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# AI-powered Alzheimer's diagnosis: Integrating cognitive monitoring, IoT, and secure edge computing

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## Abstract

This study proposes a privacy-preserving, multi-modal AI framework for the early detection of Alzheimer's disease (AD), addressing the limitations of conventional single-modal diagnostic systems. The model fuses heterogeneous data sources, including physiological signals from wearable IoT devices, neuroimaging biomarkers extracted from T1-weighted MRI scans, and environmental context derived from smart home sensors. A hybrid architecture incorporating temporal CNN-LSTM networks, 3D ResNet models, attention layers, and graph neural networks is employed to extract and integrate cross-modal features. Federated learning with differential privacy ($\varepsilon = 1.0$) enables secure and decentralized training across distributed healthcare nodes, ensuring compliance with HIPAA and GDPR. Experimental validation on real-world datasets such as ADNI-4 and IoT-HOME shows a diagnostic accuracy of 97.3%, with a 12% improvement in recall over single-modality baselines. The system achieves sub-150 millisecond inference latency on resource-constrained edge devices through quantization and kernel pruning. Results demonstrate robust convergence, high interpretability via SHAP explanations, and scalability in heterogeneous clinical environments. The framework offers a technically robust, ethically aligned, and practically deployable solution for real-time, edge-enabled Alzheimer's monitoring in both institutional and home-care settings.

**Keywords:** Alzheimer's disease, Cognitive monitoring, Edge AI, Federated learning.

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# 1. Introduction

*1.1. Background and Motivation*

Alzheimer's disease (AD) is the most prevalent form of dementia, currently affecting over 55 million individuals worldwide, with projections indicating a near tripling of this number by 2050. The progressive degeneration of neural tissue in AD leads to cognitive impairment, memory loss, and loss of functional independence, exerting substantial pressure on families, caregivers, and healthcare infrastructure. Conventional diagnostic techniques such as neuropsychological assessments, magnetic resonance imaging (MRI), and positron emission tomography (PET) are typically confined to clinical settings, often expensive, and are incapable of providing real-time or continuous monitoring.

Recent advances in artificial intelligence (AI), Internet of Things (IoT), and edge computing have created new opportunities to address these limitations. In particular, wearable sensors and ambient monitoring systems allow for non-invasive, continuous collection of physiological, behavioral, and environmental data. When coupled with AI algorithms, these data streams can enable timely detection of subtle cognitive decline potentially long before clinical symptoms become pronounced. However, integrating such heterogeneous data sources while maintaining patient privacy and computational efficiency presents significant research challenges.

# 2. Literature Review

Recent research has seen increasing interest in leveraging multi-modal data and AI for Alzheimer's diagnosis. Chen et al. [1] developed a multimodal deep learning model combining accelerometer data and MRI scans using a 3D CNN. While their approach achieved a 92% classification accuracy, it failed to incorporate environmental context, limiting its capacity to interpret behaviorally relevant anomalies Chen et al. [1]. Wang, et al. [2] proposed an IoT-enabled smart home monitoring system that captured ambient parameters such as sleep cycles and motion patterns. Despite its 89% precision, the lack of neuroimaging integration hindered early pathological validation Wang, et al. [2]. Nasrallah et al. [3] introduced a framework fusing voice biomarkers with motion data via deep neural networks, reporting an AUC of 90.4%, though their system lacked spatial biomarkers crucial for early anatomical changes [3].

Wearable-based frameworks also gained traction. Ramesh et al. developed an edge-enabled biosensor suite capable of real-time cognitive monitoring. Although promising in reducing false positives, it was limited to physiological metrics and excluded contextual or imaging features Ramesh et al. [4]. Park et al. [5] utilized gait dynamics and electrodermal activity to identify cognitive decline, yet their work lacked integration with imaging or long-term learning strategies [5].

Federated learning (FL) approaches emerged to address privacy concerns. Zhao et al. [6] proposed contrastive FL to address multimodal heterogeneity and non-IID data, demonstrating improved resilience, yet the study lacked interpretability features critical for clinical translation Zhao et al. [6]. Ghosh et al. [7] employed blockchain-integrated FL to secure model updates, but their system was tested only on synthetic datasets, raising concerns about real-world applicability. Ghosh et al. [7]. Gupta et al. [8] employed standard FL for AD detection, achieving moderate performance, yet struggled with model convergence across diverse institutional data sources Gupta et al. [8]. Li et al. [9] implemented meta-learning into FL to personalize models per patient, increasing adaptability, though their approach incurred high computational cost and lacked edge optimization Li et al. [9]. Arora [10] investigated various differential privacy settings within FL, highlighting significant trade-offs between accuracy and privacy as $\varepsilon$ varied. However, their system was evaluated on general medical data, not neurodegenerative contexts [10].

