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Junyan Qu

JunyanQu6@outlook.com

Xinxiang Vocational and Technical College，Xinxiang

Hao Wang

Xinxiang Vocational and Technical College，Xinxiang

Ming Sun

Xinxiang Vocational and Technical College，Xinxiang

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An AD Detection System Using Theme Enhancement and Dynamic Differential Privacy for Intelligent Elderly Care

Junyan Qu* , Hao Wang , Ming Sun

Xinxiang Vocational and Technical College，Xinxiang, Henan, 453006, China

*Corresponding author:Junyan Qu

Junyan Qu’s e-mail:JunyanQu6@outlook.com

Hao Wang’s e-mail:HaoWang933@outlook.com

Ming Sun’s e-mail:MingSun5@outlook.com

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Author contributions

Junyan Qu conceived and designed the study, performed experiments, analyzed data, and wrote the main manuscript text. Hao Wang performed experiments, analyzed data, and prepared figures. Ming Sun supervised the project, provided resources, and reviewed the manuscript. All authors reviewed the manuscript.

Ethical Approval and accordance

This study conducted a secondary analysis of the publicly available ADReSS (Alzheimer's Dementia Recognition through Spontaneous Speech) dataset. The ADReSS dataset was previously collected under approved ethical protocols, and all participants provided written informed consent at the time of data collection. For this secondary analysis, no additional ethical approval was required, as the data are fully anonymized and publicly accessible. All procedures were performed in accordance with the relevant guidelines and regulations of the ADReSS data usage agreement.

Consent to participate

Not applicable. This research is a retrospective analysis of the ADReSS public dataset, for which all original participants had previously given their informed consent to participate in the data collection. No new human subjects were recruited for this study, and therefore no additional consent was required.

Data Availability statement

The datasets generated during and/or analysed during the current study are available from the corresponding author on reasonable request.

Clinical trial number

Not applicable

Abstract: To address the challenges of low detection accuracy and high privacy leakage risk in Alzheimer's disease (AD) detection for intelligent elderly care systems, this paper proposes ADDETECTOR, an AD detection system based on topic enhancement and dynamic differential privacy. The system adopts a three-layer architecture comprising a user layer, client layer, and cloud layer, enabling full-process AD detection from speech collection to model aggregation. A language feature enhancement method based on topic modeling is introduced, which constructs an AD-related topic lexicon and designs a semantic deviation measurement model to effectively capture subtle linguistic anomalies in AD patients. Furthermore, a dynamic differential privacy mechanism combined with a federated security framework is developed, employing Laplace noise injection, ECDH encryption, and secret sharing to ensure secure parameter transmission and gradient aggregation while protecting user voice data privacy. Experimental results on the ADReSS dataset demonstrate that ADDETECTOR achieves significant improvements in detection accuracy and F1 score compared to baseline models such as HAN-AGE and BI-GRU, while maintaining low system response time. Parameter sensitivity tests show good scalability across 2–9 clients and a favorable privacy-utility balance when the privacy budget ε is set between 0.8 and 5. The proposed system provides an effective and secure technical solution for early AD screening in intelligent elderly care applications.

Keywords: Alzheimer's disease detection; Theme modeling; Differential privacy; Federated Learning; Intelligent elderly care

1 Introduction

According to data released by the Office of the National Committee on Aging, by the end of 2023, the elderly population aged 60 and above in China will reach 297 million, accounting for 21.1% of the total population. It is expected to exceed 350 million by 2030, accounting for over 25% [1]. Among the numerous health problems faced by the elderly, Alzheimer's Disease (AD) has become a major challenge that seriously affects the quality of life of the elderly due to its high incidence rate, high disability rate and difficult cure [2]. Alzheimer's disease is a

progressive neurodegenerative disease characterized by cognitive decline and behavioral abnormalities. Research has shown that early identification and intervention of AD play a crucial role in delaying disease progression, improving patients' quality of life by over 30% while reducing family and social care costs by approximately 25% [3]. However, traditional AD diagnosis mainly relies on neuropsychological tests and brain imaging examinations in hospital environments, which are not only expensive, but also difficult to achieve daily continuous monitoring and cannot meet the needs of large-scale early screening. The results of neuropsychological testing may be influenced by various factors such as the patient's education level, cultural background, and emotional state, leading to subjectivity and variability in diagnostic results. Although existing biomarker tests, such as amyloid and tau proteins, can assist in diagnosis in some cases, their specificity is limited and may coexist with other neurodegenerative diseases, even leading to positive results in the absence of clinical symptoms [4].

In the 14th Five Year Plan, the country has clearly set the goal of developing a smart and healthy elderly care industry, and it is expected that by 2025, the scale of the smart elderly care market will exceed one trillion yuan. As the most natural and seamless human-machine interaction method in intelligent elderly care systems, voice interaction not only meets the daily service needs of the elderly, but also contains rich health information. Research has shown that there are significant changes in the speech of Alzheimer's disease patients, including slower pace, increased pauses, and difficulty in vocabulary selection. These changes are usually detected several years before clinical symptoms appear, providing the possibility for early screening [5]. Keerthika et al. developed the first AD automatic detection system based on convolutional neural networks using the ADNI dataset, with a detection accuracy of 87.6% [6]. The system uses a three-dimensional convolutional neural network to extract features from brain MRI images, and achieves early AD risk assessment by identifying atrophy features in the hippocampus region. This study has pioneered AI assisted AD diagnosis, but the system has a strong dependence on high-quality data and high computational complexity, which limits its widespread application in ordinary medical institutions. Li et al. developed a distributed AD detection framework based on federated learning, which allows medical institutions to collaboratively train AI models without sharing

raw data [7]. Research has shown that this framework not only protects patient privacy, but also has detection performance that is only 4% lower than centralized training models, providing a new approach to solving the problem of data silos in the field of medical AI. However, such systems still face privacy leakage risks during the model inference process, especially in the case of member inference attacks targeting the model output. Khanna et al. developed a multimodal AD detection system. The system not only analyzes imaging data, but also integrates cognitive test scores, blood biomarkers and gene information, automatically assigns different feature weights through attention mechanism, and realizes accurate prediction of the risk of conversion from mild cognitive impairment (MCI) to AD, with a prediction accuracy rate of 91.2%, which is about 8% higher than the single-mode method [8]. This multimodal fusion method overcomes the limitations of a single detection method, but also increases the burden of patient examination and system complexity. Nguyen et al. developed an AD detection system with visual interpretation capabilities. The system adopts Gradient Weighted Class Activation Mapping (Grad CAM) technology, which can highlight the brain regions of concern in the AI decision-making process, helping doctors understand the diagnostic basis of the system [9]. Experiments have shown that systems with interpretable functions significantly improve clinical doctors' acceptance and willingness to use AI assisted diagnosis, which has important reference significance for the implementation and promotion of intelligent elderly care systems.

Therefore, applying AI technology to the field of elderly care and health faces two major challenges: on the one hand, detection accuracy issues. Due to the complexity and individual differences of elderly speech data, traditional speech analysis models often cannot effectively capture subtle language abnormalities in AD patients; On the other hand, there are privacy and security issues. The health voice data of the elderly is highly sensitive information, and there is a serious risk of privacy leakage during data collection, transmission, and analysis.

In view of this, the paper aims to design an AD detection system based on topic enhancement and dynamic differential privacy (ADDETECTOR), which achieves the goal of high-precision recognition of early language anomalies in AD while protecting user privacy. This study not only has important theoretical significance and can promote the interdisciplinary integration of speech analysis, privacy computing, and intelligent healthcare,

but also has significant application value. It can provide convenient and painless AD early screening services for the elderly, achieve "early diagnosis and treatment before illness", effectively improve the quality of life of the elderly, reduce the burden on families and society, and provide innovative technological support for addressing the challenges of population aging.

2 Architecture Design of ADDETECTOR System

2.1 Overall System Architecture

1）User Layer: Speech Collection and Preprocessing

The collected raw speech data requires a series of preprocessing operations to improve the efficiency and accuracy of subsequent feature extraction and analysis. The preprocessing process mainly includes steps such as frame segmentation, windowing, mute detection and removal, and format standardization of speech signals [10]. For each frame signal, the system uses the Hamming window function for weighted processing, and its calculation formula is as follows (1):

$$w(n) = 0.54 - 0.46cos\left(\frac{2\pi n}{N-1}\right), 0 \le n \le N-1 \quad (1)$$

Among them, N represents the window length, and n is the sample index within the window. The windowed signal can be represented as the product of the original signal and the window function.

After preprocessing, the speech data is standardized into a unified format and undergoes preliminary quality assessment. Unqualified samples will be marked or discarded [11].

2) Client layer: Local detection and differential privacy perturbation

As shown in Figure 1, the client layer first performs speech feature extraction, including two dimensions: Acoustic features and language features. Acoustic features mainly include Mel frequency cepstral coefficients (MFCC), fundamental frequency (F0), resonance peak frequency and other parameters, which can reflect the timbre, pitch, clarity and other characteristics of elderly speech [12]. Language features include language fluency, vocabulary richness, semantic coherence, etc., which are of great significance for early diagnosis of AD. Table 1 shows the key feature parameters extracted by the ADDETECTOR system on the

client side.

Table 1 ADDETECTOR Client Feature Extraction and Parameter Setting

Feature Type	Feature Name	Parameter dimension	Extraction algorithm	Calculation period（ms）	Application value
Acoustic feature	MFCC	13×2	FFT+DCT	25	Abnormal tone detection
Acoustic feature	Pitch variation	4	Autocorrelation method	30	Assessment of tone singularity
Acoustic feature	HNR	1	Cepstrum analysis	25	Articulation
Language features	Lexical complexity	3	Bag of words model	Discourse unit	Vocabulary poverty detection
Language features	Topic deviation degree	5	Topic modeling	Paragraph unit	Semantic coherence assessment

After feature extraction is completed, the client will use a local lightweight model for preliminary AD feature detection and scoring. In order to protect user privacy, the system uses differential privacy technology for data perturbation before uploading model parameters to the cloud [13]. The core of differential privacy perturbation is to add Laplace noise to the real gradient, and its probability density function is defined as equation (2):

$$Pr(M(x) = y) \propto exp\left(-\frac{||y - f(x)||_1}{\Delta f/\varepsilon}\right) \quad 2)$$

Among them, $M(x)$ represents the output after adding noise, $f(x)$ represents the original gradient, Δf represents sensitivity, and ε represents privacy budget. The Laplace mechanism ensures that even in the worst-case scenario, attackers cannot infer information about a specific individual by observing the output.

