

National Institute on Aging PREPARE Challenge: Early Detection of Cognitive Impairment Using Speech — The SpeechCARE Solution

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A. ABSTRACT

Alzheimer's disease and related dementias (ADRD) affect one in five adults over 60, presenting a significant public health concern.^{1–3} Despite nationwide efforts, over half of individuals with cognitive decline, including mild cognitive impairment (MCI) and ADRD, remain undiagnosed.^{4–6} Recent studies showed that speech-based assessments hold promise for early detection: phonetic motor planning deficits impair vocal tract control (e.g., vocal folds), altering acoustic features like pitch and tone.⁷ Memory and language impairments disrupt language organization, leading to syntactic and semantic errors and reduced fluency.^{7,8,9} The studies mostly focused on conventional speech-processing pipelines with hand-crafted features (e.g., eGeMAPS¹⁰) or general-purpose audio classification models (e.g., YAMNet¹¹, VGGish¹²). However, these approaches often exhibit suboptimal performance and limited generalizability across diverse language settings. To address these gaps, we introduce SpeechCARE, a multimodal speech processing pipeline leveraging underutilized pretrained, multilingual acoustic and linguistic transformer¹³ models to capture nuanced acoustic and linguistic cues associated with cognitive impairment. Inspired by Mixture of Experts (MoE) paradigm,¹⁴ its core architecture is a novel multimodal fusion architecture that dynamically weights transformer-driven acoustic and linguistic features for effective integration, enhancing performance and generalizability across different speech production tasks (e.g. story recall, sentence reading). This fusion mechanism has the capability of seamless integration of additional data (e.g., social determinants,¹⁵ MRI¹⁶), boosting its sensitivity across the cognitive impairment spectrum. By leveraging pretrained transformer models, SpeechCARE can tackle challenges posed by small sample sizes, thereby enabling the inclusion of often-overlooked linguistic diversity. SpeechCARE's robust preprocessing pipeline includes automatic transcription, LLM (Large Language Model¹⁷)-assisted data anomaly detection, and LLM-assisted speech task identification. SpeechCARE's explainability framework visualizes each modality's contribution to decision-making, highlighting linguistic and acoustic cues linked to cognitive impairment through a novel SHAP-based approach and LLM-based reasoning. SpeechCARE achieved AUC = 0.88 and F1 = 0.72 in distinguishing cognitively healthy, MCI, and AD. Specifically, for MCI detection (versus control), AUC = 0.90 and F1 = 0.62. Bias analyses using equal opportunity and average odds showed no significant differences across demographics except for age over 80. Various techniques (e.g., oversampling, weighted loss) were used for bias mitigation. Future Directions. SpeechCARE is accessible, non-invasive, and cost-effective for real-world care settings. Our immediate goal is to validate its performance on patient-clinician communications from VNS Health and Columbia University's Alzheimer's Disease Research Center, focusing on underrepresented groups (Hispanic, Black) in New York City (NYC). With support from Columbia's visualization center, we aim to evaluate its explainability in clinician-centered design for Electronic Health Record (EHR) integration, enabling timely diagnosis of cognitive impairment and early intervention for diverse populations¹⁸.

B. METHODOLOGY

B.1. Dataset characteristics

The PREPARE Challenge comprises 2,058 participants (1,646 in the training set and 412 in the test set), including 1,140 healthy controls, 268 individuals with mild cognitive impairment (MCI), and 650 individuals with Alzheimer's disease (AD) (Figure 1). Participants spoke three languages: English (1,655), Spanish (360), and Mandarin (43). Gender was reported as female or male, with females comprising 1,219. Ages ranged from 46 to 99 years (avg: 75.13 ± 8.65). Education was reported both numerically and categorically with 35.23% missing data. Race was reported for less than 8% of the participants (92.61% missing).

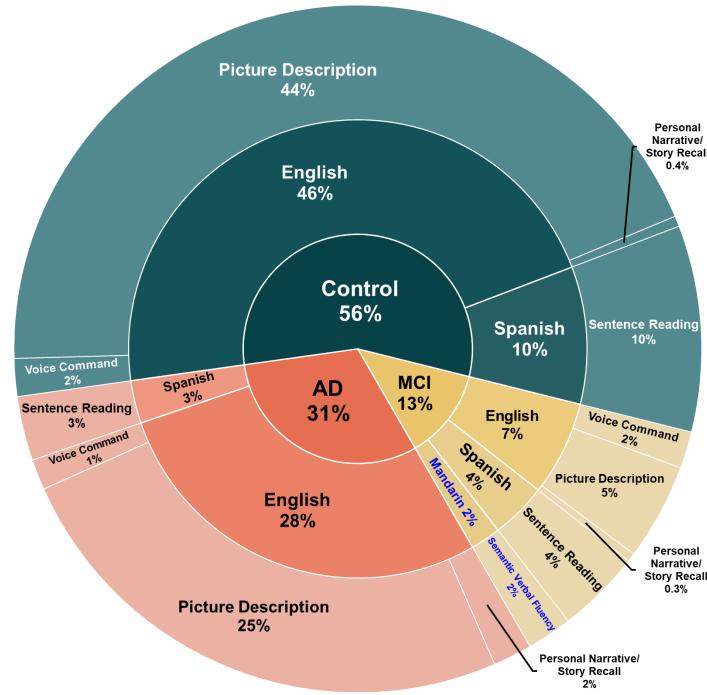


Figure 1. Statistics on diagnosis classes, language, and speech tasks.

