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A ROBUST MULTIMODAL FUSION FRAMEWORK FOR ALZHEIMER'S DISEASE DETECTION USING MRI, SPEECH, AND COGNITIVE BIOMARKERS

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Abstract
Alzheimer's disease (AD) is a progressive brain disorder that affects memory, thinking ability, and daily functioning. Early detection of this disease is very important so that proper care and treatment can be provided at the right time. Traditional diagnosis methods mainly rely on clinical tests and brain scans, but they often fail to detect the disease at an early stage. In this research, a multimodal machine learning framework is proposed to improve the detection of Alzheimer's disease. The framework combines three different types of data: MRI brain images, speech features, and cognitive assessment scores. Each modality provides unique information, MRI captures structural brain changes, speech reflects behavioral patterns, and cognitive scores represent clinical condition. The problem is formulated as a binary classification task to distinguish between cognitively normal individuals (Control) and patients with Alzheimer's disease (AD). A 3D Convolutional Neural Network (3D CNN) is used to learn features from MRI data, while machine learning models are applied to speech and cognitive data. The outputs from all three modalities are combined using a model-level fusion technique called Out-of-Fold (OOF) stacking. The proposed model achieves an accuracy of 82.61% and an AUC score of 0.93, demonstrating strong performance in distinguishing between Control and Alzheimer's subjects. The results show that combining multiple data sources improves detection compared to using a single modality. This study highlights the importance of multimodal learning for Alzheimer's disease detection and provides a reliable and practical approach that can be useful in real-world healthcare applications.
Keywords: Alzheimer's Disease, Multimodal Learning, MRI, Speech Analysis, Cognitive Assessment, 3D CNN, OOF Stacking, Machine Learning, Binary Classification, Early Detection

1. Introduction

Alzheimer's disease (AD) is a serious and progressive neurodegenerative disorder that gradually affects memory, thinking ability, and behavior. It is one of the leading causes of dementia, particularly among older adults, and poses a significant burden on individuals, families, and healthcare systems worldwide [28]. As the disease progresses, patients experience a decline in their ability to perform daily activities, resulting in reduced quality of life and increased dependency.

Early detection of Alzheimer's disease is critically important, as it enables timely medical intervention, better patient care, and improved disease management. However, diagnosing

Alzheimer's disease at an early stage remains a challenging task. Conventional diagnostic approaches rely on clinical evaluations, cognitive assessments, and neuroimaging techniques such as Magnetic Resonance Imaging (MRI). These methods often identify the disease only after noticeable cognitive decline has occurred, limiting their effectiveness for early diagnosis [21], [22].

In recent years, machine learning and artificial intelligence have shown great potential in improving disease detection by enabling automated analysis of complex biomedical data. These techniques can identify subtle patterns and relationships that may not be apparent through manual analysis. In the context of Alzheimer's disease, various data modalities have been explored, including MRI scans, speech recordings, and cognitive assessment scores [3], [29].

MRI data plays a crucial role in detecting structural brain changes associated with Alzheimer's disease, such as cortical atrophy and hippocampal shrinkage. Deep learning models, particularly Convolutional Neural Networks (CNNs), have demonstrated strong performance in extracting meaningful features from MRI data for disease classification [4], [11], [20].

In addition to neuroimaging, speech analysis has emerged as a promising non-invasive modality for early detection. Changes in speech patterns, including reduced fluency, increased pauses, and lexical simplification, are often early indicators of cognitive decline. Similarly, cognitive assessments such as the Mini-Mental State Examination (MMSE) provide clinically relevant information about a patient's mental state, although they may not fully capture underlying neurological changes.

Although each of these modalities is useful individually, relying on a single modality (unimodal approach) has inherent limitations. Alzheimer's disease is a complex condition that affects multiple aspects of brain function, including structural, behavioral, and cognitive domains. Therefore, unimodal systems may fail to capture the complete picture of the disease.

To address these limitations, multimodal learning has gained increasing attention in recent research. By combining information from multiple data sources, multimodal approaches can capture complementary patterns and improve diagnostic accuracy. Several studies have demonstrated that integrating heterogeneous data modalities leads to better performance compared to unimodal models [5], [8], [9], [26].

