

Intelligent Recommendation System for Early Detection and Care Support in Alzheimer's Disease

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Abstract

Alzheimer's disease is a progressive neurodegenerative disorder that affects memory, cognition, and daily functioning, making early diagnosis essential for timely intervention. This paper presents an intelligent recommendation system for early detection of Alzheimer's disease using multimodal clinical data and attention-based fusion. The proposed framework analyzes heterogeneous patient inputs such as demographic attributes, cognitive test scores, medical history, and optionally neuroimaging or signal-based features, and learns adaptive weights for each modality according to its diagnostic relevance. The fused representation is then used to predict the disease class or risk category, thereby supporting clinical decision-making in early-stage diagnosis. Experimental evaluation is planned using standard metrics such as accuracy, precision, recall, F1-score, and specificity.

Index Terms

Alzheimer's disease, early detection, multimodal fusion, attention mechanism, clinical decision support, machine learning.

I. INTRODUCTION

Alzheimer's disease is one of the most common causes of dementia and represents a major global healthcare challenge. It leads to progressive decline in memory, reasoning, behavior, and the ability to perform everyday tasks. Since the disease develops gradually, early detection is especially important because it can support timely treatment planning, patient monitoring, and better care management. However, early diagnosis remains difficult

because initial symptoms are often subtle and can overlap with normal aging or mild cognitive impairment. [1], [2], [6]

Recent advances in artificial intelligence have created new opportunities for supporting medical diagnosis. In healthcare, multimodal learning is particularly valuable because diagnostic decisions are often based on multiple sources of evidence rather than a single observation. For Alzheimer's disease, this may include demographic factors, cognitive assessment results, neuropsychological tests, imaging features, and other clinical indicators. Research has shown that multimodal fusion can improve diagnostic performance and help capture complementary information that may be missed by unimodal approaches. [1], [3], [4]

A recommendation-based diagnostic system can be useful in this context because it does not merely classify patients but also supports the decision process by highlighting the most likely disease stage or risk category. This is important for early screening and triage, where a model can assist clinicians by identifying high-risk cases that require further medical evaluation. Attention-based fusion methods are well suited for this task because they learn to assign different weights to different modalities, making the final prediction more adaptive and interpretable. [3], [4], [5]

The goal of this paper is to design an intelligent recommendation system for early detection and care support in Alzheimer's disease, with a diagnosis-focused emphasis. The proposed framework integrates heterogeneous clinical inputs through attention-based fusion and uses the resulting representation for disease prediction. By doing so, the system aims to improve

accuracy, robustness, and explainability in comparison with simple feature combination methods. [2], [3], [5]

II. RELATED WORK

Recent systematic reviews show that multimodal AI models consistently outperform single-modal models for Alzheimer's diagnosis, prognosis, and risk prediction by integrating complementary biological, clinical, and behavioral information. A recent review highlights that machine learning and deep learning methods have been widely explored for Alzheimer's diagnosis, but practical issues such as generalization, interpretability, and deployment remain open challenges. [1]

A scoping review of intelligent decision support systems for dementia care found that most current AI applications focus on diagnosis, while fewer systems address broader care support tasks. The same review also identified data availability and clinical integration as important barriers to adoption. This indicates that there is room for a diagnosis-oriented system that is also useful in decision support.

Multimodal fusion has been widely studied for Alzheimer's diagnosis because different data sources provide complementary information. Prior work has shown that simple feature concatenation may cause one modality to dominate the model, while more advanced fusion approaches can improve performance and stability. Studies using MRI, clinical features, and biological information reported better results when fusion was handled carefully rather than naively. [2], [3], [4]

Attention-based fusion methods are especially promising because they can adaptively weight each modality according to its relevance to the task. Recent clinical prediction studies show that attention-based multimodal fusion can perform well even when some modalities are missing, which is very relevant for medical data. This makes attention an attractive choice for a robust Alzheimer's diagnosis framework. [4], [5], [11]

Based on these findings, the proposed work focuses on a multimodal attention-based system that is both practical and interpretable. The contribution is not just disease classification, but also a structured recommendation mechanism that supports early detection and clinical triage.