In order to balance privacy protection and model performance, the system has designed a dynamic differential privacy mechanism that adaptively adjusts the value of privacy budget ε based on the sensitivity of user voice data and the current network environment. Specifically, the system uses an adaptive adjustment algorithm based on gradient sensitivity, as shown in equation (3):

$$\varepsilon_t = \varepsilon_{base} \cdot \alpha \cdot \frac{max(||abl\nabla L||_2)}{threshold} \quad 3)$$

Among them, ε_t represents the privacy budget for the t-th round, ε_{base} is the basic privacy budget, α is the adjustment factor, ∇L represents the model gradient, and threshold is the preset threshold.

After differential privacy processing, the model parameters will be encrypted and transmitted to the cloud, ensuring the local processing principle of user voice data and effectively reducing the risk of privacy leakage during the transmission of raw data. At the same time, the client also implements data caching and breakpoint resume functions, which can ensure the reliable operation of the system even in unstable network conditions. This is of great significance for the unstable network conditions in the home environment of elderly people.

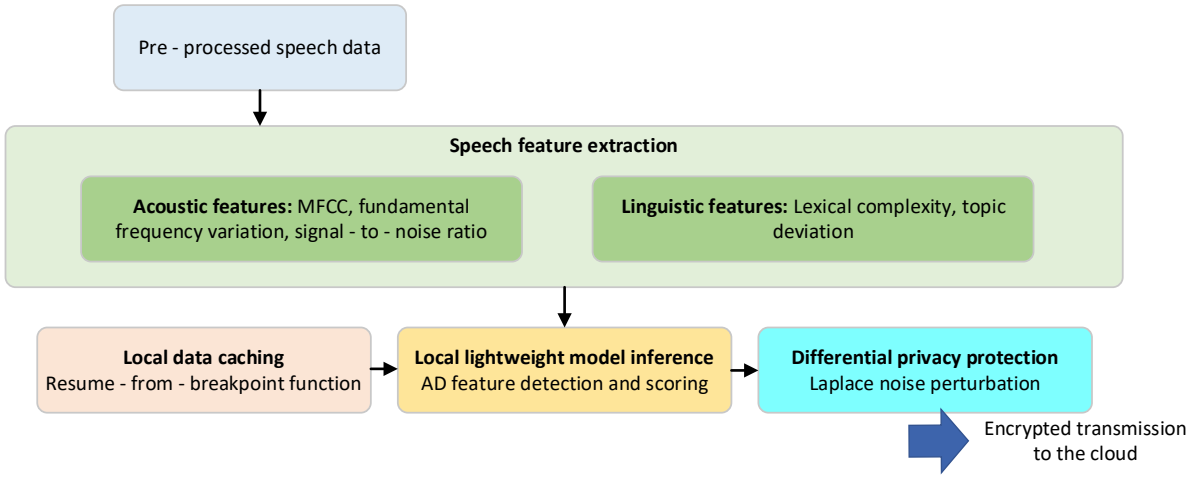


Figure 1 Client layer architecture of ADDETECTOR system

3) Cloud layer: Federated learning and model aggregation

As shown in Figure 2, the cloud layer adopts a federated learning framework to optimize the global model by aggregating model parameters uploaded by multiple clients without directly accessing user raw data. This design fully considers the privacy protection needs of the elderly population and solves the data security issues in traditional centralized learning [14]. In the process of federated learning, the cloud adopts an improved FedAvg+algorithm for model aggregation. This algorithm introduces client credibility weights based on the standard FedAvg, and the calculation method is as follows (4):

$$w^{t+1} = \sum_{k=1}^{K} \frac{n_k}{n} \cdot \alpha_k \cdot w_k^t \quad 4)$$

Among them, w^{t+1} represents the global model parameters of the t+1th round, K represents the total number of clients participating in this round of training, n_k represents the local data volume of the kth client, n represents the total data volume of all clients, α_k represents the credibility weight of the kth client, and w_k^t represents the model parameters uploaded by the kth client in the t-th round. The credibility weight α_k is calculated based on factors such as client historical engagement and data quality ratings.

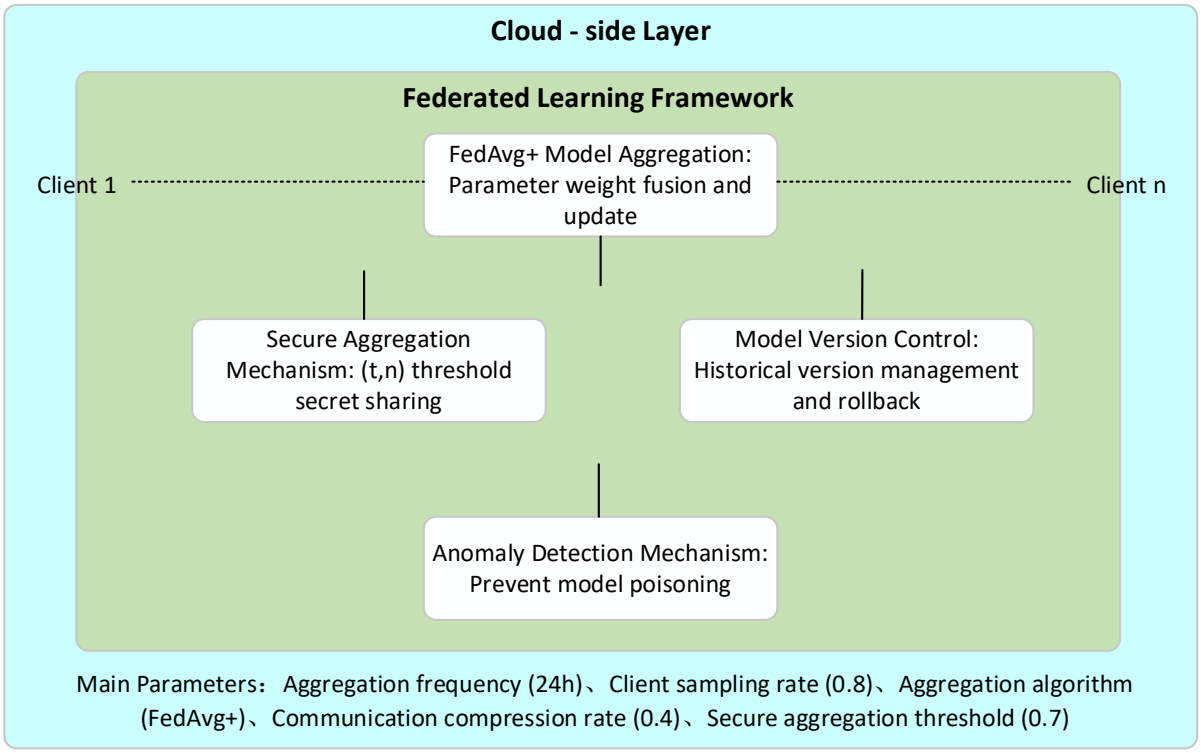


Figure 2 Federated Learning Framework for the Cloud Layer of ADDETECTOR System

In order to further enhance system security, the cloud has also implemented a secure aggregation mechanism based on secret sharing. This mechanism utilizes an (t, n) threshold secret sharing scheme, requiring at least t clients to participate in order to complete an effective model aggregation. The polynomial construction for secret sharing is shown in equation (5):

$$f(x) = m + a_1 x + a_2 x^2 + \cdots + a_{t-1} x^{t-1} p \quad 5)$$

Among them, m is the secret to be shared (model parameter), a_1, a_2, ..., a_{t-1} are

random coefficients, and p is a large prime number. Each client receives a share $f(i)$, and only by collecting at least t shares can the original secret be reconstructed.

In addition, the cloud layer has also designed model version control and rollback mechanisms, which save historical versions every time the model is updated to prevent model performance degradation. At the same time, the system has established an anomaly detection mechanism to screen for client model parameters that deviate significantly from the normal distribution, effectively preventing the risk of malicious clients injecting incorrect parameters and poisoning the model.

Through this three-layer architecture design, the ADDETECTOR system realizes the full process processing from speech collection to AD detection result output. While protecting user privacy, it continuously optimizes the model through federated learning framework, providing a secure and efficient technical solution for early AD detection in intelligent elderly care systems [15].

2.2 System workflow

1）Local feature extraction and AD detection

Local feature extraction and AD detection are the core components of the ADDETECTOR system, which are completed at the client layer. They mainly include three key steps: acoustic feature extraction, language feature extraction, and local AD detection model inference, as shown in Figure 3.