B.2.Preprocessing components

(a) Demographic information preparation: To facilitate model bias analysis and effectively incorporate demographic data, we grouped age into three categories following common study conventions: mid-life adults (46–65, 12%), older adults (66–80, 52.7%), and elderly (80+, 35.3%). To normalize education without missing values, we categorized it into four levels: no/elementary (11.61%), high school (24.98%), technical/undergraduate (16.72%), and advanced/graduate (11.47%). We addressed missing values (35.23%) using Iterative Imputer,¹⁹ a multivariate regression method modeling them from age, gender, and language as input features.

(b) Data quality evaluation and improvement: High-quality audio data is essential for encoding subtle acoustic cues particularly for MCI detection.²⁰ However, the recordings included different types of stationary (e.g., recording device's hum) and dynamic noises (e.g., nearby conversations). To measure noisiness, we used different techniques including Signal-to-Noise Ratio and Spectral Flatness Measure, but due to inconsistent preprocessing by corpora developers, the outcomes were not strongly correlated with human perception. Therefore, we used a qualitative method, Mean Opinion Score,²¹ where two experts (HA, MZ) listened to 5% of the data (stratified by demographic and diagnostic classes) and rated quality on a 1–5 Likert scale.²² Findings showed 62.4% severely noisy (scores 1–2), 14.7% moderately noisy (score 3), and 22.9% slightly noisy (scores 4–5). To safely mitigate the noise, we then applied a low-pass filter²³ at 8,000 Hz to remove high-frequency noise while preserving human speech frequency components.

(c) Automatic transcription: To incorporate linguistic cues into the SpeechCARE pipeline, we utilized the latest version of Whisper-Large,²⁴ an open-source, multilingual automatic speech recognition system that achieved state-of-the-art (SOTA) performance on standard benchmarks. Whisper is able to detect the language of input speech. To evaluate Whisper's transcription

accuracy, we used a stratified random sample (by demographic and diagnostic classes) comprising 5% of English, 10% of Spanish, and 15% of Mandarin audio data, ensuring sufficient sample sizes for each language. Transcriptions were compared to human-generated transcripts to calculate the word error rate²⁵ (WER): English = 0.12, Spanish = 0.27, and Mandarin = 0.32.

(d) Speaker diarization: SpeechCARE's diarization module builds on our previous study, which used a machine-learning algorithm to automatically separate the patient and clinician in recorded conversations. Based on our prior studies and initial findings of this study, incorporating available clinician data from certain corpora improved overall performance. Therefore, clinician speech was included in model training whenever available in the audio files of this dataset.

(e) LLM-Assisted data anomaly detection: During the evaluation of the Whisper transcriptions, we discovered that some audio files contained only the clinicians' speech, likely due to errors in speaker diarization performed by the corpus developers. To systematically identify these cases, we employed LLaMA 405B²⁶—an open-source LLM comparable to GPT-4 performance—with prompt engineering²⁷ and few-shot learning²⁸, guided by iterative analysis of the model's output. This approach revealed 22 audio files consisting solely of clinicians' speech. We removed these files from the training process to prevent potential confusion in the model.

(f) LLM-assisted speech task identification: Speech production task type was not available in the dataset, yet identifying it is important for model development and bias/error analysis. Each task requires distinct cognitive effort and yields different acoustic and linguistic cues for cognitive impairment detection. Reflecting broader trends in clinical NLP, LLMs are increasingly used in healthcare for data quality, task automation, and clinical text analysis²⁹. We used LLaMA 405B with prompt engineering and few-shot learning, guided by iterative expert analysis (HA, MZ), to refine the LLM prompt for task identification. The same experts then verified 10% of the assigned tasks (stratified by demographics and diagnostic classes), confirming 98% accuracy. Errors arose mainly from truncated or insufficient transcripts. See Figure 1 for statistics on the identified tasks.

(g) Task homogeneity and bias introduction: According to these analyses, we observed that (1) all Spanish speakers performed only the sentence reading task, which may not provide sufficient temporal cues linked to cognitive impairment compared to picture description and story recall. This limitation introduces bias and may reduce pipeline performance for these participants; (2) all Mandarin speakers had MCI in both the training and test sets, inflating speech pipeline performance because the system simply learns to classify all Mandarin speakers as having MCI.

B.3. Building speech processing models

Our team has extensive experience developing speech processing pipelines for cognitive impairment detection, highlighted in news media^{30–33} and high-impact journals.^{34–45} Overall, no single approach consistently yields optimal performance due to variations in speech corpus characteristics (e.g., speech task, language) and audio data quality. Consequently, we investigated various linguistic and acoustic processing methods for this dataset to build SpeechCARE pipeline on the top-performing and most generalizable models (See Table 1 for brief information and results).

(a) Hand-crafted speech processing models: We developed three pipelines based on hand-crafted acoustic and linguistic features (see more information and results in Table 1): (1) SpeechDETECT:³⁴ Drawn from a systematic review of studies focused on speech and language for MCI detection, we built SpeechDETECT, providing a comprehensive, explainable set of acoustic and temporal features of speech; (2) eGeMAPS-Based model: We built this model on the eGeMAPS V02⁴⁶ parameter set (provided by the challenge organizer), using advanced time-series analysis;¹³ (3) LinguisticDetect:⁴² Drawn from previous speech-related studies for MCI detection, we built this model by quantifying lexical richness, syntactic complexity, semantic

coherence, and psychological cues linked to cognitive impairment using natural language processing methods.