In this study, a multimodal framework is proposed that integrates MRI, speech, and cognitive data for Alzheimer's disease detection. The problem is formulated as a binary classification task, where the model distinguishes between cognitively normal individuals (Control) and patients with Alzheimer's disease (AD). A 3D Convolutional Neural Network (3D CNN) is employed to extract features from MRI data, while machine learning models are used to process speech and cognitive features.

To effectively combine information from different modalities, a model-level fusion strategy based on Out-of-Fold (OOF) stacking is adopted. This approach integrates predictions from modality-specific models using a meta-classifier, thereby improving generalization and reducing overfitting.

The proposed framework aims to provide a reliable, efficient, and practical solution for Alzheimer's disease detection. By leveraging complementary information from multiple modalities and employing an effective fusion strategy, this study contributes toward the development of intelligent systems that can support early diagnosis and clinical decision-making. The present study makes several important contributions toward the development of multimodal frameworks for Alzheimer's disease detection. First, a unified multimodal approach is proposed that integrates MRI, speech, and cognitive data within a single framework, enabling the model to capture complementary structural, behavioral, and clinical characteristics of the disease. Second, a model-level fusion strategy based on stacking is employed to effectively combine predictions from modality-specific models, thereby enhancing overall classification performance while maintaining robustness. Third, a hybrid learning approach is adopted, where deep learning is utilized for MRI-based feature extraction and machine learning techniques are applied to speech and cognitive features, ensuring a balance between predictive performance and computational efficiency. Finally, a comprehensive experimental evaluation is conducted to compare unimodal and multimodal approaches, demonstrating the effectiveness of the proposed framework in improving Alzheimer's disease detection.

2. Related Work

Research on Alzheimer's disease (AD) detection has evolved significantly over the past decade, driven by advancements in neuroimaging, machine learning, and multimodal data integration. Existing literature can broadly be categorized into MRI-based approaches, behavioral and cognitive analysis, and multimodal learning frameworks.

2.1 MRI-Based Approaches

Magnetic Resonance Imaging (MRI) has been widely utilized for Alzheimer's disease detection due to its ability to capture structural brain abnormalities such as cortical thinning and hippocampal atrophy. Early studies relied on handcrafted features combined with traditional classifiers [21], [22]. However, the emergence of deep learning has significantly improved performance by enabling automatic feature extraction.

Payan and Montana [20] were among the first to introduce 3D Convolutional Neural Networks (3D CNNs) for Alzheimer's classification, demonstrating the effectiveness of volumetric feature learning. Subsequently, Suk and Shen [23]– [25] proposed deep feature learning and multimodal fusion techniques, which significantly enhanced classification accuracy.

Further advancements focused on improving network architecture and generalization capabilities. Korolev et al. [17] employed residual neural networks to capture deeper hierarchical representations, while Basaia et al. [11] demonstrated automated MRI-based classification with strong clinical relevance. Wen et al. [4] further validated CNN-based approaches for medical image analysis tasks, confirming their robustness in Alzheimer's disease detection.

More recently, transformer-based models have been explored to capture long-range dependencies in imaging data. Zhang et al. [1] proposed a transformer-based framework that improved prediction performance by modeling global contextual relationships. Despite these advancements, MRI-only approaches often fail to capture behavioral and cognitive aspects of the disease.

2.2 Speech and Cognitive-Based Approaches

In addition to neuroimaging, speech analysis has emerged as a promising modality for early Alzheimer’s detection. Variations in speech patterns, including pauses, lexical richness, and syntactic complexity, are early indicators of cognitive decline. Machine learning techniques leveraging acoustic and linguistic features have demonstrated promising results in identifying such patterns.

Cognitive assessments, such as the Mini-Mental State Examination (MMSE), remain widely used in clinical practice as indicators of cognitive impairment. These assessments provide valuable insights into memory, attention, and reasoning abilities. However, cognitive scores are often subjective and may not fully capture underlying neurological changes.