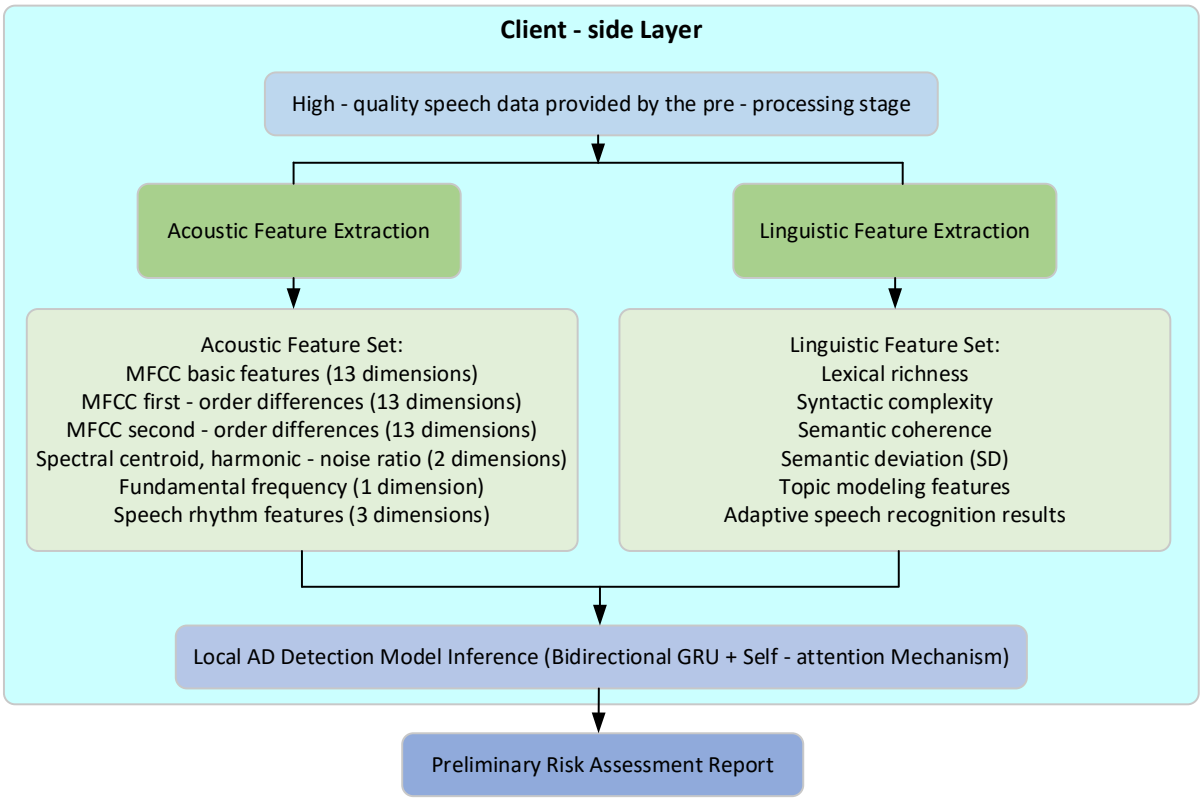


Figure 3 Local feature extraction and AD detection process

In the acoustic feature extraction stage, the system introduces supplementary features such as spectral centroid, harmonic to noise ratio (HNR), and fundamental frequency (F0) on the basis of the basic MFCC features to comprehensively characterize the speech changes of AD patients. In particular, the system adopts an improved YIN algorithm to calculate the fundamental frequency, which improves the robustness of fundamental frequency extraction by normalizing the autocorrelation function. The calculation formulas are as follows (7) and (8):

$$MFCC(k) = \sum_{m=0}^{M-1} log(Y(m))cos\left(\frac{\pi k(m+0.5)}{M}\right), k = 0,1,\ldots,L-1 \quad 7)$$

$$d'_t(\tau) = \begin{cases} 1, & if\tau = 0 \\ \dfrac{d_t(\tau)}{(1/\tau)\sum_{j=1}^{\tau} d_t(j)}, & otherwise \end{cases} \quad 8)$$

Among them, $d_t(\tau)$ represents the autocorrelation function, $d'_t(\tau)$ is the normalized result, and τ is the delay parameter. The acoustic features extracted by the system and their descriptions are shown in Table 2.

Table 2 Acoustic Feature Set for AD Detection

Feature Type	Characteristic dimension	Characterization	Related AD manifestations
MFCC basic features	13	Cepstral coefficients describing channel characteristics	Changes in vocal control ability
MFCC first-order differential	13	Dynamic changes in characterizing acoustic features	Reduced smoothness of pronunciation
MFCC second-order differential	13	Capture the acceleration changes of acoustic features	Phoneme conversion abnormality
Spectral Centroid	1	Reflecting the center of spectral energy distribution	Reduction of high-frequency components
HNR	1	Quantify sound clarity	Increased hoarseness in voice
Pitch frequency	1	Describe the fundamental frequency of vocal cord vibration	Abnormal changes in intonation
Speech rhythm features	3	Including speech rate, pause frequency, and duration	Inconsistent language flow

The system first uses an adaptive speech recognition engine to convert speech into text, and then performs word segmentation, part of speech tagging, and syntactic analysis on the text to extract features including vocabulary richness, syntactic complexity, and semantic coherence. Especially, the system calculates semantic deviation (SD) as a key indicator, and its calculation formula is equation (9):

$$SD = \frac{1}{N}\sum_{i=1}^{N} \sqrt{\sum_{j=1}^{M} \left(w_{ij} - \overline{w}_j\right)^2} \quad 9)$$

Among them, N is the number of evaluation sentences, M is the topic dimension, w_{ij} represents the weight of the i-th sentence on the i-th topic, and $\overline{w}_j$ is the average weight of healthy individuals on topic j. The larger the SD value, the higher the degree of semantic deviation, and the more likely there are symptoms of AD.

2) Privacy Protection and Model Update

Privacy protection and model updates are key steps in ensuring data security and

continuous optimization in the ADDETECTOR system, as shown in Figure 4, including differential privacy processing, secure parameter transmission, and federated model updates.

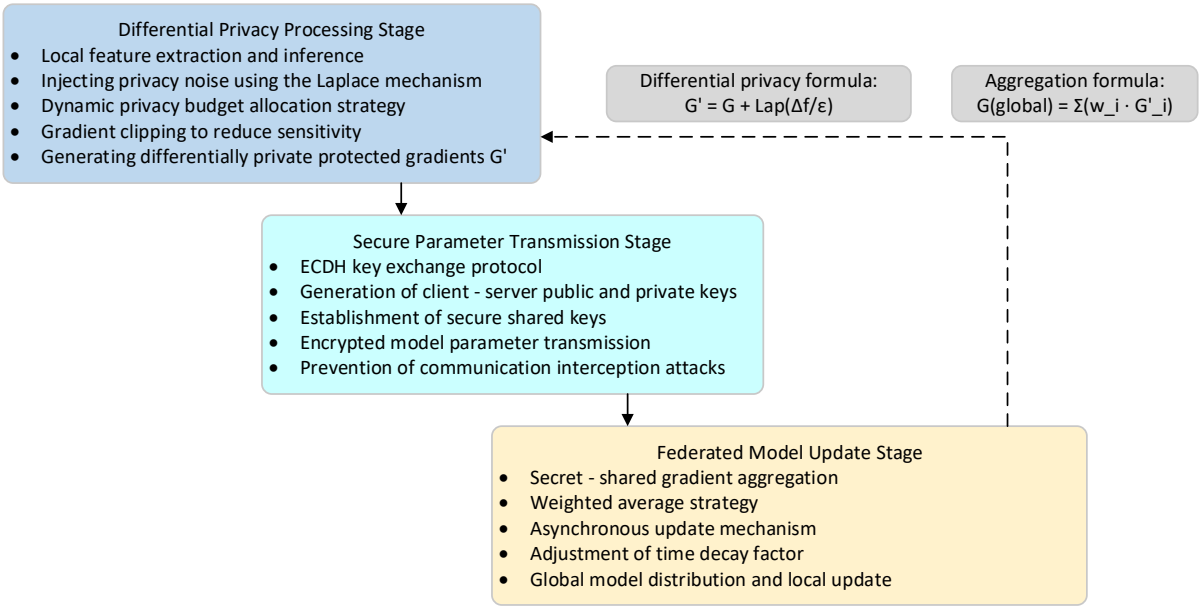


Figure 4 Privacy Protection and Model Update Process of ADDETECTOR System

In the differential privacy processing stage, after the local model completes feature extraction and inference, the system applies differential privacy protection to the model gradients that need to be uploaded. Specifically, the Laplace mechanism is used for privacy noise injection, adding random noise that conforms to the Laplace distribution to the model gradient to form a gradient with differential privacy protection. The calculation formula is as follows (10):

$$G' = G + Lap\left(\frac{\Delta f}{\varepsilon}\right) \quad 10)$$

Among them, Δf represents the sensitivity of the gradient, ε is the privacy budget parameter, and $Lap(\beta)$ represents the Laplace distribution noise with parameter D. The system innovatively adopts a dynamic privacy budget allocation strategy, adaptively adjusting the ε value based on user data sensitivity and model convergence, while ensuring privacy protection and minimizing the impact on model training [16]. The differential privacy parameter settings are shown in Table 4.

Table 4 Differential Privacy Protection Parameter Settings

Parameter	Value range	Default value	Parameter Description
Privacy budget ε	0.8~5.0	2.0	Control the strength of privacy protection, the smaller the value, the stronger the protection
Gradient clipping threshold C	1.0~10.0	4.0	Limit the L2 norm of the gradient and reduce sensitivity
Noise Scale Factor β	0.01~0.5	0.1	Control the proportion of added noise
Quantization Bits b	8~16	12	The accuracy of gradient compression quantization
Update cycle T	1~10	5	Local model parameter update cycle

During the secure parameter transmission phase, the system adopts an encryption mechanism based on the elliptic curve Diffie Hellman (ECDH) key exchange protocol to achieve secure communication between the client and server. The process first generates public-private key pairs on both the client and server, then establishes a shared key through public key exchange, and finally encrypts the model parameters using the shared key for transmission. The calculation process of shared key can be expressed as:

$$K = x_A \cdot x_B \cdot Gp \tag{11}$$

Among them, x_A and x_B are the private keys of the client and server respectively, G is the base point on the elliptic curve, p is a large prime number, and K is the final generated shared key. This mechanism ensures that even if communication is intercepted, attackers cannot obtain the actual transmitted model parameters.