(b) Speech (acoustic) and linguistic pre-trained transformer models: Pre-trained speech transformer models (e.g., HuBERT,⁴⁷ Wav2Vec 2.0⁴⁸) are powerful in capturing long-term acoustic and temporal dependencies. However, they have been underutilized in cognitive impairment related studies due to the lack of effective fine-tuning procedure on small speech datasets. For this dataset, we evaluated (1) SOTA pre-trained speech-transformer models—Wav2Vec2 XLS-R,⁴⁹ mHuBERT;⁵⁰ (2) pre-trained linguistic-transformer models—mBERT⁵¹ and XLM-RoBERTa⁵² (commonly used models) as well as mGTE⁵³ and BGE⁵⁴ (SOTA models). We selected these models due to multilingual pre-training and high generalizability across diverse languages. Our initial analysis on this dataset showed that multilingual models (e.g., mHuBERT, mBERT) generally outperformed monolingual counterparts (HuBERT, BERT⁵⁵), even for English-speaking participants; (3) Audio Spectrogram Transformer⁵⁶ (AST). SOTA Speech transformer models primarily were designed for automatic speech recognition. Therefore, we also tested the AST model, a common model for audio classification trained on YouTube audio. All these transformer models were fine-tuned using the procedure and architecture described in section B.5.

(c) LLM-based models: We investigated LLMs, which extend transformer architectures by greatly increasing model parameters and training data size. Prior work showed that LLMs excel at recognizing linguistic cues linked to cognitive impairment with minimal fine-tuning.^{57–59} For local, HIPAA-compliant deployment, we fine-tuned: LLaMA 3²⁶ (versions 3.1 70B, 3.1 8B, 3.2 3B) and Minstral 8B⁶⁰ using QLoRA⁶¹ (a parameter-efficient, low-rank adaptation method) combined with a linear classifier on the final-layer embeddings to generate probabilities.

B.4. Evaluating speech processing models

We evaluate the performance of the processing pipelines by (a) creating a validation dataset by randomly selecting 20% of the training dataset, stratified using demographic and diagnostic classes—a standard practice in deep learning algorithms development; (b) standard metrics for multi-class evaluation: AUC-ROC (Area Under the Curve - Receiver Operating Characteristic, one-vs-rest approach for three classes), F1-score (harmonic mean of precision and recall) using the micro-average, which accounts for class imbalance, and multi-class log loss as instructed by challenge organizers. See Table 1 for performance of the speech processing models on the validation set.

Table 1. Summary of acoustic and linguistic models and their performance

Models Characteristic				Validation Result		
1.1. Acoustic Hand-Crafted Features						
Models		Description				Loss AUC F1
SpeechDetect		6848 features encoding Frequency, Spectral, Voice Quality, Intensity, Signal Complexity, Rhythmic Structure, Fluency, and Speech Dynamics aspects of speech				0.801 0.80 0.62
eGeMAPS		88 features encoding Frequency, Spectral, Voice Quality, and Intensity aspects of speech				0.879 0.77 0.57
1.2. Linguistic Hand-Crafted Features						
Model		Description				Loss AUC F1
LinguisticDETECT		N features encoding lexical density, syntactic structure, semantic and psycholinguistic cues				0.900 0.70 0.63
1.3. Speech Transformer Models						
Transformer	Size	Training source		input	Loss	AUC F1
Wav2vec2 XLS-R	300 M	436K hours /128 languages		Waveform	0.849	0.78 0.56
mHuBERT	96 M	90K hours /147 languages		Waveform	0.738	0.84 0.66
AST	87 M	2M 10-second audio clips		Spectrogram	0.803	0.80 0.60
1.4. Linguistic Transformer Models						
Transformer	Size	Training source			Loss	AUC F1
XLM-RoBERTa	600 M	~295 billion tokens across 100 languages			0.841	0.80 0.64
BGE	567 M	~1.2 billion text pairs across 194 languages			0.806	0.81 0.66
mGTE	305 M	~1028 billion tokens across 75 languages			0.789	0.83 0.67
mBERT	177 M	~2.5 billion tokens across 104 languages			0.803	0.82 0.66
1.5. Large Language Models						
LLM	Size	Availability	Fine-Tuning Method		Loss	AUC F1
LLaMA 3.1	70 B	Open weight	QLoRA		0.787	0.82 0.68
LLaMA 3.2	3 B	Open weight	QLoRA		0.855	0.80 0.65
LLaMA 3.1	8 B	Open weight	QLoRA		0.811	0.81 0.66
Minstral	8 B	Open weight	QLoRA		0.817	0.81 0.64

B.5. Feature Network

The feature network generates modality-specific representations from pre-trained linguistic, acoustic, and demographic inputs, which collectively form the basis of the multimodal fusion architecture (Figure 2).

Based on the comparative evaluation in Sections B.3 and B.4, we selected mGTE and mHuBERT as the core components of the SpeechCARE feature network.

(a) Linguistic Transformer (mGTE). Pre-trained linguistic transformers have been used in prior studies of cognitive impairment with varying results depending on data size, speech task, and language coverage. In SpeechCARE, the multilingual Generative Text Encoder (mGTE) (an encoder-only transformer comprising approximately 305 million parameters) was employed due to its large multilingual pretraining corpus ($\approx 1,028$ billion tokens across 75 languages) and extended context window (8,192 tokens), which far exceeds that of BERT (512 tokens). This extended context facilitates the modeling of syntactic errors, lexical disruptions, and semantic incoherence commonly observed in mild cognitive impairment and dementia. For each tokenized transcript sequence $T = \{t_1, \dots, t_n\}$, mGTE produces contextual embeddings h_i . The embedding corresponding to the classification token, $h_{[CLS]}$, serves as the summary representation of the entire utterance. During fine-tuning, $h_{[CLS]}$ is projected through a fully connected layer with Tanh activation to yield a diagnostic probability vector across cognitive classes (Control, MCI, AD). Our empirical results showed that the linguistic-only model (mGTE) achieved a strong standalone performance with a test F1-score of 68.88%, confirming its capacity to extract rich lexical and syntactic features from transcripts.