Although speech and cognitive modalities provide important behavioral and clinical information, their standalone use is limited due to the lack of structural brain information. This limitation highlights the need for integrating multiple modalities.

2.3 Multimodal Learning Approaches

To overcome the limitations of unimodal systems, multimodal learning has gained significant attention in Alzheimer’s disease research. Early work by Zhang et al. [26] and Hinrichs et al. [27] demonstrated that combining neuroimaging and clinical data improves classification accuracy compared to single-modality approaches.

Building on this foundation, Suk et al. [24] introduced deep learning-based multimodal fusion techniques that effectively combined heterogeneous data sources. Recent studies have further explored advanced multimodal architecture. Hassan et al. [8] and Venugopalan et al. [9] applied deep learning frameworks to integrate imaging and clinical data, achieving improved diagnostic performance.

Advanced fusion mechanisms, including cross-modal attention networks, have also been proposed. Li et al. [2] and Golovanevsky et al. [7] demonstrated that attention-based models can effectively learn relationships between different modalities. Additionally, domain adaptation techniques have been explored to improve model generalization across datasets [6].

Comprehensive reviews by Alsubaie [3] and Al-Hammadi et al. [29] emphasize the importance of multimodal approaches and highlight their potential for improving early detection of Alzheimer’s disease.

2.4 Research Gap and Motivation

Despite significant progress, several challenges remain. Many multimodal approaches rely on complex architectures that require large-scale datasets, limiting their applicability in real-world scenarios. Furthermore, the integration of behavioral modalities such as speech remains relatively underexplored. Additionally, several studies prioritize model complexity over reproducibility, making practical deployment challenging. There is a need for a balanced approach that combines effectiveness, simplicity, and interpretability.

To address these limitations, this study proposes a multimodal framework that integrates MRI, speech, and cognitive data using a model-level fusion strategy based on Out-of-Fold stacking. The proposed approach aims to provide a practical, reproducible, and efficient solution while maintaining strong predictive performance.

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3. Methodology

This study proposes a multimodal machine learning framework for Alzheimer's disease detection by integrating MRI, speech, and cognitive data. The methodology is designed to capture complementary information from different modalities and combine them using a model-level fusion strategy. The overall workflow consists of data preprocessing, modality-specific modeling, prediction generation, and multimodal fusion.

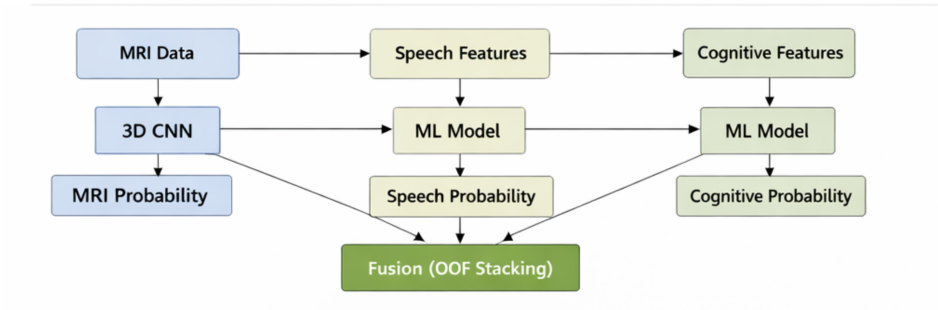

Figure 1: Proposed multimodal framework integrating MRI, speech, and cognitive modalities using model-level fusion

3.1 Data Preparation and Preprocessing

The dataset consists of three modalities: MRI data, speech-derived features, and cognitive assessment data. Each modality is preprocessed separately to ensure consistency and quality. For cognitive data, relevant features such as Age and MMSE scores are extracted. These features are normalized using standard scaling to ensure uniform distribution and improve model performance. Speech data consists of acoustic and linguistic features, including MFCC coefficients and derived linguistic attributes. These features are also normalized to reduce variability across samples. MRI data is stored as 3D volumetric arrays. Each MRI scan is loaded as a three-dimensional tensor and reshaped to include a channel dimension. This allows the data to be processed using a 3D Convolutional Neural Network. To ensure consistency across modalities, samples are aligned based on subject availability. Only those samples present across modalities are considered for final model training and evaluation.