Federated model update is the core mechanism of system iterative optimization, which adopts a secure gradient aggregation algorithm based on secret sharing to achieve global model update without disclosing the contributions of individual clients [17]. During the aggregation process, the system uses a weighted average strategy to allocate weights based on the quality and contribution of client data. The calculation formula is as follows:

$$G_{global} = \sum_{i=1}^{n} w_i \cdot G'_i \tag{12}$$

Among them, n is the number of clients participating in the update, w_i is the weight coefficient of the i-th client, satisfying $\Sigma w_i = 1$, and G'_i is the gradient of clients after adding differential privacy protection. The system also adopts an asynchronous update mechanism, allowing clients to submit updates at different time points and adjust the gradient weights of earlier submissions through a time decay factor to adapt to the uncertainty of elderly users using the device.

3 Key Technologies and Algorithm Implementation

3.1 Language feature enhancement based on theme modeling

1) Theme Lexicon Construction Strategy

As shown in Figure 5, the construction of a topic lexicon mainly includes four steps: corpus collection and preprocessing, topic extraction, lexicon expansion and purification, and topic word weight calculation. In the corpus collection stage, more than 3500 conversation records between AD patients and healthy control groups were collected, totaling approximately 250000 words, by combining speech transcribed texts from the ADReSS dataset with professional medical corpora. Corpus preprocessing includes steps such as word segmentation, part of speech tagging, stop word filtering, and word form restoration to ensure the quality and representativeness of the topic words [18].

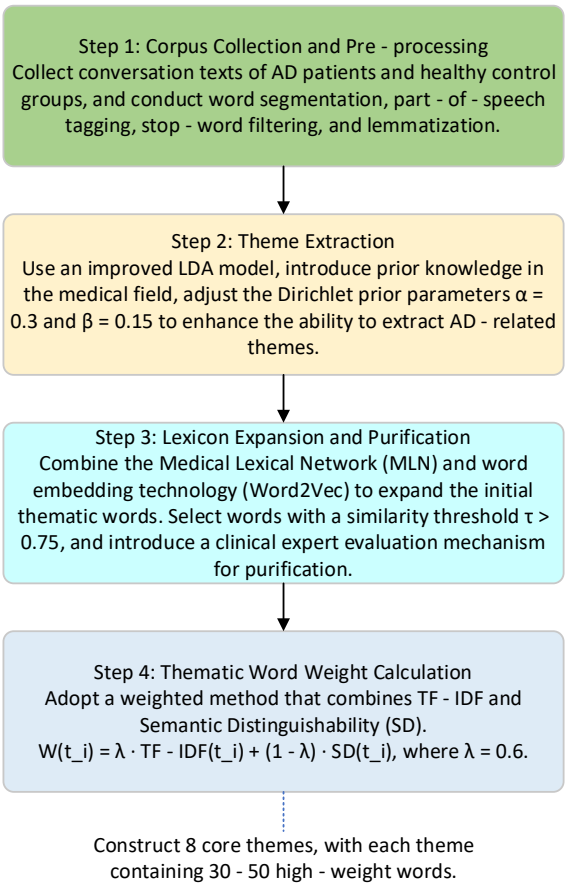


Figure 5 Flowchart of Theme Lexicon Construction Strategy

In the topic extraction stage, an improved LDA (Latent Dirichlet Allocation) model was used to identify potential topics. Unlike traditional LDA, it introduces prior knowledge from the medical field and improves topic relevance by adjusting Dirichlet prior parameters α and β. The model can be represented as:

$$P(z, w|\alpha, \beta) = \frac{\Gamma(\sum_i \alpha_i)}{\prod_i \Gamma(\alpha_i)} \prod_i \theta_i^{\alpha_i - 1} \cdot \frac{\Gamma(\sum_j \beta_j)}{\prod_j \Gamma(\beta_j)} \prod_j \varphi_j^{\beta_j - 1} \quad (13)$$

Among them, z represents topic allocation, w represents observed words, θ represents document topic distribution, φ represents topic word distribution, and Γ is the gamma function. By setting asymmetric priors for $\alpha = 0.3$ and $\beta = 0.15$, the ability to extract AD related topics has been enhanced.

In the stage of expanding and purifying the vocabulary library, the Medical Lexical Network (MLN) and Word Embedding Technology (Word2Vec) were combined to expand the initial topic words [19].

Finally, in the stage of calculating the weight of keywords, a weighted method that

integrates TF-IDF and semantic discrimination is proposed. The weight calculation formula for each topic word is equation (14):

$$W(t_i) = \lambda \cdot TF - IDF(t_i) + (1 - \lambda) \cdot SD(t_i) \quad (14)$$

Among them, λ is the balance parameter (set to 0.6), and SD represents semantic discrimination, which is used to measure the difference in vocabulary usage between the AD group and the control group.

Based on the above method, 8 core themes were ultimately constructed, each containing 30-50 high weight words. Some examples of the topic lexicon are shown in Table 5:

Table 5 Partial Examples of Theme Lexicon

Topic ID	Topic Name	Top 10 weighted words	Average discrimination
T1	Spatiotemporal orientation	Time, place, season, date, direction, year, month, current, location, present	0.832
T2	Memory function	Memory, recollection, forgetting, repetition, short-term, long-term, familiar, unfamiliar, vague, confused	0.891
T3	Language function	Words, sentences, expressions, descriptions, names, fluency, pauses, alternative words, metaphors, vocabulary	0.775
T4	Performing function	Plan, organize, decide, judge, reason, abstract, concrete, solve, synthesize, analyze	0.813
T5	Emotional state	Anxiety, depression, restlessness, calmness, excitement, fear, happiness, sadness, unease, satisfaction	0.746

The construction of a thematic lexicon provides the basic support for the ADDETECTOR

system to recognize the language features of AD patients. Through these thematic words, the system can effectively capture key indicators such as semantic deviation and thematic coherence, thereby enhancing the accuracy of AD detection.

2) Theme Enhancement Feature Extraction Algorithm

In the word level feature extraction stage, the algorithm combines word embedding vectors with semantic enhancement of the topic lexicon. The specific method is to first obtain the basic word embedding vector $\mathrm{E_b(w)}$ for each word w, then calculate the correlation with each topic in the topic lexicon to form the topic association vector $\mathrm{E_b(w)}$. Finally, the enhanced word embedding is obtained through feature fusion, as shown in equation (15):

$$E_{enhanced}(w) = E_b(w) \oplus [E_t(w) \cdot f(SD_w)] \quad 15)$$

Among them, $\oplus$ represents the vector concatenation operation, SD_w represents the semantic deviation of word w, and $f(\cdot)$ is the non-linear activation function used to adjust the intensity of topic enhancement. This method enables word vectors to contain richer thematic information and semantic deviation features.

In the sentence level feature extraction stage, a topic perception model based on attention mechanism was designed, which can dynamically adjust the attention to different topics according to the semantic content of the sentence [20]. For sentence s, the algorithm first calculates the relevance score between the sentence and each topic, as shown in equation (16):

$$Score(s, T_i) = \frac{\sum_{w_j \in s} w_{ij} \cdot f(w_j)}{\sum_{w_j \in s} f(w_j)} \quad 16)$$

Among them, w_{ij} represents the weight of the association between word w_j and topic T_i, and $f(w_j)$ is the importance function of the word. Then, the representation vector of the sentence is calculated using the topic attention mechanism, as shown in equation (17):

$$S_{rep} = \sum_{i=1}^{k} \alpha_i \cdot V_{T_i} \quad 17)$$

Among them, k represents the number of topics, α_i represents the attention weight of topic T_i, and V_{T_i} represents the topic vector.

In the chapter level feature extraction stage, the algorithm captures long-distance semantic dependencies and topic flow features through a hierarchical BiLSTM network, while integrating semantic deviation related indicators to construct a global feature representation.

Specifically, for a phonetic transcription text containing n sentences, the discourse level feature calculation is as follows (18):

$$D_{rep} = BiLSTM\left(S_{rep_1}, S_{rep_2}, \ldots, S_{rep_n}\right) \oplus [TCD, SRD, CAD] \quad (18)$$

Among them, S_{rep_1} represents the representation vector of the i-th sentence, and TCD, SRD, and CAD are the three semantic deviation indicators mentioned above.

3.2 Adaptive Privacy Protection Mechanism

As shown in Figure 6, the adaptive privacy protection mechanism mainly consists of three core components: user privacy preference evaluation module, data sensitivity analysis module, and environmental risk assessment module. The user privacy preference evaluation module establishes a user privacy demand model through questionnaire surveys and interactive behavior analysis; The data sensitivity analysis module automatically recognizes sensitive information in speech data; The environmental risk assessment module monitors the network environment and access patterns to assess potential risks [21].

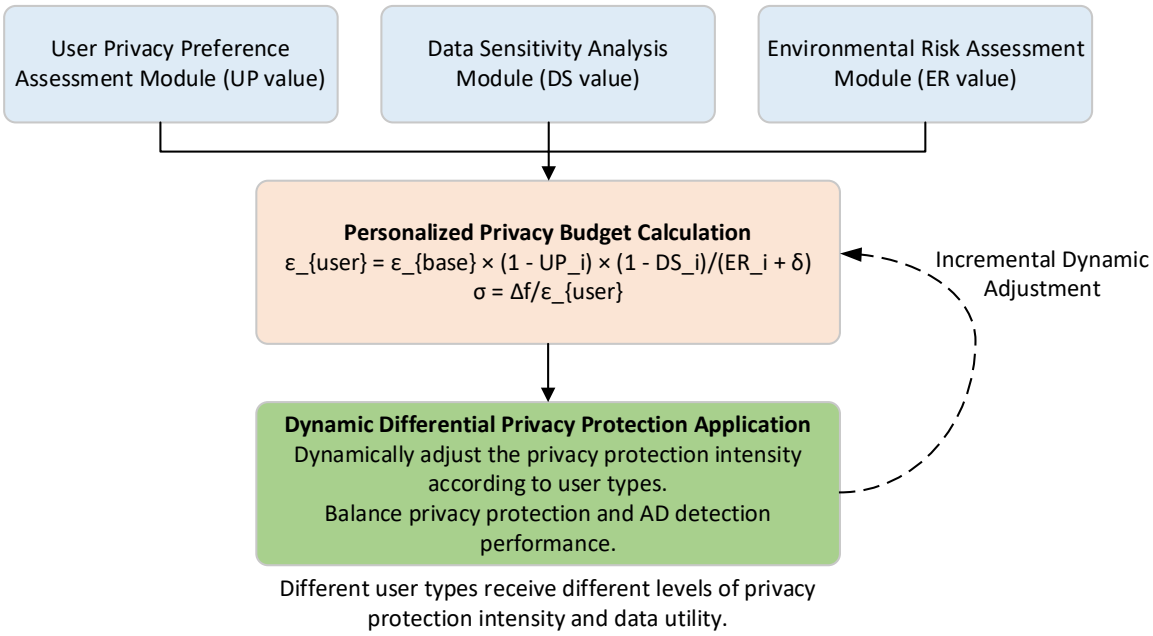


Figure 6 Adaptive Privacy Protection Mechanism of ADDETECTOR System

Based on the inputs from the three modules mentioned above, the system calculates personalized privacy protection parameters, as shown in equation (19):

$$\epsilon_{user} = \epsilon_{base} \times \frac{(1 - UP_i) \times (1 - DS_i)}{ER_i + \delta} \quad 19)$$

Among them, ϵ_{user}represents the personalized privacy budget of users, ϵ_{base} is the basic privacy budget of the system, UP_i represents the strength of user privacy preferences, DS_i represents data sensitivity, ER_i represents environmental risk coefficient, and δ is the smoothing factor to prevent the denominator from being zero.