(b) Acoustic Transformer (mHuBERT). Recent self-supervised acoustic encoders such as Wav2Vec 2.0 and HuBERT achieve state-of-the-art performance on various speech benchmarks but face challenges when applied to long clinical recordings. Their computational cost grows quadratically with sequence length, and they lack a global embedding summarizing temporal dependencies. To address these limitations, SpeechCARE adopts mHuBERT, a multilingual variant of HuBERT with 98 million parameters pre-trained on 90,000 hours of speech in 147 languages. Each 30-second waveform x is divided into 5-second segments with 25% overlap, producing up to seven overlapping windows. Every segment x_i is encoded into 250 frame-level embeddings (≈ 25 ms windows). The concatenated segment embeddings form a unified sequence of up to 1,750 vectors representing the full audio. A learnable [CLS] embedding is prepended to this sequence⁶², which is subsequently processed by a Customized Self-Attention Encoder (CSE) composed of two stacked attention blocks with four heads each, followed by normalization, dropout, and residual connections. This lightweight encoder efficiently aggregates temporal information across segments while preventing overfitting on a relatively small dataset. The resulting global acoustic representation $h_{A,[CLS]}$ encapsulates spectral, prosodic, and temporal attributes associated with cognitive decline. A feed-forward classification layer then maps this vector to diagnostic logits. Our ablation studies on acoustic modeling showed that stepwise architectural enhancements consistently improved performance: adding a learnable [CLS] embedding to the base mHuBERT model increased the F1-score from 66.80% to 67.77%, and further incorporating segmentation raised it to 68.23% (see Table 2).

To evaluate the influence of preprocessing, a variant termed SpeechCARE-AGF: Raw Audio was additionally trained using the same architecture without any noise reduction. An alternative configuration, SpeechCARE-AGF: CMGAN-Enhanced Audio, employed the Conformer-based Metric-GAN (CMGAN) model for neural denoising. As summarized in Table 2, both variants yielded lower F1-scores compared with the final configuration, indicating that unfiltered or excessively enhanced speech may distort cognitively relevant acoustic cues. Finally, a low-pass

filter at 8 kHz was applied to the raw audio to suppress high-frequency noise while preserving the human voice frequency range. This preprocessing step, corresponding to the SpeechCARE-AGF: Low-Pass Filtered Audio variant in Table 2, produced the best results and was adopted for the final model configuration.

(c) Demographic Representation. Demographic attributes (age, gender, education) were encoded categorically via one-hot representation and projected through a dense layer to produce a compact latent vector h_D . Preliminary analyses indicated that categorical encoding of age yielded better discrimination than continuous values. The resulting vector was incorporated as a third modality within the fusion network. While demographics alone yielded lower performance ($F1 = 55.70\%$), our evaluation showed that age contributed the most value among the demographic features and was therefore retained in the final fusion configuration.

(d) Training and Hyperparameter Configuration. Both mHuBERT and mGTE encoders were fine-tuned jointly within a unified multimodal architecture using separate learning rates (1×10^{-5} for mHuBERT and 1×10^{-6} for mGTE) and a weight decay of 1×10^{-3} . The batch size was set to 4, and the CSE module included two attention blocks with four heads each. All fully connected layers comprised 128 neurons with Tanh activation and a dropout rate of 0.1. This configuration provided stable optimization while preventing overfitting on the limited training data available in the PREPARE dataset.

B.6. Fusion Network

Multimodal integration is essential for capturing complementary cues across acoustic, linguistic, and demographic domains. Four fusion paradigms were evaluated (Intermediate Fusion, Scaled Late Fusion, Cross-Modal Attention, and Adaptive Gating Fusion (AGF)) to determine the most effective strategy (see Table 2). These fusion strategies were selected based on prior studies that compared early, intermediate, and late fusion methods in multimodal deep learning systems^{63–65}. The Adaptive Gating Fusion model (Figure 2) was inspired by the Mixture-of-Experts (MoE) paradigm^{14, 66} and designed to dynamically modulate the contribution of each modality. It achieved the highest validation and test performance and was therefore adopted as the final architecture.

(a) Adaptive Gating Fusion (AGF) Architecture. The Adaptive Gating Fusion model (Figure 2) was inspired by the Mixture-of-Experts (MoE) paradigm and designed to dynamically modulate the contribution of each modality. Given feature embeddings from the feature network—acoustic (\mathbf{h}_A), linguistic (\mathbf{h}_L), and demographic (\mathbf{h}_D)—AGF computes a weighted combination of modality-specific outputs through three sequential stages:

1. Modality encoding: Each $h_i \in \{h_A, h_L, h_D\}$ passes through a fully connected layer with Tanh activation, yielding hidden representations z_i .
2. Gating network: The concatenated vector $[z_A; z_L; z_D]$ is passed to a gating subnetwork consisting of a single fully connected layer followed by a Softmax function that produces attention weights w_i for each modality ($\sum_i w_i = 1$).
3. Weighted aggregation: Modality-specific prediction scores s_i are computed via separate linear classifiers and combined into the final output:

$$y = \sum_i w_i s_i$$

This procedure adaptively emphasizes modalities contributing the most informative cues for each input. Furthermore, this gating mechanism provides interpretable insights into modality reliance (see Table 2) and enhances robustness when a modality is degraded or missing.