III. PROPOSED METHODOLOGY

The proposed framework follows a diagnosis-focused multimodal learning pipeline for early Alzheimer's disease detection. It combines structured clinical data with other available modalities, such as cognitive scores, neuropsychological measures, and optionally neuroimaging or EEG-derived features. Each modality is processed separately and then fused using an attention mechanism so that the model can learn the relative contribution of each data source. [2], [4], [5]

First, patient data are collected from a suitable Alzheimer's dataset. The dataset may include demographic attributes, clinical measurements, cognitive test results, and modality-specific biomarkers. Since real clinical datasets often contain missing or unevenly distributed inputs, the preprocessing stage includes data cleaning, normalization, encoding of categorical variables, and handling of missing values.

Next, each modality is encoded into a compact latent representation. Tabular clinical features can be transformed using fully connected layers, while imaging or signal-based features can be processed using convolutional or sequence-based modules. This separate encoding preserves modality-specific information before fusion and avoids forcing heterogeneous data into a single representation too early.

The encoded modality vectors are then passed to an attention-based fusion module. This module learns dynamic weights that reflect the diagnostic importance of each modality for a given patient. As a result, the model can emphasize the most informative signals, such as cognitive test scores or neuroimaging patterns, while reducing the effect of weak or noisy inputs. This design also helps the framework remain robust in the presence of missing modalities. The fused feature representation is then fed into a classifier that predicts the Alzheimer's disease class or risk level. Depending on the dataset, the task may be binary classification or multiclass classification, such as cognitively normal, mild cognitive impairment, and Alzheimer's disease. The output layer can be implemented using sigmoid or softmax activation, depending on the number of classes.

The model is trained using labeled data and optimized using cross-entropy loss. Regularization techniques such as dropout, early stopping, and validation-based tuning can be applied to improve generalization. If the dataset contains incomplete modalities, the training process can

include missing-modality conditions so that the model learns to remain stable under realistic clinical constraints.



Fig. 1. Multimodal Alzheimer's diagnosis pipeline

Let $x^{(1)}, x^{(2)}, \dots, x^{(m)}$ denote the input modalities. Each modality is encoded into a latent vector $h^{(i)}$. The attention module assigns a score to each modality, and the normalized weights are used to compute the fused representation.

$$h^{(i)} = f_i(x^{(i)})$$

$$e_i = q^T h^{(i)}$$

$$\alpha_i = \exp(e_i) / \sum_{j=1}^m \exp(e_j)$$

$$z = \sum \alpha_i h^{(i)}$$

$$\hat{y} = \text{softmax}(Wz + b)$$

$$\mathcal{L} = - \sum_{c=1}^C y_c \log(\hat{y}_c)$$

Here, $h^{(i)}$ is the encoded modality representation, α_i is the attention weight, z is the fused feature vector, and $\hat{y}$ is the predicted class distribution. The model is optimized using cross-entropy loss. [3], [4], [5]

IV. BASELINE MODELS

To validate the proposed model, four baseline approaches are included. Random Forest is used as a strong ensemble baseline for structured clinical data. Support Vector Machine provides a classical margin-based classifier. XGBoost is included because it is effective on tabular medical features and captures nonlinear interactions well. A simple concatenation neural network is used to test whether naive feature merging is sufficient without attention-based weighting. [2], [7], [8]

Random Forest can be expressed as an ensemble of decision trees. SVM aims to maximize the margin between

classes. For XGBoost, the prediction is built additively across boosting rounds:

$$\hat{y}_i = \sum f_k(x_i)$$

The concatenation NN simply joins all modality vectors:

$$x_{\text{concat}} = [h^{(1)}; h^{(2)}; \dots; h^{(m)}]$$

These baselines are useful because they provide direct comparisons against the proposed attention-based fusion model. [2], [7], [8]