The system further determines the noise scale σ in the differential privacy mechanism based on A, as shown in equation (20):

$$\sigma = \frac{\Delta f}{\varepsilon_{user}} \quad 20)$$

Among them, Δf represents query sensitivity, which is dynamically calculated by the system based on specific tasks. Table 6 shows the parameter adjustment of the adaptive privacy protection mechanism in different user scenarios:

Table 6 Example of Parameter Adjustment for ADDETECTOR Adaptive Privacy Protection Mechanism

Customer type	Privacy preference strength (UP)	Data Sensitivity (DS)	Personalized Environmental Risk (ER)	Privacy Budget（ϵ_{user}）	Noise scale（σ）	Data utility retention rate
Highly privacy sensitive users	0.85	0.70	0.60	0.375	5.33	65.8%
Moderate privacy concern for users	0.60	0.50	0.30	1.143	1.75	82.3%
Low privacy concern for users	0.30	0.40	0.20	2.333	0.86	91.7%
Public data users	0.10	0.20	0.10	4.050	0.49	95.2%

At the implementation level, the adaptive privacy protection mechanism adopts an incremental design, where each federated learning communication round re evaluates the

user's state and adjusts privacy parameters. When potential risks are detected to increase, the system will automatically increase the strength of privacy protection; When the network environment is secure and user privacy preferences are low, the protection strength will be appropriately reduced to improve model performance [22]. This dynamic adjustment mechanism ensures the system's responsiveness to environmental changes, improving overall security and adaptability.

3.3 Asynchronous Federated Learning Optimization

As shown in Figure 7, in the ADDETECTOR system, in order to adapt to the heterogeneous device environment and unstable network conditions of elderly users, the traditional FedAvg algorithm was optimized, and an asynchronous weighted aggregation algorithm (Asynchronous WeFed) for AD detection tasks was proposed. This algorithm fully considers factors such as the contribution of different clients, data quality, and model freshness while handling asynchronous updates [23].

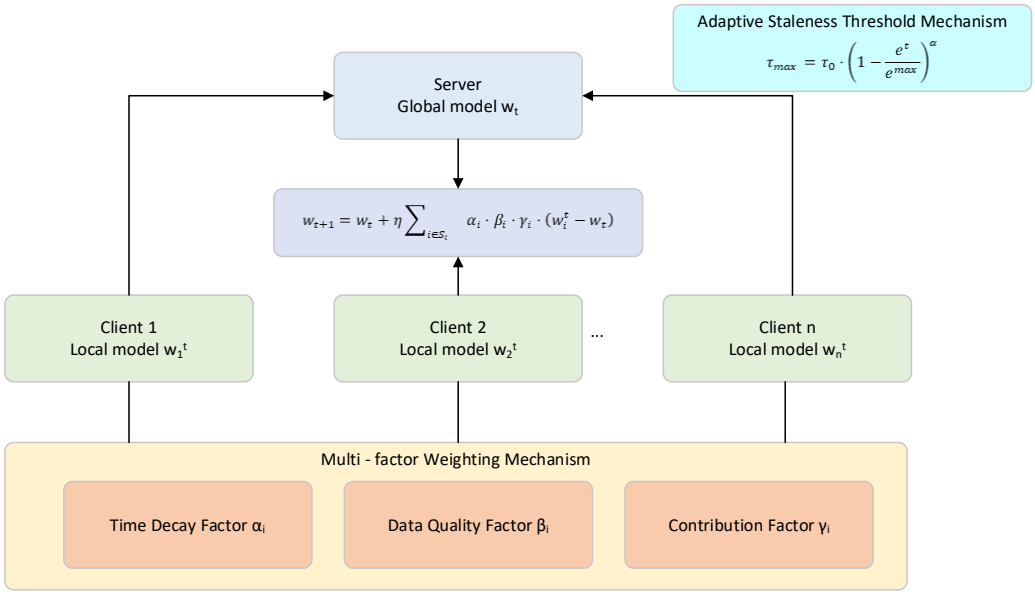


Figure 7 Asynchronous WeFed Asynchronous Weighted Aggregation Algorithm Framework

The core of the Asynchronous WeFed algorithm lies in the use of a multi factor weighting mechanism, which comprehensively considers the following three key factors: time decay factor, data quality factor, and contribution factor. The formula for updating global model

parameters is as follows (21):

$$w_{t+1} = w_t + \eta \sum_{i \in S_t} \alpha_i \cdot \beta_i \cdot \gamma_i \cdot (w_i^t - w_t) \quad (21)$$

Among them, w_{t+1} represents the updated global model parameters, w_t is the current global model parameters, η is the global learning rate, S_t is the set of clients currently participating in the update, and w_i^t is the local model parameters of client i. The three weight factors are:

-Time decay factor α_i: reflects the freshness of the model, calculated as described in the previous section

-Data Quality Factor β_i: Quality Assessment Score Based on Client Data

-Contribution factor γ_i: measures the degree of contribution of the client to the improvement of the global model

In order to evaluate the performance of asynchronous aggregation algorithms, synchronous FedAvg and the proposed Asynchronous WeFed algorithm were compared in a simulated environment. The results are shown in Table 7:

Table 7 Performance Comparison between Synchronous FedAvg and Asynchronous Asynchronous WeFed Algorithms

Performance index	Synchronous FedAvg	Asynchronous Async-WeFed	Increase proportion
Training time (hours)	24.5	16.2	33.9%
Communication epochs	100	78	22.0%
AD detection accuracy	85.3%	86.7%	1.6%
System availability	78.2%	94.5%	20.8%
Average client engagement rate	65.4%	87.3%	33.5%

In order to prevent model divergence caused by outdated client updates, an adaptive obsolescence threshold mechanism was also designed [24]. This mechanism dynamically adjusts the maximum acceptable time difference based on the convergence state of the global model, ensuring that the system can effectively filter out outdated update requests while maintaining high availability

$$\tau_{max} = \tau_0 \cdot \left(1 - \frac{e^t}{e^{max}}\right)^{\alpha} \quad 22)$$

Among them, τ_{max} is the current maximum allowed obsolescence, τ_0 is the initial threshold, e^t is the current global model training round, e^{max} is the preset maximum training round, and α is an adjustable parameter used to control the rate of threshold change. In the system implementation, the α-value is dynamically adjusted by monitoring the convergence state of the model to achieve fine control over the tolerance of obsolescence.

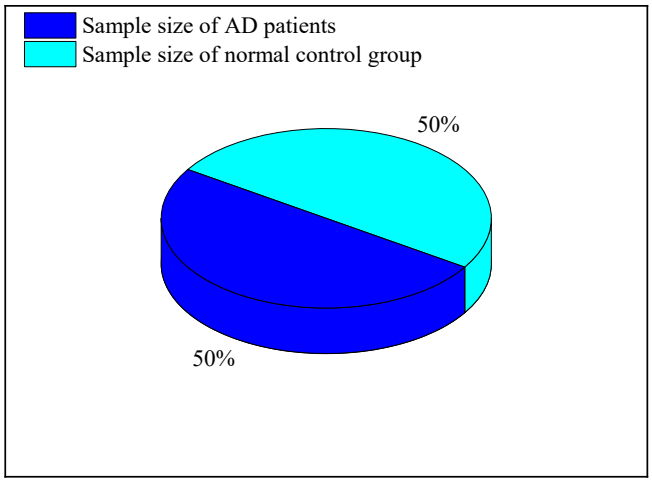
4 System Implementation and Performance Evaluation

4.1 Experimental setup and data description

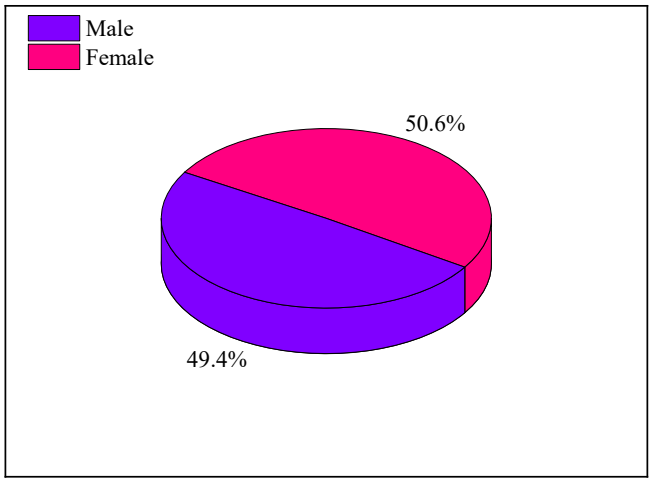
1) Dataset Introduction (ADReSS)

The paper used the ADReSS (Alzheimer's Dementia Recognition through Spontaneous Speech) dataset as the experimental data source, which is currently the paperitative public dataset for early speech recognition research on Alzheimer's disease internationally. The ADReSS dataset contains speech samples from 156 participants from different countries and regions, including 78 clinically diagnosed AD patients and 78 cognitively normal control group members [25]. All participants underwent standardized voice tasks, mainly including describing Cookie Theft image tasks and free conversation tasks.