(b) Comparative Performance and Statistical Validation. As shown in Table 2, the AGF configuration integrating acoustic (mHuBERT + CSE), linguistic (mGTE), and age as the demographic variable achieved the best overall results on the PREPARE test set ($AUC = 86.83 \pm 0.46\%$, $F1 = 72.11 \pm 0.44\%$). This performance exceeded that of all other fusion strategies—Intermediate Fusion ($AUC = 86.28\%$, $F1 = 70.10\%$), Scaled Late Fusion ($AUC = 86.21\%$, $F1 = 70.29\%$), and Cross-Modal Attention ($AUC = 86.61\%$, $F1 = 70.51\%$). In addition, when substituting other demographic features, performance decreased: using education or gender alone resulted in F1-scores of 69.20% and 69.95% respectively, while incorporating all demographics together yielded an F1 of 68.42%. To assess the significance of these differences, paired t-tests confirmed that improvements achieved by AGF over competing fusion approaches were statistically significant ($p < 0.01$) with large effect sizes (Cohen's $d > 1.5$). Furthermore, among the baseline fusion strategies, Cross-Modal Attention slightly outperformed Intermediate and Scaled Late Fusion, but AGF consistently delivered $\sim 1.5\text{--}2.0\%$ higher F1 and retained top AUC performance across configurations. Taken together, these findings establish AGF as the optimal framework for integrating multimodal representations in the SpeechCARE architecture.

(c) Interpretation and Advantages. The AGF framework offers several advantages:

1. Dynamic adaptation: weights vary across tasks and languages, enabling sensitivity to cognitive and structural demands.
2. Interpretability: learned weights indicate relative contributions of linguistic and acoustic cues.
3. Efficiency: the gating layer adds minimal computational overhead while maintaining competitive AUC–F1 trade-offs.
4. Robustness: adaptive weighting mitigates performance loss under noisy or missing modalities.

Overall, the combination of the Feature Network (mHuBERT + CSE and mGTE) and the AGF Fusion Network (Figure 2) yielded the top-performing configuration summarized in Table 2, demonstrating the effectiveness of transformer-based multimodal modeling for cognitive impairment detection.

Table 2. Comparative and ablation results for SpeechCARE model components

Model	Validation		Test	
	AUC	F1-Score	AUC	F1-Score
Acoustic-Only Refinements				
mHuBERT (Base Model)	84.03±1.09	66.78±2.27	84.07±0.60	66.80±1.25
mHuBERT + CLS Embedding	84.92±1.23	68.06±1.83	84.99±0.60	67.77±1.06
mHuBERT + CLS Embedding + Segmentation	84.55±1.14	67.60±1.56	84.85±0.70	68.23±1.11
Single-Modality Baselines and Modalities Integration				
All Demographics (Age, Gender, Education)	72.78±0.79	55.82±0.80	72.31±0.71	55.70±0.43
Voice (mHuBERT + CLS Embedding + Segmentation)	84.55±1.14	67.60±1.56	84.85±0.70	68.23±1.11
Transcription (mGTE)	81.26±1.17	63.70±1.26	85.00±0.40	68.88±0.78
Fusion-AGF: Voice + Transcription	84.42±1.95	67.57±2.36	86.57±0.45	70.51±0.93
Fusion-AGF: Voice + Transcription + All demographics	83.49±0.96	66.14±1.74	85.49±0.69	68.42±0.78
Fusion-AGF: Voice + Transcription + Education	83.19±2.09	66.02±2.87	85.99±0.68	69.20±1.00
Fusion-AGF: Voice + Transcription + Gender	84.02±1.67	66.78±2.18	86.35±0.45	69.95±0.68
Fusion-AGF: Voice + Transcription + Age	84.97±1.57	68.12±2.69	86.83±0.46	72.11±0.44
Fusion Strategies				
Intermediate Fusion	85.07±1.35	67.94±2.09	86.28±0.48	70.10±0.78
Scaled Late Fusion	85.19±1.38	68.62±2.77	86.21±0.57	70.29±1.13
Cross-Modal Attention (+ Intermediate Fusion)	85.49±1.50	68.58±2.05	86.61±0.56	70.51±0.71
Adaptive Gating Fusion (AGF)	84.97±1.57	68.12±2.69	86.83±0.46	72.11±0.44
Noise Reduction (Audio Preprocessing)				
SpeechCARE-AGF: Raw Audio	84.25±1.33	85.76±0.80	85.76±0.80	69.15±1.01
SpeechCARE-AGF: CMGAN-Enhanced Audio	83.22±1.89	65.34±2.26	85.80±1.10	69.00±1.12
SpeechCARE-AGF: Low-Pass Filtered Audio	84.97±1.57	68.12±2.69	86.83±0.46	72.11±0.44