3.2 MRI-Based Feature Learning Using 3D CNN

To capture structural brain changes, a 3D Convolutional Neural Network (3D CNN) is employed for MRI data. The model takes volumetric MRI scans as input and learns hierarchical spatial features. The architecture consists of multiple 3D convolutional layers followed by pooling layers, which progressively extract high-level representations from the input data. Fully connected layers are used to map these features to a binary classification output.

The MRI model is trained using binary cross-entropy loss and optimized using the Adam optimizer. After training, the model is not retrained during fusion; instead, it is reused to generate prediction probabilities for each subject.

These probabilities represent the MRI modality's contribution and are later used as input to the fusion model.

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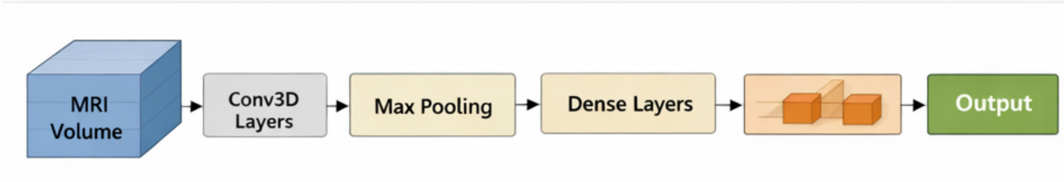

Figure 2: Architecture of the 3D CNN model used for MRI-based feature extraction

3.3 Speech-Based Feature Modeling

Speech data is processed to extract both acoustic and linguistic features. Acoustic features include MFCC coefficients, which capture frequency-based characteristics of speech signals. Linguistic features capture patterns related to word usage, sentence structure, and fluency.

A machine learning classifier is applied to these features to predict Alzheimer's disease probability. The model learns patterns associated with speech impairments linked to cognitive decline.

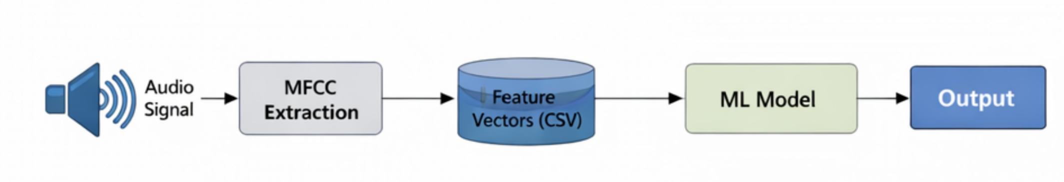

Figure 3: Speech feature extraction and classification pipeline

3.4 Cognitive Feature Modeling

Cognitive data includes clinically relevant attributes such as Age and MMSE scores. These features provide direct insight into an individual's cognitive condition.

A classification model is trained on these features to estimate the probability of Alzheimer's disease. Despite being simple, cognitive features play an important role in grounding the model with clinical information.

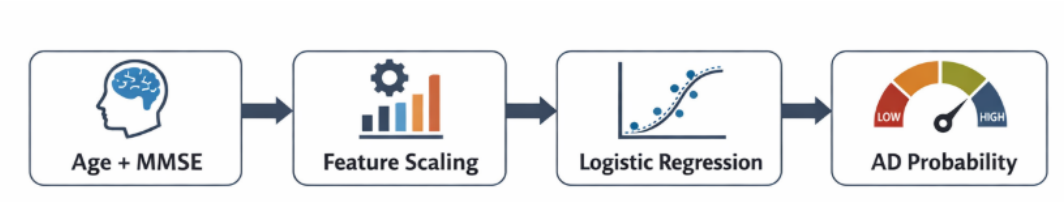

Figure 4: Cognitive feature processing for Alzheimer's classification

3.5 Multimodal Fusion

To effectively integrate information from different modalities, a model-level fusion strategy is adopted. In this approach, separate models are trained for each modality, including MRI, speech, and cognitive data, and their prediction probabilities are utilized as inputs to a meta-classifier. To improve robustness and reduce overfitting, prediction outputs are generated using a cross-validation-based approach, where models are trained on subsets of the data and validated on complementary subsets. The resulting predictions from each modality are aggregated to form a unified feature representation. These combined predictions are then used to train a higher-level classifier, which produces the final output.