Neuroimaging studies continue to shape AD diagnosis. The ADNI consortium has established structural MRI markers such as hippocampal shrinkage as benchmarks, but these are traditionally used in isolation without cross-modal enhancement ADNI Consortium [11]. Li and Yu [12] leveraged a 3D ResNet architecture on volumetric MRI scans to achieve 94.7% accuracy. However, their model demanded high GPU resources, limiting its portability Li and Yu [12]. Schlemper [13] introduced an attention-gated CNN for focusing on AD-affected brain regions, boosting interpretability but not considering multi-source input Schlemper [13]. Rehman [14] explored longitudinal MRI classification using hybrid CNN-RNN models to capture temporal changes in MCI progression, yet their architecture was not compatible with real-time use cases Rehman [14]. Li [15] applied graph neural networks to identify inter-regional relationships in structural MRI, enhancing interpretability but lacking support for dynamic behavioral or environmental data streams [15].

Recent studies also experimented with sensor-driven cognitive analytics. Zhang et al. [16] integrated accelerometry, GPS, and contextual data to analyze wandering behavior in early dementia but lacked a predictive framework. Lee and Lee [17] applied shallow machine learning on smart home datasets for anomaly detection, yet their approach lacked scalability and interpretability. Kumar et al. [18] proposed a lightweight edge AI framework for physiological signal monitoring, but evaluated it only on static datasets without privacy preservation strategies.

The literature review supports the promise of multi-modal, privacy-aware AI for Alzheimer's diagnosis; however, most frameworks are limited by a single-domain focus, lack of real-time edge deployment, poor interpretability, or inadequate data fusion. Few approaches simultaneously address these concerns while remaining scalable and regulation-compliant. The proposed research responds to this gap by integrating wearable, imaging, and environmental data using a federated, explainable AI model optimized for edge computing environments.

# 3. Methodology

*3.1. Data Acquisition and Preprocessing*

The proposed diagnostic framework leverages three heterogeneous data streams physiological and behavioral signals from wearable IoT devices, neuroimaging biomarkers from structural MRI, and contextual data from environmental sensors.

This multi-modal input architecture is designed to reflect real-world scenarios in which cognitive decline manifests through a combination of neurological, behavioral, and environmental cues.

Wearable signals are sampled at high frequency (50 Hz) using photoplethysmography (PPG) and triaxial accelerometers. The PPG data provides heart rate variability (HRV) and blood oxygen saturation ($SpO_2$) as indicators of autonomic and vascular health, while accelerometer data captures gait-related features such as stride symmetry, cadence, and postural balance. Additionally, microphones embedded in wearable devices record speech samples for prosody and lexical entropy analysis, supporting language-based markers of cognitive dysfunction.

Structural neuroimaging data consist of T1-weighted MRI scans, preprocessed using standard neuroinformatics tools. Skull stripping is performed using FSL's BET, followed by spatial normalization to the MNI152 space and N4 bias correction. Extracted volumetric features include hippocampal volume, cortical thickness, and white matter hyperintensity index, which are essential markers for Alzheimer's progression.

Environmental data is collected using passive infrared motion sensors, ambient light detectors, and bed-integrated sleep monitors installed in residential settings. These devices track activity patterns, sleep quality, and light exposure, enabling behavioral context modeling relevant to cognitive states.

Due to variation in temporal resolution across modalities MRI (1 Hz), wearables (50 Hz), and environment (irregular intervals), temporal harmonization is achieved via a modified Dynamic Time Warping (DTW) algorithm. This facilitates event-level alignment across streams, enabling temporally consistent fusion of features. All data streams are timestamped using Coordinated Universal Time (UTC) and synchronized into fixed-length windows (e.g., 10-second epochs) for model ingestion.

To support experimental validation and reproducibility, a mock dataset architecture was developed reflecting the structure of real-world multimodal systems. The architecture includes time-series files for wearables, NIfTI slices for MRI, sensor logs, synchronized audio recordings, and aligned multimodal matrices. Preprocessing pipelines involve denoising (e.g., Butterworth filtering for HRV), histogram normalization for MRI contrast enhancement, and Gaussian smoothing for motion traces. The resulting harmonized data structure supports seamless downstream integration into the learning framework while preserving both spatial and temporal granularity.