V. EXPERIMENTAL SETUP

The experimental setup should describe the data source, preprocessing pipeline, model configuration, and evaluation protocol used to test the proposed framework. For multimodal Alzheimer's classification, recent studies commonly use train/validation/test splits or stratified cross-validation and report performance with accuracy, precision, recall, F1-score, specificity, and balanced accuracy. [2], [7], [9]

A suitable dataset may be a public Alzheimer's benchmark that includes clinical and multimodal patient information. Inputs may include demographic variables, cognitive scores, neuropsychological measures, and optionally MRI, PET, EEG, or speech-derived features. Prior work suggests that combining clinical and neurological information can improve diagnosis compared with using only one type of feature. [2], [4], [6]

To validate the benefit of the proposed method, baseline models should include Random Forest, SVM, XGBoost, and a simple concatenation-based neural network. These baselines are important because they provide a clear comparison against the proposed attention-based fusion model. Recent studies show that fusion architectures can outperform simpler approaches, especially when designed to handle heterogeneous medical data properly.

The proposed model can be evaluated using accuracy, precision, recall, F1-score, specificity, and balanced accuracy. If the problem is multiclass, macro-averaged and weighted metrics should also be reported. Stratified cross-validation is recommended when class imbalance is present, since Alzheimer's datasets are often not evenly distributed across classes

VI. RESULTS AND DISCUSSION

The experimental results are expected to show that multimodal fusion improves Alzheimer's disease diagnosis compared with unimodal baselines. Recent studies on multimodal Alzheimer's classification report strong performance from fusion-based systems, with attention or weighted fusion often outperforming simple concatenation and single-modality models. [2], [7], [8]

The proposed attention-based fusion model is expected to achieve the best balance among accuracy, precision, recall, and F1-score. This is because Alzheimer's data are heterogeneous, and not every feature contributes equally to diagnosis. Attention can prioritize more useful clinical signals while reducing the influence of weaker or noisy inputs. [3], [4], [5]

Another important result to discuss is interpretability. If the model assigns higher attention weights to cognitive or neuropsychological features, that would support the clinical relevance of those inputs in early diagnosis. Such interpretability is valuable because it helps clinicians understand why the system made a given prediction, which increases trust in the model. [1], [4], [5]

The model should also be discussed in terms of robustness. In practical healthcare settings, some modalities may be unavailable, expensive, or noisy. Attention-based multimodal prediction models are useful in this scenario because they can still produce stable outputs when one modality is missing or less reliable. This makes the framework more realistic for deployment than methods that depend heavily on a single data source.

A key comparison should be made against previous multimodal Alzheimer's systems. Compared with earlier methods that rely only on MRI or only on tabular data, the proposed model is more flexible because it combines complementary evidence. Compared with simple feature concatenation, attention-based fusion is better at learning modality importance dynamically. This makes it a strong candidate for clinical decision support.

VII. CONCLUSION AND FUTURE WORK

This paper presented an attention-based multimodal fusion framework for early Alzheimer's disease detection. The proposed approach integrates heterogeneous clinical inputs and assigns adaptive weights to each modality, allowing the model to focus on the most informative features for prediction. The framework is designed to

improve diagnostic accuracy, robustness, and interpretability compared with simple single-modality or concatenation-based methods. [2], [4], [5]

The main contribution of the work is a structured diagnosis-support pipeline that can help identify Alzheimer's disease at an early stage. By combining multimodal clinical data with attention-based fusion, the system is aligned with current research trends in multimodal AI for Alzheimer's diagnosis and prognosis.

Future work will focus on incorporating additional modalities such as MRI, EEG, PET, speech, and biomarker data to improve diagnostic performance. Explainable AI methods can also be added to make the system more transparent for clinicians. In addition, future studies should evaluate the framework under missing-modality conditions, cross-site datasets, and longitudinal records to improve generalization, fairness, and progression analysis. [1], [4], [11]

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