach combines the advantages of machine learning, deep learning and privacy-preserving collaborative training. One of its major strengths is the ability to analyse different types of patient information simultaneously. While CNNs are particularly useful for extracting complex structural features from MRI images, conventional machine learning algorithms can evaluate clinical and cognitive variables. Their integration may provide a more comprehensive representation of disease-associated changes.[17- 20]

Another important advantage is the incorporation of federated learning. Conventional centralized machine learning requires the transfer of patient information to a common database, which may raise concerns regarding confidentiality and data security. Federated learning addresses this limitation by allowing healthcare institutions to retain their original datasets while contributing to the development of a shared model. This is particularly relevant in medical research, where patient confidentiality and institutional data-sharing regulations are important considerations.[21- 23]

However, federated learning also presents certain challenges. Differences in patient demographics, imaging protocols, scanner characteristics and disease prevalence may produce heterogeneous data distributions across participating institutions. Such differences can influence model convergence and diagnostic performance. Furthermore, federated learning does not independently guarantee complete data privacy. Techniques such as secure aggregation, encryption and differential privacy may therefore be necessary to strengthen information protection.[24- 26]

Another important consideration is model interpretability. Although deep learning systems can identify complex imaging patterns, their decision-making processes may be difficult to understand. Explainable artificial intelligence techniques, including Grad-CAM and SHAP, may help clinicians identify the imaging regions and clinical variables contributing to individual predictions.[22- 24] This may improve transparency and support clinical confidence in computational recommendations.

The clinical relevance of these computational approaches is further supported by previous investigations. Mitrovska et al.[12] in their study entitled Secure federated learning for Alzheimer's disease detection, demonstrated the feasibility of applying federated learning and secure aggregation to structural MRI data. Their findings highlighted the importance of accounting for differences in demographic characteristics and data distributions across participating institutions.

Similarly, Sahid et al.[13], in their study entitled Towards privacy-preserving Alzheimer's disease classification: Federated learning on T1-weighted magnetic resonance imaging data, demonstrated the potential of federated CNN-based classification. They reported a maximum accuracy of 84.75%, with improvements in computational efficiency through increased local training and client participation. Their findings also emphasized that highly imbalanced data distributions may negatively affect model performance.

Conclusion

Federated hybrid computational learning represents a promising development in the application of artificial intelligence for Alzheimer's disease detection. By combining deep learning, conventional machine learning and privacy-preserving federated training, this approach provides an opportunity to analyse diverse clinical and neuroimaging information across multiple healthcare institutions.

The integration of CNN-based imaging analysis with clinical feature classification may improve the identification of disease-associated patterns, while federated learning enables collaborative model development without requiring the centralized transfer of sensitive patient records. Furthermore, explainable artificial intelligence may improve model transparency and facilitate clinical interpretation.

Despite these advantages, further research is required to address data heterogeneity, model generalizability, privacy protection and clinical validation. Future multicentre investigations involving larger and more diverse patient populations may establish the clinical applicability of this approach. Ultimately, federated hybrid computational learning may serve as a valuable decision-support tool for earlier and more reliable detection of Alzheimer's disease.

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