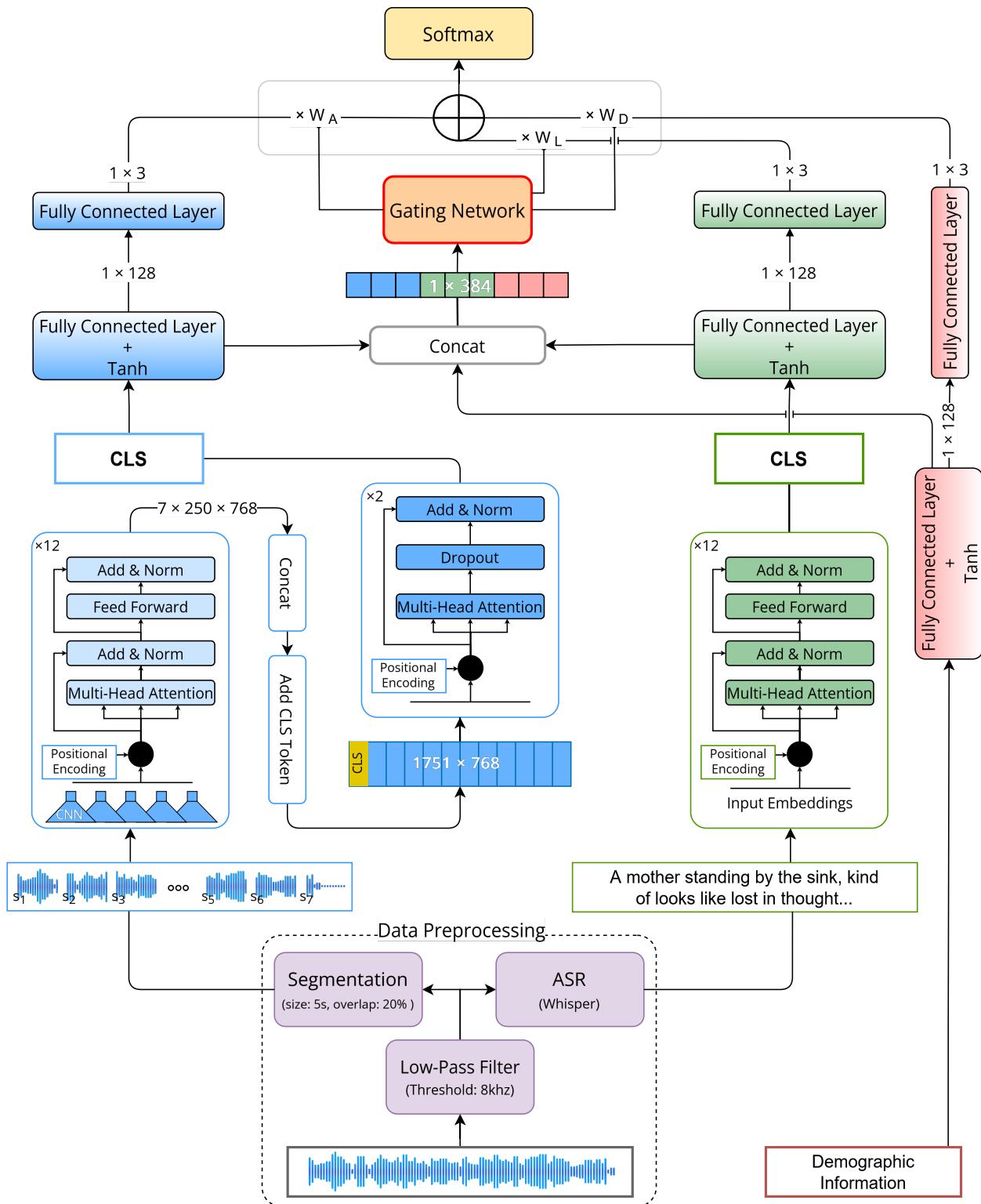


Figure 2. Architecture of the SpeechCARE Feature and Fusion Networks. The diagram illustrates how raw audio (up to 30 s) is processed via low-pass filtering (8 kHz cutoff) and segmentation (5 s chunks with 25 % overlap), followed by automatic speech recognition (ASR) to produce text. The acoustic pathway uses a multilingual HubERT encoder plus a Customized Self-Attention Encoder (CSE) to extract a global [CLS] embedding, while the linguistic pathway processes transcripts with mGTE. Demographic data enter as a third modality. Each modality's embedding passes through its own dense layer, and the Adaptive Gating Network fuses these representations to generate final predictions.

C. PERFORMANCE ANALYSIS

(a) Performance metrics. We used AUC-ROC (one-vs-rest approach) to evaluate how well the model distinguishes each class. We computed micro-average and weighted-average AUC: micro-average aggregates decisions across all classes equally, while weighted-average accounts for class imbalance. We also calculated Precision-Recall (PR) curves using the same approach. Additionally, we introduced Information Gain curves to measure how much uncertainty the model's predictions reduce compared to random guessing (Figures 3.A–3.C).

(b) Performance of SpeechCARE's models (Figures 3.A–3.C). **(a) SpeechCARE-AGF** with adaptive gating fusion (AGF) on mHuBERT, mGTE, and demographics achieved AUC=87.59 (Micro) and PR=77.17 (Micro). The cumulative gain curve showed that by targeting the top 40% of the population, ~80% of True diagnoses were captured; **(b) SpeechCARE-Whisper** replaces mHuBERT with Whisper-Medium (using encoder embeddings). Overall, Whisper dominated mGTE and demographics, causing the model to assign minimal/zero weight to them. This likely happened because Whisper was trained on a larger labeled dataset (680k h) compared to mHuBERT's smaller unlabeled set (90k h). Nonetheless, SpeechCARE-Whisper's performance did not significantly differ from SpeechCARE-AGF, indicating the robust AGF architecture for speech processing.