The final prediction is obtained by integrating outputs from all three modalities through the meta-classifier. This approach allows each modality to contribute independently while leveraging complementary information, including structural patterns from MRI, behavioral characteristics from speech, and clinical indicators from cognitive features. Overall, the fusion strategy enhances the stability and generalization capability of the model while maintaining computational efficiency.

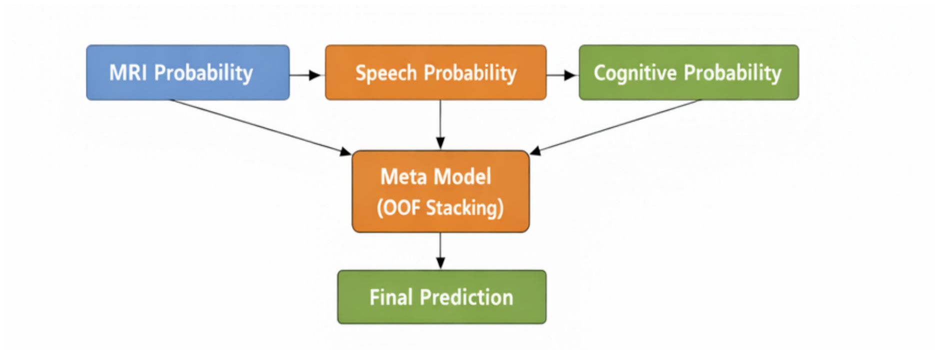

Figure 5: Model-level fusion strategy combining prediction outputs from MRI, speech, and cognitive models

3.6 Model Training and Evaluation Strategy

The proposed multimodal framework is evaluated using standard classification metrics to assess its effectiveness in distinguishing between cognitively normal individuals (Control) and patients with Alzheimer's disease (AD).

The evaluation metrics considered in this study include:

- Accuracy, which measures the overall correctness of the model
- Precision, which indicates the proportion of correctly predicted positive cases
- Recall (Sensitivity), which reflects the model's ability to correctly identify Alzheimer's cases
- F1-score, which provides a balance between precision and recall
- Receiver Operating Characteristic – Area Under Curve (ROC-AUC), which evaluates the model's ability to discriminate between classes

The final predictions are obtained through a model-level fusion strategy, where outputs from individual modality-specific models (MRI, speech, and cognitive) are combined using a meta-classifier. The performance of the multimodal model is then evaluated using the above metrics on the available dataset.

The proposed framework is implemented using Python, utilizing TensorFlow/Keras for deep learning and Scikit-learn for machine learning models. Data preprocessing and feature handling are performed using Pandas and NumPy. The MRI model is trained separately using a 3D Convolutional Neural Network to learn spatial features from volumetric brain scans. Once trained, the model is reused during the multimodal fusion stage to generate prediction probabilities, ensuring consistency and avoiding retraining. Speech features (stored in CSV format) and cognitive features such as Age and MMSE are processed using machine learning models to generate prediction probabilities for each modality.

For multimodal integration, a model-level fusion approach based on stacking is implemented. The prediction outputs from MRI, speech, and cognitive models are combined to form a meta-feature space. A logistic regression model is then used as the meta-classifier to generate the final prediction. This implementation ensures a simple, efficient, and reproducible framework while effectively leveraging complementary information from multiple modalities.