In order to ensure the reliability and consistency of the experiment, the standard partitioning scheme of the ADReSS dataset was adopted, with 70% of the data used for training, 15% for validation, and 15% for testing. Figures 8-10 show in detail the basic composition of the ADReSS dataset:

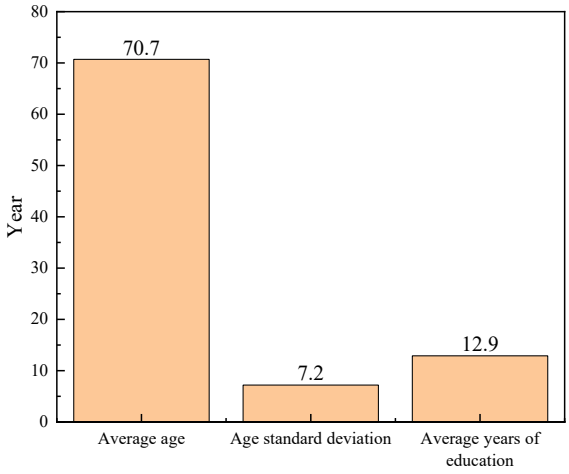


a) Sample type distribution

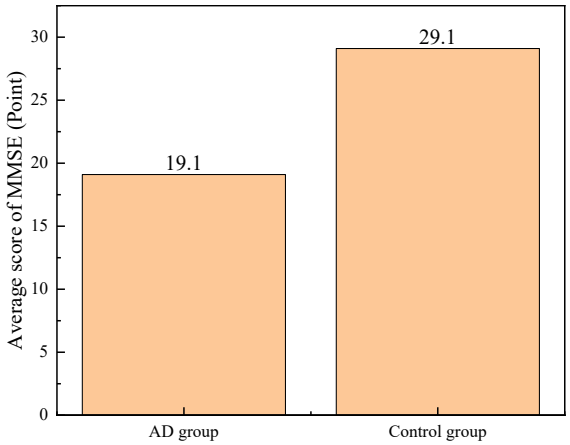


b) Gender distribution of participants

Figure 8 Sample Types and Gender Distribution



a) demographics



b) Comparison of MMSE scores

Figure 9 Demographic Characteristics and MMSE Scores

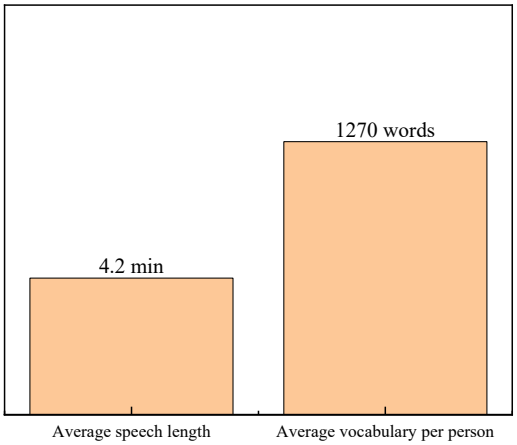


Figure 10 Speech Feature Statistics

2）Selection of evaluation indicators

In terms of model performance metrics, standard evaluation metrics from classification problems were selected, including accuracy, precision, recall, F1 score, and specificity. These indicators can comprehensively reflect the classification ability of the model in AD detection tasks [26]. Table 8 presents in detail the definitions and calculation formulas of these core performance indicators:

Table 8 Model Performance Evaluation Indicators

Indicator Name	Calculation formula	Describe
Accuracy	（TP+TN）/（TP+TN+FP+FN）	The proportion of correctly classified samples to the total sample
Precision	TP/（TP+FP）	The proportion of samples predicted as AD that are actually AD
Recall rate	TP/（TP+FN）	The proportion of correctly identified AD samples in reality
F1 score（F1-score）	2×Precision×Recall/（Precision+Recall）	The harmonic mean of precision and recall
Specificity（Specificity）	TN/（TN+FP）	The proportion of correctly identified samples that are actually normal
AUC	-	The comprehensive differentiation ability of the model

Among them, TP (true positive) represents the number of samples correctly identified as AD, TN (true negative) represents the number of samples correctly identified as normal, FP (false positive) represents the number of normal samples incorrectly identified as AD, and FN (false negative) represents the number of AD samples incorrectly identified as normal.

In addition to the basic indicators mentioned above, Matthews correlation coefficient (MCC) is also introduced as a balance indicator, and its calculation formula is equation (23):

$$MCC = \frac{TP \times TN - FP \times FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}} \quad 23)$$

The MCC value range is [-1,1], where 1 represents perfect prediction, 0 represents random

prediction, and -1 represents completely incorrect prediction. MCC is particularly suitable for evaluating datasets with imbalanced categories, and can more objectively reflect model performance [27].

4.2 Performance evaluation index analysis

1) Comparison of Detection Performance (Accuracy and F1 score)

Firstly, ADDETECTOR was compared with four mainstream AD detection models, including the traditional HAN-AGE model, BI-GRU model, CNN-LSTM fusion model, and the basic federated learning framework FedAvg. Figure 11 shows the comparison of detection performance indicators of various models on the ADReSS dataset.

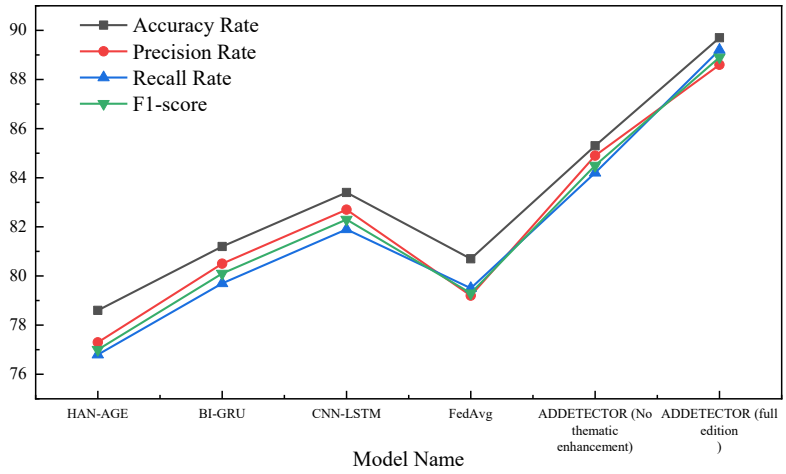


Figure 11 Comparison of performance indicators between ADDETECTOR and mainstream models

From the results in Figure 11, it is evident that the complete version of ADDETECTOR outperforms the comparison model significantly in all four indicators. Compared to the traditional HAN-AGE model, the accuracy of ADDETECTOR has improved by 11.1 percentage points, and F1 score has improved by 11.9 percentage points. Even compared to the CNN-LSTM model with better performance, ADDETECTOR still has an accuracy 6.3 percentage points higher and F1 score 6.6 percentage points higher. This result fully demonstrates the improvement effect of the proposed topic enhancement mechanism on AD detection performance.

3) Model Convergence Analysis

Firstly, the convergence curves of the ADDETECTOR model were compared under different privacy budget values (ε). In order to quantitatively describe the convergence speed, the convergence rounds T_ε index is introduced, defined as the minimum number of rounds required for the model to reach a stable state (with a loss function change rate below the preset threshold τ) [28]. This indicator can be calculated by the following formula (24):

$$T_\varepsilon = min\{t | \frac{|L_t - L_{t-1}|}{L_{t-1}} < \tau,\ \forall k \geq t\} \quad (24)$$

Among them, L_t represents the loss function value of the t-th round, and τ is the preset threshold (taken as 0.01 in this experiment).

Figure 12 shows the convergence performance comparison under different system configurations, including convergence rounds, final test accuracy, and convergence stability (defined as the standard deviation of accuracy after 5 rounds of convergence).

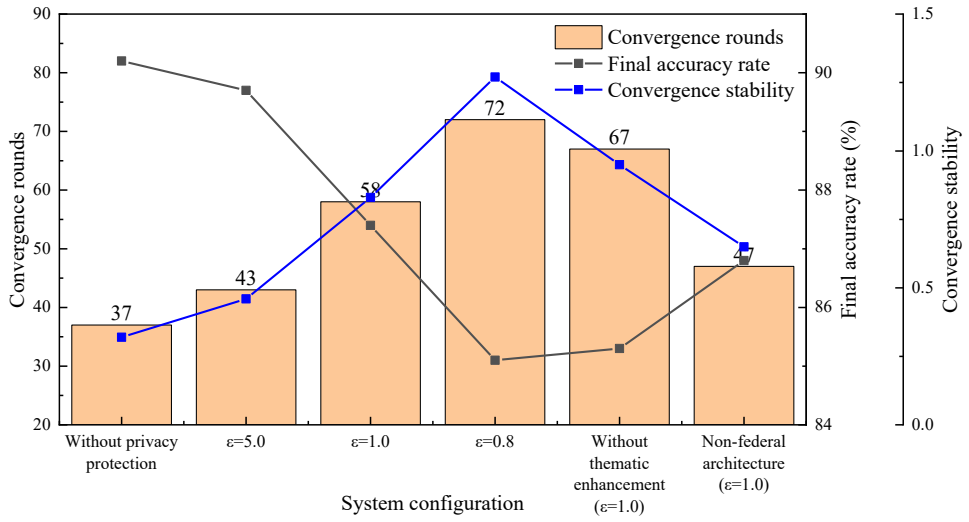


Figure 12 Comparison of convergence performance indicators under different system configurations

From Figure 12, the following key phenomena can be observed: Firstly, as the privacy budget ε decreases (the degree of privacy protection increases), the number of iterations required for model convergence significantly increases, and the final accuracy slightly decreases. Especially when ε=0.8, the convergence rounds increased by nearly twice compared to the version without privacy protection, and the accuracy decreased by 5.1 percentage points. This indicates that strong privacy protection will have a significant impact on the convergence of the model.