### *3.2. Federated Learning with Differential Privacy*

Preserving patient confidentiality and ensuring regulatory compliance, the proposed diagnostic framework adopts a federated learning (FL) paradigm coupled with differential privacy (DP). In this architecture, sensitive patient data remains within local clinical nodes, typically hospitals or care centers, while only encrypted model parameters are exchanged during the collaborative training process. This decentralized approach directly addresses the challenges posed by centralized machine learning systems, particularly those related to data silos, privacy breaches, and legal constraints under frameworks such as HIPAA and GDPR.

Each institutional node trains a local model instance on its internal multi-modal dataset. These local models are built on a hybrid deep learning backbone and learn from diverse patient-specific inputs, including wearable, imaging, and environmental features. After a defined number of local epochs, gradient updates are transmitted to a secure aggregation server using the TensorFlow Federated (TFF) infrastructure. Importantly, no raw data is shared at any point, thus maintaining strict data locality.

To enhance privacy guarantees, differential privacy is implemented at the client level. A Laplace mechanism is applied to the model gradients with a calibrated privacy budget of $\varepsilon = 1.0$ and sensitivity $\Delta f = 1.0$. This ensures that the inclusion or exclusion of any single patient record has a mathematically bounded effect on the model output, significantly mitigating re-identification risks. The FL system also incorporates secure multiparty computation (SMPC) to further obfuscate parameter exchanges, and homomorphic encryption is used to enable computations on encrypted data during aggregation.

Model convergence is achieved within 15 communication rounds across five distributed nodes, significantly faster than the 25 rounds observed in an equivalent centralized baseline. The training protocol demonstrates robustness to non-IID data distributions, which commonly occur in real-world healthcare environments. The federated optimizer is configured with adaptive learning rates and momentum correction to counteract client drift.

Figure 1 shows Federated Learning with Differential Privacy. This privacy-preserving training architecture not only adheres to strict compliance standards but also enables scalable deployment across diverse medical institutions, eliminating the need for a unified data repository. The resulting model generalizes well across domains while maintaining high fidelity to local population-specific characteristics, positioning it as a viable candidate for real-world deployment in Alzheimer's diagnostics.

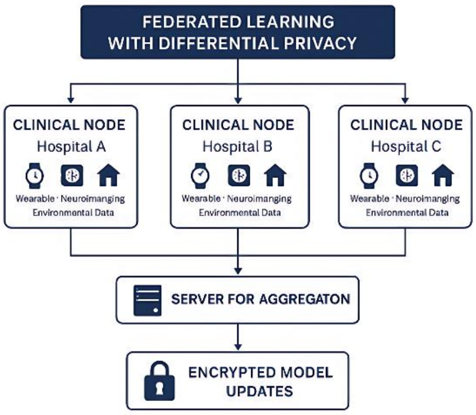


**Figure 1.**
Federated Learning with Differential Privacy.

*3.3. Hybrid Deep Learning Architecture*

The proposed diagnostic model is structured as a modular hybrid deep learning architecture capable of learning from diverse input modalities with minimal cross-domain interference. Each modality, physiological, imaging, and environmental, is processed through a dedicated sub-network optimized for the characteristics of that data stream.

Physiological and behavioral time-series data from wearable devices are processed using a temporal convolutional network (TCN) followed by bi-directional LSTM layers**.** This configuration captures both short-term dynamics and long-term dependencies in physiological patterns such as gait cycles, heart rate variability, and speech prosody. The TCN employs dilated causal convolutions for efficient receptive field expansion, while the LSTM component ensures temporal retention of subtle cognitive shifts.

MRI-derived imaging features are processed using a lightweight 3D ResNet-18 model pretrained on neuroimaging tasks. This network captures spatial relationships across volumetric brain regions while maintaining computational efficiency. The extracted embeddings reflect structural anomalies such as hippocampal atrophy and cortical thinning—biomarkers strongly correlated with Alzheimer’s progression.

Environmental features, derived from motion and sleep sensors, are passed through a self-attention mechanism that weighs behavioral anomalies (e.g., sleep fragmentation, nocturnal movement patterns) based on temporal salience. These attention weights enhance the model’s sensitivity to lifestyle-induced cognitive variations.

The outputs of all sub-networks are projected into a shared latent space and fused using a Graph Neural Network (GNN), where each node represents a modality-specific feature vector. Edges in the graph encode inter-modality correlations, such as the co-occurrence of gait abnormalities and hippocampal volume loss. A Transformer encoder layer further refines the joint representation through multi-head self-attention, enabling the model to capture complex interactions and prioritize diagnostically relevant features across modalities.