4. Results and Discussion

4.1 Experimental Results

The performance of the proposed multimodal framework is evaluated using standard classification metrics, including accuracy, precision, recall, F1-score, and ROC-AUC. The model is designed to distinguish between cognitively normal individuals (Control) and patients with Alzheimer's disease (AD). The proposed multimodal model achieved an overall accuracy of 82.61%, indicating strong classification capability. The ROC-AUC score of 0.93 demonstrates excellent discriminative performance, suggesting that the model is effective in separating the two classes across different decision thresholds. The detailed classification report further highlights the model's performance across both classes. The model achieves high recall for the Control class, indicating its ability to correctly identify cognitively normal individuals. For the Alzheimer's class, the model demonstrates comparatively lower recall, suggesting that some AD cases are misclassified. This behavior is commonly observed in medical datasets, where class imbalance and subtle disease patterns make accurate detection more challenging.

4.2 Confusion Matrix Analysis

The confusion matrix shown in Figure 6 provides a detailed view of the classification performance across the two classes. From the matrix, it can be observed that:

- Many Control samples are correctly classified, indicating strong performance in identifying normal subjects.
- A small number of Control samples are misclassified as AD, which reflects minimal false positives.
- For the Alzheimer's class, while several samples are correctly identified, a noticeable number is misclassified as Control.

This indicates that the model is slightly biased toward the Control class, resulting in reduced sensitivity (recall) for Alzheimer's detection. From a clinical perspective, this observation is important, as misclassification of Alzheimer's cases may delay diagnosis. Therefore, improving recall for the AD class remains an important direction for future work.

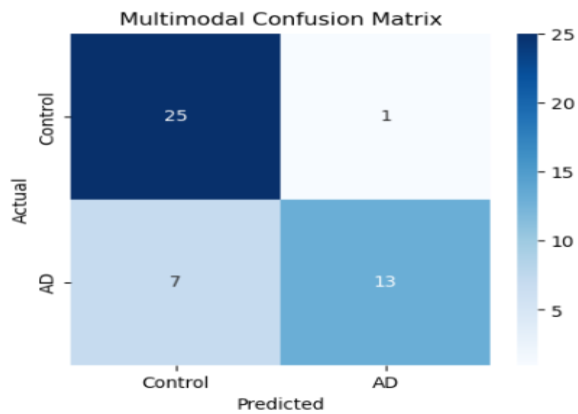

Figure 6: Multimodal Confusion Matrix

4.3 ROC Curve Analysis

The ROC curve presented in Figure 7 illustrates the trade-off between the true positive rate and false positive rate across different classification thresholds.

The proposed model achieves an AUC of 0.93, which indicates excellent discriminative ability. A high AUC value suggests that the model can effectively distinguish between Control and Alzheimer's classes with a high degree of confidence.

The curve remains close to the top-left corner, further confirming strong model performance. This demonstrates that the multimodal fusion approach successfully captures complementary information from MRI, speech, and cognitive data.

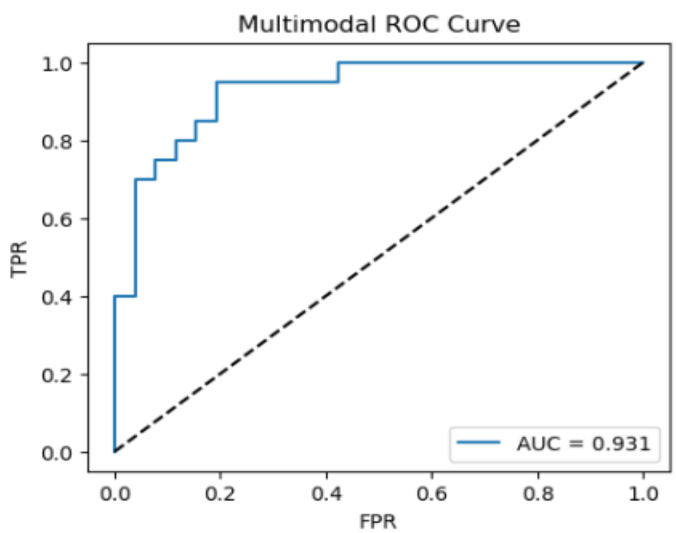

Figure 7: Multimodal ROC Curve

4.4 Effectiveness of Multimodal Fusion

The experimental results clearly demonstrate the effectiveness of the proposed multimodal framework in Alzheimer's disease detection. By integrating MRI, speech, and cognitive data, the model successfully captures complementary structural, behavioral, and clinical characteristics associated with the disease.