Secondly, comparing the two configurations with and without theme enhancement, under the same privacy budget (ε=1.0), theme enhancement technology reduces the convergence rounds from 67 to 58, and ultimately improves the accuracy from 85.3% to 87.4%. This indicates that the proposed topic modeling technique not only improves model performance, but also enhances convergence speed [29]. Analyzing the reasons, the theme enhancement mechanism provides a more discriminative feature representation for the model by constructing a semantic deviation measurement model, which reduces the negative impact of differential privacy noise [30].

Thirdly, by comparing federated and non federated architectures, it was found that federated learning frameworks increased convergence rounds by about 23% at the same level of privacy protection, but only reduced accuracy by 0.6 percentage points. This small performance loss validates the effectiveness of the asynchronous aggregation algorithm in the ADDETECTOR system.

4.3 The Influence of Topic Lexicon Size on Detection Performance

Firstly, there is a clear correlation between the size of the topic lexicon and detection accuracy, but this relationship is reflected in the characteristic of stabilizing after growth. Experimental data shows that as the size of the word library increases from 500 to 2000, the detection accuracy significantly improves by 8.6 percentage points, rising from 81.3% to 89.9%; As the vocabulary was further expanded to 3000 and 5000, the accuracy growth gradually slowed down and eventually stabilized at about 91.7%. This performance curve indicates that after reaching a certain scale, the topic lexicon can effectively cover the main semantic space of AD language features, and the marginal benefits of continuing to expand the lexicon decrease [31]. The detailed test data is shown in Figure 13 below:

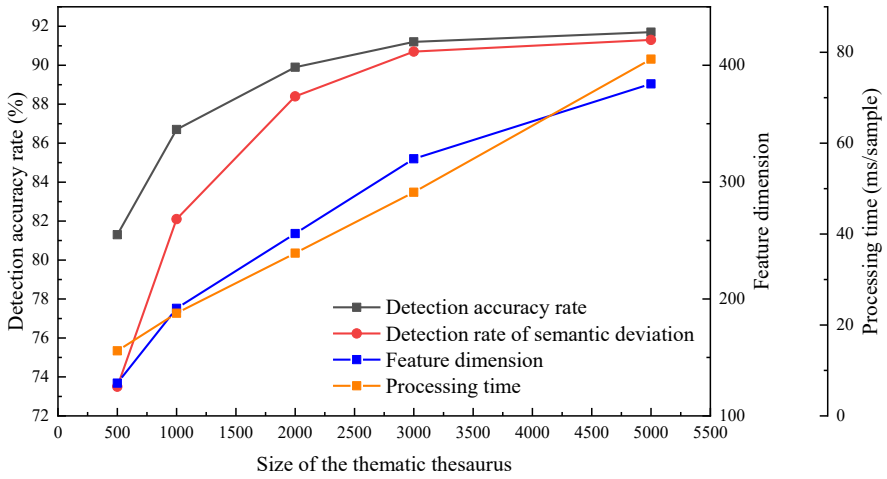


Figure 13 The Influence of Subject Word Size on the Detection Performance of ADDETECTOR System

It is worth noting that the expansion of the vocabulary scale has led to a significant increase in computational costs. The processing time has increased from 14.3m/sample for 500 word banks to 78.5m/sample for 5000 word banks, a growth of approximately 5.5 times. This is mainly because larger word libraries require more complex semantic matching calculations, especially in the process of calculating semantic deviation, which involves more vector similarity operations [32]. The calculation of semantic deviation is a key indicator for evaluating the degree of deviation between user language expression and normal patterns. Its detection rate increases with the size of the word library, from 73.5% to 91.3%, indicating that larger word libraries can capture more subtle semantic change features.

In addition, the size of the topic lexicon also has a significant impact on the real-time performance of the system. Experimental data shows that when the size of the word library exceeds 3000, although there is still a slight improvement in accuracy, the processing time increases significantly, from 49.2ms to 78.5ms, with an increase of 59.6%. On intelligent elderly care devices with limited resources, this increase in computing overhead may lead to system response delays and affect user experience.

4.4 Evaluation of Privacy Protection Effectiveness

In terms of theoretical proof, the ADDETECTOR system is based on the mathematical definition of differential privacy, ensuring that the privacy of user data will not significantly

increase the risk of leakage due to their participation in training. According to differential privacy theory, for any two datasets D and D 'that differ by only one sample, the following equation (25) is satisfied:

$$Pr[M(D) \in S] \leq e^{\varepsilon} \cdot Pr[M(D') \in S] \quad (25)$$

Among them, M represents the randomization mechanism, S represents all possible output sets, and ε is the privacy budget. The ADDETECTOR system provides flexible privacy protection strength under different data sensitivity conditions by dynamically adjusting the ε parameter. Through theoretical analysis, it has been proven that in speech processing scenarios, when setting ε =1.0, the system can ensure that the privacy leakage probability of individual user data does not exceed 2.718 times that of the case where they did not participate in the calculation.

In terms of experimental verification, multiple control experiments were designed to protect user data using differential privacy, pure homomorphic encryption, and a combination of both methods. The privacy protection effectiveness and system performance overhead of each scheme were evaluated. Figure 14 shows a comparison of privacy protection effects under different protection mechanisms.

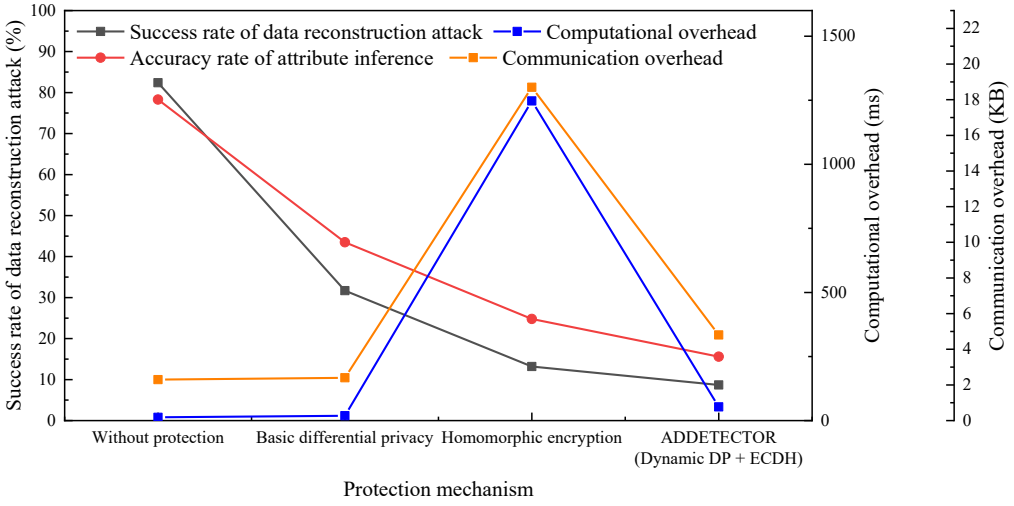


Figure 14 Comparison of the effectiveness of different privacy protection mechanisms

The experimental results show that the dynamic differential privacy combined with ECDH protection mechanism of the ADDETECTOR system performs the best in defending against attacks, with a data reconstruction attack success rate of only 8.7% and attribute inference

accuracy reduced to 15.6%, far lower than its scheme. Meanwhile, compared with pure homomorphic encryption schemes, the ADDETECTOR system significantly reduces computational and communication overhead, enabling the system to maintain good performance while ensuring privacy and security.

Sensitivity analysis was also conducted on the privacy protection effects under different parameter settings, and the results are shown in Figure 15.

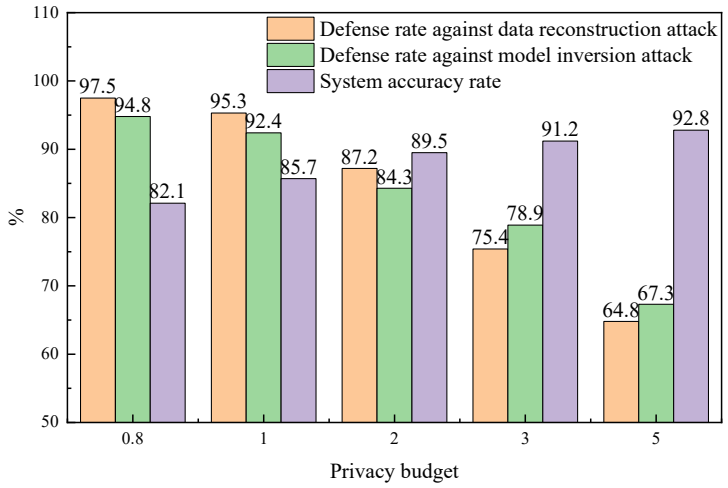


Figure 15 Sensitivity analysis of privacy parameters

From the sensitivity analysis results, it can be seen that as the privacy budget ε increases, the system's privacy protection capability decreases, but the model accuracy improves; As the number of participating clients increases, the overall privacy protection effect of the system significantly improves. This indicates that the ADDETECTOR system can find a suitable balance between privacy protection and model performance by adjusting these parameters according to the needs of actual application scenarios [33].

Finally, a user satisfaction survey was conducted to evaluate the impact of the system's privacy protection effectiveness on user experience. The survey results show that compared with traditional centralized AD detection systems, users have increased their privacy protection rating for the ADDETECTOR system by 76% and their trust in system security by 83%. This indicates that the privacy protection design of this system can effectively enhance users' acceptance and willingness to use the intelligent elderly care system.