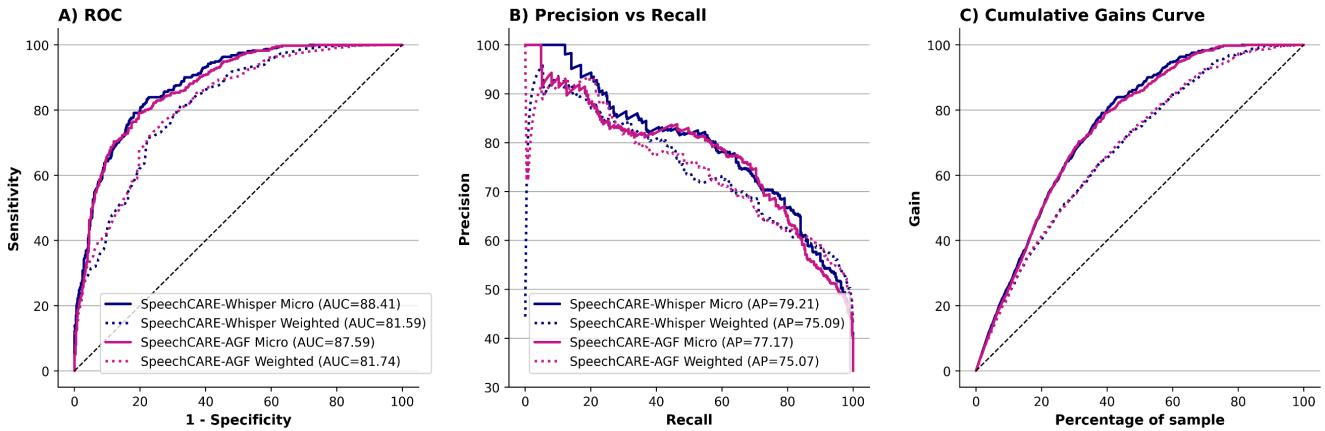


Figure 3. SpeechCARE-AGF & Whisper

(c) Performance of SpeechCARE-AGF and SpeechCARE-Whisper for MCI detection (Figures 4.A–4.C). Similarly to C.2, there was no significant difference between both models for MCI detection (MCI class vs. Control class). Overall, the result is promising with AUC-ROC = 90.50, RP = 68. **After threshold optimization,** we achieved F1= 0.62, recall=0.73, precision=0.54 for MCI, indicating a good performance of SpeechCARE for early detection.

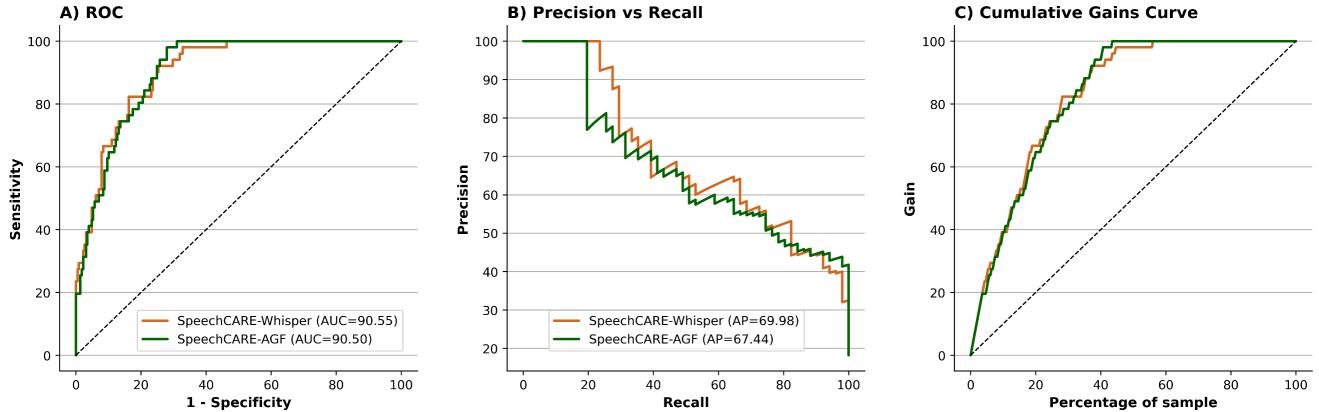


Figure 4. SpeechCARE-AGF & Whisper: MCI vs. Control

(d) Error analysis (Figure 5). We observed no false negatives (misclassified MCI/AD as controls) in Mandarin speakers because all Mandarin speakers in the dataset had MCI. Spanish speakers showed the highest false negatives, likely reflecting the limited ability of sentence-reading tasks to capture acoustic/linguistic cues (see B.2.(f)). English speakers primarily completed picture-description and narrative tasks. For these participants, we used a T-test ($p=0.05$) to compare acoustic (fundamental frequency, jitter, shimmer, intensity, MFCC) and linguistic (lexical richness, repetition, fillers, sentence structure) features between false negative class and control class (true negative). No significant differences were found in either feature set between these two groups. This may indicate that language-related brain regions may be less affected in the false-negative group. Incorporating additional modalities (e.g. medical history, MRI) may improve SpeechCARE sensitivity.

		Predicted Labels		
		Control	MCI	AD
True Labels	Control	190	30	9
	MCI	10	41	0
AD	47	19	66	

Figure 5. SpeechCARE-AGF Confusion Matrix. Note that the Thresholds were adjusted for three classes.

D. BIAS ANALYSIS

(a) Metrics. We used Equality of Opportunity⁶⁷ (EOO) and Average Odds, two of the most common bias metrics, as widely adopted in recent evaluations of ASR fairness⁶⁸. For demographic data (Figure 6.A), no significant bias was observed except for the age-over-80 group. For languages (Figure 6.A), bias stemmed from dataset constraints: (1) all Mandarin speakers had

only MCI, inflating EOO; (2) all Spanish speakers only completed sentence-reading tasks, limiting critical speech cues for detection.

(b) Methods. We applied oversampling as a preprocessing method, incorporating Frequency Masking⁶⁹ and Voice Conversion⁷⁰ for speech augmentation, alongside in-processing methods such as Adversarial Debiasing⁷¹ and reweighting⁷². For Spanish speakers, SpanBERTa (a Spanish transformer) was replaced with mGTE.