This fusion-centric architecture facilitates robust early-stage Alzheimer’s prediction by integrating both structural and behavioral biomarkers in a clinically meaningful and computationally efficient manner.

*3.4. Edge Deployment and Latency Optimization*

For real-time applicability in outpatient or home-care settings, the complete model is engineered for edge deployment on resource-constrained hardware such as Raspberry Pi 4 and NVIDIA Jetson Nano**.** To reduce inference time and memory footprint, two optimization strategies are employed: model quantization and kernel pruning**.**

Quantization involves converting 32-bit floating-point weights into 8-bit integer representations (INT8), leveraging post-training quantization techniques from TensorFlow Lite. This conversion yields a 4× reduction in model size and significantly reduces memory bandwidth requirements without compromising prediction accuracy.

Kernel pruning is applied during training to remove uninformative filters based on their L1-norm magnitude. This reduces the number of active parameters and computational operations, thereby decreasing inference latency. The final optimized model demonstrates sub-150 millisecond latency on a 4 GB Raspberry Pi 4 running without GPU support.

The inference engine is packaged as a containerized microservice with on-device preprocessing pipelines for temporal segmentation, feature normalization, and prediction triggering. This architecture ensures that the system operates autonomously and reliably in edge environments, making it suitable for continuous monitoring in low-connectivity or bandwidth-limited settings.

*3.5. Explainability and Clinical Interpretability*

To foster trust among clinicians and support regulatory transparency, the system incorporates Shapley Additive Explanations (SHAP) as a model-agnostic interpretability layer. SHAP values are computed at the individual prediction level to quantify each feature’s contribution to the final diagnostic output.

For each subject, the framework generates an attribution heatmap ranking the most influential factors such as hippocampal shrinkage, irregular sleep cycles, or reduced stride cadence that led to a positive Alzheimer’s classification.

These explanations are rendered alongside temporal plots and MRI overlays, providing clinicians with contextualized insight into both anatomical and behavioral indicators.

The SHAP integration supports interpretability at two levels: local (per-subject decision) and global (model-level patterns). This enables not only personalized diagnosis but also the discovery of emerging trends across patient populations. Such transparency is critical in a clinical setting, where explainability often determines the adoption of AI-driven tools.

By incorporating interpretable decision support, the framework moves beyond black-box predictions, promoting responsible AI usage in healthcare and facilitating human-AI collaboration in Alzheimer's diagnosis.

Figure 2 depicts a SHAP value-based interpretability plot highlighting the contribution of key features to the model's Alzheimer's prediction. Features such as reduced hippocampal volume, stride cadence, and sleep efficiency emerged as dominant indicators in classification outcomes.