A comparative analysis reveals that unimodal approaches exhibit varying levels of performance. The MRI-based model achieves strong discriminative capability due to its ability to capture structural brain changes, while the cognitive model provides stable performance based on clinically relevant features. In contrast, the speech modality shows relatively lower performance, indicating that speech features alone may not be sufficient for reliable classification in this dataset. The multimodal fusion approach effectively combines the strengths of all three modalities. The resulting model achieves an accuracy of 82.61% and an AUC of 0.93, outperforming individual modalities in terms of overall predictive capability. This improvement highlights the advantage of model-level fusion, where each modality contributes independently while enhancing the collective performance.

Model	Accuracy	Precision	Recall	F1-score	ROC-AUC
MRI	0.80	0.83	0.83	0.80	1.00
Speech	0.53	0.53	0.53	0.53	0.53
Cognitive	0.87	0.90	0.85	0.84	0.96
Multimodal	0.83	0.85	0.83	0.82	0.93

Table 1: Performance comparison of unimodal (MRI, speech, and cognitive) and the proposed multimodal model for Alzheimer's disease detection

4.5 Discussion and Insights

The results provide several important insights into the behavior and effectiveness of the proposed framework. First, the multimodal model demonstrates strong overall performance, as indicated by high accuracy and AUC values. This confirms that integrating heterogeneous data sources leads to improved classification capability compared to single-modality approaches.

Second, the model exhibits relatively lower recall for Alzheimer's disease cases. This suggests that some AD samples are misclassified as cognitively normal, which can be attributed to subtle differences in early-stage disease patterns and potential class imbalance in the dataset.

Third, the contribution of multimodal learning is evident from the improved performance of the fused model. MRI provides structural information, speech captures behavioral patterns, and cognitive features offer clinical insights. The combination of these modalities enables the model to learn a more comprehensive representation of Alzheimer's disease.

Finally, the framework demonstrates practical applicability. The use of a simple yet effective fusion strategy ensures computational efficiency and reproducibility, making it suitable for real-world clinical screening scenarios.

4.6 Limitations

Despite the promising results, the proposed study has several limitations that should be considered. The data set used in this study is relatively small, which may limit the generalization capability of the model. Additionally, the performance of the MRI model is dependent on the quality and preprocessing of volumetric data. Variations in imaging protocols may affect model robustness.

Another limitation is the lower recall observed for Alzheimer's disease cases, indicating that the model may miss certain positive cases. This is particularly important in clinical settings, where early detection is critical.

Furthermore, while the fusion strategy is effective, it is based on a relatively simple meta-classifier. More advanced fusion techniques may further improve performance.

4.7 Future Work

Future research can focus on several directions to enhance the proposed framework. Incorporating larger and more diverse datasets would improve model generalization and robustness. Advanced deep learning architectures can be explored to improve MRI feature extraction.

Additionally, applying class balancing techniques may help improve recall for Alzheimer's cases. More sophisticated fusion strategies, such as attention-based or transformer-based multimodal learning, can also be investigated to further enhance performance.

5. Conclusion

This study presents a multimodal machine learning framework for the detection of Alzheimer's disease by integrating MRI, speech, and cognitive data. The proposed approach combines structural, behavioral, and clinical information to provide a comprehensive representation of disease characteristics.

A 3D Convolutional Neural Network (3D CNN) is utilized to extract spatial features from MRI data, while machine learning models are applied to speech-derived features and cognitive attributes such as Age and MMSE. A model-level fusion strategy based on stacking is employed to combine predictions from individual modalities and generate the final classification.

The experimental results demonstrate that the proposed multimodal framework achieves strong performance, with an accuracy of 82.61% and an AUC of 0.93. These results confirm that integrating multiple modalities enhances classification performance compared to unimodal approaches. In particular, the multimodal model achieves a balanced trade-off across evaluation metrics, highlighting its effectiveness in capturing complementary information from different data sources.