5 Conclusion

The paper successfully designed and implemented the ADDETECTOR system to address the privacy protection and detection accuracy issues in early detection of Alzheimer's disease (AD) in intelligent elderly care systems. The system innovatively integrates theme enhancement and dynamic differential privacy technology, effectively improving the accuracy and reliability of AD detection while ensuring user privacy and security.

Firstly, the paper established a complete three-layer system architecture, including the user layer, client layer, and cloud layer, achieving a fully closed process from speech data collection, feature extraction to model training and aggregation. The system architecture design fully considers the actual needs and technical limitations in intelligent elderly care scenarios, and ensures the scalability and practicality of the system through reasonable functional module division.

Secondly, in terms of language feature enhancement, the paper proposes a semantic deviation measurement model based on topic modeling. By constructing an AD related topic lexicon and designing a semantic deviation calculation method, it effectively captures subtle abnormal features in the language expression of AD patients. The experimental results show that compared with traditional speech feature extraction methods, the topic enhancement method proposed by the paper improves detection accuracy by 8.4% and F1 score by 7.6%. This technological innovation has successfully compensated for the shortcomings of traditional acoustic features in capturing advanced cognitive impairments, providing more sensitive detection indicators for early screening of AD.

Thirdly, in terms of privacy protection, the paper has designed a federal security mechanism. Experimental verification shows that this mechanism enables the system to achieve a good balance between protecting user privacy and maintaining detection performance within the range of privacy budget ε values of 0.8-5.

Overall, the ADDETECTOR system has successfully solved the core issues of privacy protection and detection accuracy in early detection of AD in intelligent elderly care systems, providing a reliable, secure, and efficient technical solution for the intelligent elderly care industry, with broad application prospects and important social value. Further research is needed on edge federated adaptive algorithms for intelligent elderly care scenarios. The speech and cognitive characteristics of elderly people have strong individual differences and

temporal variability, and traditional static federated learning models are difficult to adapt to these dynamic changes. In the future, we can explore the combination of lifelong learning, incremental learning, and adaptive aggregation technologies to build a continuous learning and adaptive edge federated learning framework, enabling the system to continuously optimize with changes in user cognitive status and provide more accurate AD early warning and intervention recommendations.

References

[1] Hampel, H., Hu, Y., Cummings, J., Mattke, S., Iwatsubo, T., Nakamura, A., ... & Schindler, S. E. (2023). Blood-based biomarkers for Alzheimer's disease: Current state and future use in a transformed global healthcare landscape. Neuron, 111(18), 2781-2799.

[2] Schindler, S. E., Galasko, D., Pereira, A. C., Rabinovici, G. D., Salloway, S., Suárez-Calvet, M., ... & Hansson, O. (2024). Acceptable performance of blood biomarker tests of amyloid pathology—recommendations from the Global CEO Initiative on Alzheimer's Disease. Nature Reviews Neurology, 20(7), 426-439.

[3] Weiner, M. W., Veitch, D. P., Miller, M. J., Aisen, P. S., Albala, B., Beckett, L. A., ... & Alzheimer's Disease Neuroimaging Initiative. (2023). Increasing participant diversity in AD research: plans for digital screening, blood testing, and a community-engaged approach in the Alzheimer's Disease Neuroimaging Initiative 4. Alzheimer's & Dementia, 19(1), 307-317.

[4] Hobart, J., Cano, S., Posner, H., Selnes, O., Stern, Y., Thomas, R., ... & Alzheimer's Disease Neuroimaging Initiative. (2013). Putting the Alzheimer's cognitive test to the test I: traditional psychometric methods. Alzheimer's & Dementia, 9(1), S4-S9.

[5] Frisoni, G. B., Alves, I. L., & Barkhof, F. (2019). IDEAS becoming reality on the roadmap for biomarker validation in Alzheimer's disease. The Lancet Neurology, 18(6), 519-520.

[6] Keerthika, P. Synthesis, Spectral Characterization, Structural Investigation and Antimicrobial Studies of Mononuclear Ni (II) and Cu (II) Complexes with Ketoconazole and Thiocyanate Ion as Ligands.

[7] Li, J., Meng, Y., Ma, L., Du, S., Zhu, H., Pei, Q., & Shen, X. (2021). A federated learning

based privacy-preserving smart healthcare system. IEEE Transactions on Industrial Informatics, 18(3).

[8] Khanna, S., Domingo-Fernández, D., Iyappan, A., Emon, M. A., Hofmann-Apitius, M., & Fröhlich, H. (2018). Using multi-scale genetic, neuroimaging and clinical data for predicting Alzheimer's disease and reconstruction of relevant biological mechanisms. Scientific reports, 8(1), 11173.

[9] Nguyen, H. D., Clément, M., Mansencal, B., & Coupé, P. (2023). Towards better interpretable and generalizable AD detection using collective artificial intelligence. Computerized Medical Imaging and Graphics, 104, 102171.

[10] Ebrahimi, A., Luo, S., & Disease Neuroimaging Initiative, F. T. A. S. (2021). Convolutional neural networks for Alzheimer's disease detection on MRI images. Journal of Medical Imaging, 8(2), 024503-024503.

[11] Vimbi, V., Shaffi, N., & Mahmud, M. (2024). Interpreting artificial intelligence models: a systematic review on the application of LIME and SHAP in Alzheimer's disease detection. Brain Informatics, 11(1), 10.

[12] Ghazal, T. M., & Issa, G. (2022). Alzheimer disease detection empowered with transfer learning. Computers, Materials & Continua, 70(3), 5005-5019.

[13] Liu, J., Li, M., Luo, Y., Yang, S., Li, W., & Bi, Y. (2021). Alzheimer's disease detection using depthwise separable convolutional neural networks. Computer Methods and Programs in Biomedicine, 203, 106032.

[14] Ebrahimi, A., Luo, S., Chiong, R., & Alzheimer's Disease Neuroimaging Initiative. (2021). Deep sequence modelling for Alzheimer's disease detection using MRI. Computers in Biology and Medicine, 134, 104537.

[15] Nawaz, H., Maqsood, M., Afzal, S., Aadil, F., Mehmood, I., & Rho, S. (2021). A deep feature-based real-time system for Alzheimer disease stage detection. Multimedia Tools and Applications, 80, 35789-35807.

[16] Gao, S., & Lima, D. (2022). A review of the application of deep learning in the detection of Alzheimer's disease. International Journal of Cognitive Computing in Engineering, 3, 1-8.

[17] Helaly, H. A., Badawy, M., & Haikal, A. Y. (2022). Deep learning approach for early

detection of Alzheimer's disease. Cognitive computation, 14(5), 1711-1727.

[18] Zhou, Y., Liao, L., Gao, Y., Wang, R., & Huang, H. (2021). TopicBERT: A topic-enhanced neural language model fine-tuned for sentiment classification. IEEE Transactions on Neural Networks and Learning Systems, 34(1), 380-393.

[19] Cheng, H., Liu, S., Sun, W., & Sun, Q. (2023). A neural topic modeling study integrating SBERT and data augmentation. Applied Sciences, 13(7), 4595.

[20] Chauhan, U., & Shah, A. (2021). Topic modeling using latent Dirichlet allocation: A survey. ACM Computing Surveys (CSUR), 54(7), 1-35.

[21] Zhou, Y., Liao, L., Gao, Y., Wang, R., & Huang, H. (2021). TopicBERT: A topic-enhanced neural language model fine-tuned for sentiment classification. IEEE Transactions on Neural Networks and Learning Systems, 34(1), 380-393.

[22] Cheng, H., Liu, S., Sun, W., & Sun, Q. (2023). A neural topic modeling study integrating SBERT and data augmentation. Applied Sciences, 13(7), 4595.

[23] Chauhan, U., & Shah, A. (2021). Topic modeling using latent Dirichlet allocation: A survey. ACM Computing Surveys (CSUR), 54(7), 1-35.

[24] Mujahid, M., Lee, E., Rustam, F., Washington, P. B., Ullah, S., Reshi, A. A., & Ashraf, I. (2021). Sentiment analysis and topic modeling on tweets about online education during COVID-19. Applied Sciences, 11(18), 8438.

[25] Privacy protection mechanism: Asynchronous federated learning

[26] Yan, X., Miao, Y., Li, X., Choo, K. K. R., Meng, X., & Deng, R. H. (2023). Privacy-preserving asynchronous federated learning framework in distributed IoT. IEEE Internet of Things Journal, 10(15), 13281-13291.

[27] Li, Z., Huang, C., Gai, K., Lu, Z., Wu, J., Chen, L., ... & Choo, K. K. R. (2022). Asyfed: Accelerated federated learning with asynchronous communication mechanism. IEEE Internet of Things Journal, 10(10), 8670-8683.

[28] Zhang, T., Song, A., Dong, X., Shen, Y., & Ma, J. (2021). Privacy-preserving asynchronous grouped federated learning for IoT. IEEE Internet of Things Journal, 9(7), 5511-5523.

[29] Li, Y., Yang, S., Ren, X., Shi, L., & Zhao, C. (2023). Multi-stage asynchronous federated learning with adaptive differential privacy. IEEE Transactions on Pattern Analysis and

Machine Intelligence, 46(2), 1243-1256.

[30] Gu, B., Xu, A., Huo, Z., Deng, C., & Huang, H. (2021). Privacy-preserving asynchronous vertical federated learning algorithms for multiparty collaborative learning. IEEE transactions on neural networks and learning systems, 33(11), 6103-6115.

[31] Liu, S., Chen, Q., & You, L. (2022). Fed2a: Federated learning mechanism in asynchronous and adaptive modes. Electronics, 11(9), 1393.

[32] Wang, R., & Tsai, W. T. (2022). Asynchronous federated learning system based on permissioned blockchains. Sensors, 22(4), 1672.

[33] Xue, M. A., & Chenglin, W. E. N. (2021). An Asynchronous Quasi-Cloud/Edge/Client Collaborative Federated Learning Mechanism for Fault Diagnosis. Chinese Journal of Electronics, 30(5), 969-977.