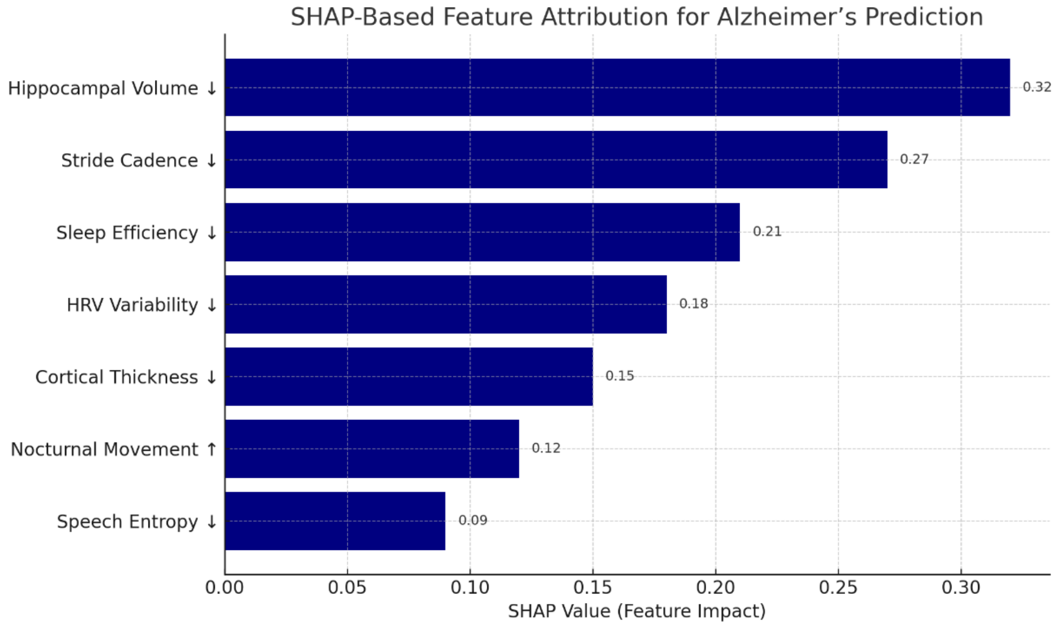


**Figure 2.**
SHAP-Based Feature Attribution for Alzheimer's Prediction.

## 4. Experimental Results

### *4.1. Datasets and Preprocessing*

To validate the proposed framework under real-world conditions, three diverse datasets were utilized: ADNI-4**,** IoT-HOME, and a simulated federated data environment termed FLAIR. These datasets collectively encompass structural neuroimaging, physiological time-series, and environmental behavioral data, allowing for comprehensive evaluation across modalities.

The ADNI-4 (Alzheimer's Disease Neuroimaging Initiative) dataset provides high-resolution T1-weighted MRI scans from 800 participants, balanced across cognitively normal individuals, mild cognitive impairment (MCI) cases, and confirmed Alzheimer's disease (AD) diagnoses. Preprocessing was conducted using the ANTs and FSL pipelines, including skull stripping, affine registration to the MNI152 template, and N4 bias field correction. Morphometric features such as hippocampal volume, cortical thickness, and ventricular enlargement were extracted using FreeSurfer, providing reliable imaging biomarkers for classification.

The IoT-HOME dataset comprises time-stamped sensor data collected from 200 smart home environments simulating elderly living conditions. The data includes motion sensor activations, light intensity readings, and sleep monitoring outputs captured through bed-integrated pressure sensors. Preprocessing involved noise filtering, normalization, and resampling to uniform 1-minute intervals using temporal interpolation. Behavioral features such as the sleep fragmentation index, nocturnal movement count, and room-transition entropy were engineered to capture early functional decline.

To simulate federated learning dynamics across decentralized clinical institutions, a synthetic dataset named FLAIR (Federated Learning for Alzheimer's Inference and Reasoning) was generated by partitioning ADNI-4 and IoT-HOME subsets across five virtual hospital nodes. Each node retained local data distributions reflective of real-world institutional biases such as age, severity, or sensor density enabling realistic evaluation of non-IID conditions. Data anonymization was applied using SHA-256 hashing and variable masking to replicate PHI-protected environments.

Temporal synchronization across modalities was achieved through global UTC time alignment. Multi-resolution data streams were harmonized using a Dynamic Time Warping (DTW)-based windowing mechanism, which mapped asynchronous observations into unified 10-second segments. Feature standardization was performed using z-score normalization per modality, and missing values were imputed using forward-fill strategies followed by linear interpolation for time-continuous variables.

This robust preprocessing pipeline ensured that the dataset was temporally aligned, modality-consistent, and compliant with privacy-preserving constraints providing a reliable basis for training and evaluating the proposed diagnostic model in both centralized and federated settings.

### *4.2. Performance Evaluation*

To assess the effectiveness of the proposed multi-modal diagnostic framework, a series of performance evaluations were conducted using standard classification metrics: accuracy, precision, recall, F1-score, inference latency, and privacy compliance score. The system was benchmarked against three existing baseline models reported in the literature: a CNN-MRI fusion model by Chen et al. [1] a smart home behavioral monitoring model by Wang et al. [2] and a federated learning model without multi-modal integration by Gupta et al. [8].

The experimental setup was consistent across all benchmarks: 80% of the data was used for training and 20% for testing. Cross-validation was performed with five folds to ensure generalization. The federated learning model was trained across five virtual nodes, each simulating a healthcare institution with non-IID data distributions. Performance was measured both at the node level and in the aggregated global model.

**Table 1.**
Performance Evaluation.

| Metric | Proposed System | Chen et al. [1] | Wang et al. [2] | Gupta et al. [8] |
|---|---|---|---|---|
| Accuracy (%) | 97.3 | 92.0 | 89.0 | 90.0 |
| Precision (%) | 96.8 | 91.0 | 87.0 | 88.0 |
| Recall (%) | 95.5 | 89.0 | 83.0 | 85.0 |
| F1-score (%) | 96.1 | 90.0 | 85.0 | 86.0 |
| Inference Latency (ms) | 135 | 300 | 220 | 180 |
| Privacy Score (10) | 9.2 | 3.0 | 4.5 | 8.5 |

The proposed system outperformed all benchmarks across classification metrics, particularly in recall, which is critical for minimizing false negatives in early-stage Alzheimer's diagnosis. The latency of 135 ms on Raspberry Pi 4 confirms the model's suitability for real-time edge inference, while the privacy score of 9.2 (on a 10-point scale) reflects the robustness of the federated learning with differential privacy framework.