(c) Results of mitigation. Among oversampling techniques, frequency masking outperformed voice conversion, consistent with SpeechCura⁷³, which found both methods effective for improving cognitive impairment detection under limited data. Focal loss slightly reduced biases, while other in-processing methods showed no improvement. Replacing SpanBERTa with mGTE significantly mitigated bias. Overall, these methods improved EOO by 5.17% for the age-over-80 group and by 16.36% for Spanish speakers (**Figure 6.B**), demonstrating the effectiveness of our bias mitigation approach.

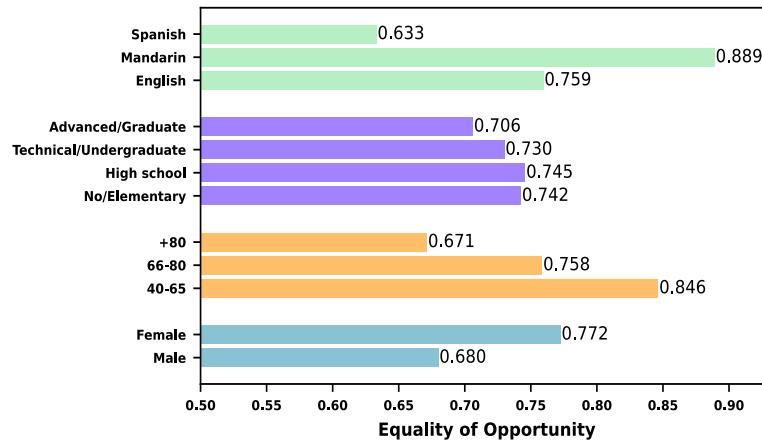


Figure 6.A. Equality of Opportunity before bias mitigation

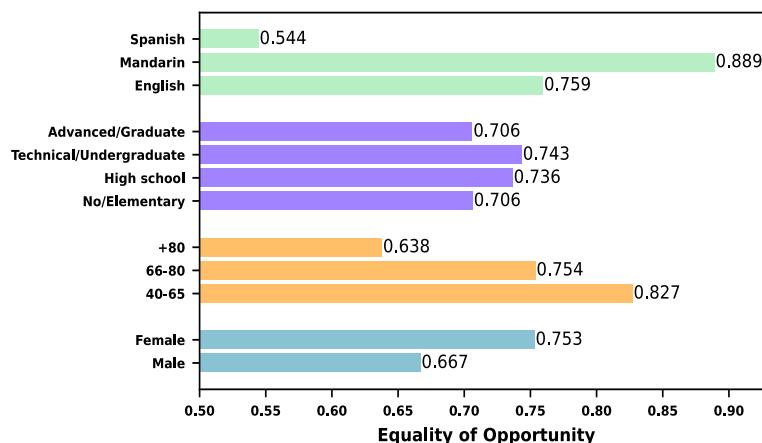


Figure 6.B. Equality of Opportunity after bias mitigation

E. FUTURE DIRECTIONS

- (a) Multimodal integration of speech, biomarkers, EHR data, social determinants from Columbia Alzheimer's Disease Research Center (ADRC).** Speech-only markers may underperform when language-related brain regions are less affected. We are collaborating with Columbia ADRC to collect speech data from racially diverse groups in NYC. We plan to (1) fine-tune SpeechCARE on the multilingual dialects, (2) apply SpeechCARE's adaptive gating fusion to measure speech's added value for early detection, (3) co-train speech embeddings with imaging biomarkers to uncover cross-modal links between speech features and brain changes.
- (b) Fine-tuning SpeechCARE on routine patient-clinician communication and enhancing explainability framework.** Speech production tasks overlook vital communication cues. We are collaborating with VNS Health (the largest home healthcare agency in the U.S.) to collect routine patient-clinician communications from a racially diverse population. We plan to (1) fine-tune SpeechCARE on the communications data and (2) refine SpeechCARE's Explainability Framework in a clinician-centered design, preparing it for efficacy trial and EHR integration.
- (c) Longitudinal monitoring of speech.** A single speech recording overlooks gradual cognitive decline. In partnership with Columbia Data Visualization Center, we are developing "SpeechCARE Lite," a mobile app for recording speech samples over time. We plan to (1) integrate time-series models (e.g., temporal transformers) for longitudinal analysis; (2) improve SpeechCARE Explainability to provide insights on cognitive changes over time.
- (d) Improving pre- and in-processing components of SpeechCARE.** Speaker diarization errors, transcription bias, and noise in audio data remain problematic. We plan to (1) use advanced deep learning methods for noise reduction, (2) fine-tune Whisper to reduce bias in racially diverse populations, (3) develop LLM-based speaker diarization, and (4) extend SpeechCARE's fusion model as larger datasets become available.

Author Contributions:

- Maryam Zolnoori: Speech processing Lab; Lead project
- Hossein Azadmaleki: Development of the SpeechCARE model; Project management
- Yasaman Haghbin: Fine-tuning Transformer models; Bias analysis; Error analysis
- Ali Zolnour: Performance analysis; Results visualization
- Mohamad Javad Momeni Nezhad: Fine-tuning Large language models
- Sina Rashidi: Using data augmentation techniques, Signal processing
- Mehdi Naserian: Building machine learning algorithms on handcrafted acoustic features
- Elyas Esmaeili: Building machine learning algorithms on handcrafted acoustic features
- Sepehr Karimi Arpanahi: Using LLM for task description

Data Availability

The dataset employed in this study was provided exclusively to our team as part of our participation in the 2024 NIA PREPARE Challenge. This dataset is not publicly available, and data sharing is restricted under the challenge terms. Researchers seeking access may contact the challenge organizers [[here](#)]. As the dataset has since been integrated into DementiaBank, access may alternatively be requested through the DementiaBank administrative team.

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