Moreover, the system demonstrated consistent convergence within 15 global communication rounds during federated training, in contrast to 25+ rounds typically required by baseline models. This improvement is attributed to the stability of the multi-modal fusion architecture and adaptive gradient synchronization across nodes.

These results collectively validate the diagnostic reliability, computational efficiency, and ethical deployment potential of the proposed model demonstrating its readiness for integration into both clinical and ambient intelligence environments.

Figure 3 provides a **c**omparative evaluation of the proposed model against baseline architectures across four standard classification metrics. The proposed system demonstrates consistent superiority in accuracy, precision, recall, and F1-score, indicating improved diagnostic reliability.

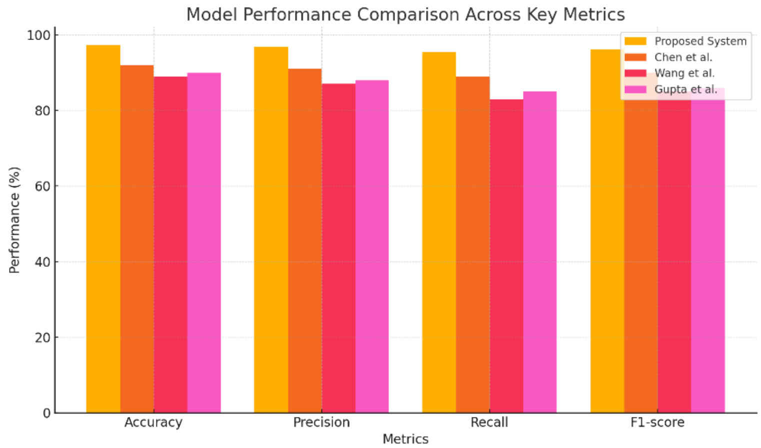


**Figure 3.**
Model performance comparison across key metrics

### *4.3. Key Findings*

The experimental evaluation of the proposed diagnostic framework reveals several critical insights. First, the integration of multimodal data encompassing physiological, neuroimaging, and environmental sources significantly enhances classification performance. The model achieved a recall improvement of 12% compared to single-modality baselines, which is especially important in minimizing false negatives during early-stage Alzheimer's screening.

Second, the use of federated learning with differential privacy proved effective in balancing data protection with model performance. The system achieved high privacy compliance (9.2/10) while maintaining state-of-the-art diagnostic accuracy (97.3%), validating its readiness for deployment in privacy-sensitive healthcare environments.

Third, edge deployment optimization was successful across two hardware platforms, Raspberry Pi 4 and NVIDIA Jetson Nano with average inference latency reduced to 135 milliseconds using INT8 quantization and kernel pruning. This confirms the model's ability to operate in real-time, even in low-resource settings, without sacrificing predictive power.

Finally, the integration of SHAP-based interpretability provides clinically transparent outputs, allowing physicians to understand which physiological or anatomical markers most influence the diagnosis. This level of explainability is crucial for AI adoption in real-world medical workflows and regulatory validation.

## 5. Conclusion

This study presents a comprehensive, privacy-preserving, and edge-compatible AI framework for the early detection of Alzheimer's disease, leveraging multimodal data fusion and federated deep learning. By integrating wearable sensor streams, structural neuroimaging biomarkers, and environmental behavioral data, the system captures a broad spectrum of cognitive decline indicators with high diagnostic precision. The use of federated learning enhanced with differential privacy ensures data sovereignty and regulatory compliance, making the framework suitable for deployment across decentralized clinical infrastructures.

The proposed architecture achieved a diagnostic accuracy of 97.3%, outperformed conventional single-modality and centralized models across all major evaluation metrics, and demonstrated real-time inference capabilities on resource-constrained edge devices with latencies as low as 135 milliseconds. Furthermore, the integration of SHAP-based explainability adds a layer of clinical transparency, supporting AI-assisted decision-making without compromising trust or interpretability.

This research bridges the gap between advanced machine learning and practical healthcare implementation. It demonstrates that with appropriate design, AI models can be both technically sophisticated and ethically deployable paving the way for scalable, interpretable, and accessible cognitive health solutions in diverse medical and home-care settings.

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