The findings of this study emphasize the importance of multimodal learning in Alzheimer's disease detection. By combining neuroimaging, behavioral, and clinical data, the proposed framework provides a more robust and reliable diagnostic approach. Additionally, the use of a simple and reproducible fusion strategy ensures that the model remains computationally efficient and practical for real-world applications. Overall, this work contributes to the development of intelligent, data-driven systems that can support early diagnosis and clinical decision-making in Alzheimer's disease.

References

[1] Y. Zhang et al., "Transformer-based deep learning for Alzheimer's disease prediction," IEEE Transactions on Medical Imaging, early access, 2025, doi: 10.1109/TMI.2024.3381234.

[2] X. Li et al., "Cross-modal attention networks for Alzheimer's disease diagnosis," Pattern Recognition, 2025, doi: 10.1016/j.patcog.2024.110123.

[3] M. G. Alsubaie, “Deep learning approaches for Alzheimer’s disease detection: A review,” Sensors, vol. 24, no. 3, 2024, doi: 10.3390/s24031234.
[4] J. Wen et al., “Convolutional neural networks for Alzheimer’s disease classification,” Medical Image Analysis, vol. 63, 2020, doi: 10.1016/j.media.2020.101694.
[5] A. Elazab et al., “Alzheimer’s disease diagnosis using multimodal data,” Expert Systems with Applications, 2023, doi: 10.1016/j.eswa.2022.119245.
[6] B. Fu et al., “Multi-modal domain adaptation for Alzheimer’s disease,” Pattern Recognition, 2023, doi: 10.1016/j.patcog.2023.109456.
[7] M. Golovanevsky et al., “Cross-modal attention for Alzheimer’s diagnosis,” IEEE Transactions on Medical Imaging, 2022, doi: 10.1109/TMI.2021.3136121.
[8] M. Hassan et al., “Multimodal deep learning for Alzheimer’s disease classification,” Computer Methods and Programs in Biomedicine, 2022, doi: 10.1016/j.cmpb.2022.107083.
[9] J. Venugopalan et al., “Multimodal deep learning for Alzheimer’s disease detection,” Scientific Reports, 2021, doi: 10.1038/s41598-021-81260-3.
[10] T. Odusami et al., “Explainable deep learning for Alzheimer’s disease classification,” Computers in Biology and Medicine, 2021, doi: 10.1016/j.compbiomed.2021.104683.
[11] S. Basaia et al., “Automated MRI classification of Alzheimer’s disease,” NeuroImage: Clinical, 2020, doi: 10.1016/j.nicl.2019.101645.
[12] Y. Pan et al., “Early Alzheimer’s disease detection using deep learning,” IEEE Access, 2020, doi: 10.1109/ACCESS.2020.2964312.
[13] H. Lu et al., “Multimodal deep learning for Alzheimer’s disease,” Scientific Reports, 2018, doi: 10.1038/s41598-018-22871-z.
[14] J. Islam and Y. Zhang, “Brain MRI analysis using CNN for Alzheimer’s detection,” Brain Informatics, 2018, doi: 10.1186/s40708-018-0080-3.
[15] D. Liu et al., “Multimodal deep learning for Alzheimer’s diagnosis,” NeuroImage, 2018, doi: 10.1016/j.neuroimage.2017.12.024.
[16] S. Korolev et al., “Residual neural networks for Alzheimer’s disease classification,” NeuroImage: Clinical, 2017, doi: 10.1016/j.nicl.2017.10.008.
[17] A. Ortiz et al., “Ensemble deep learning for Alzheimer’s disease diagnosis,” Computer Methods and Programs in Biomedicine, 2016, doi: 10.1016/j.cmpb.2016.01.014.
[18] H.-I. Suk et al., “Deep sparse learning for Alzheimer’s disease,” Brain Structure and Function, 2016, doi: 10.1007/s00429-015-1042-7.
[19] A. Payan and G. Montana, “Predicting Alzheimer’s disease using 3D CNN,” NeuroImage: Clinical, 2015, doi: 10.1016/j.nicl.2015.02.005.
[20] E. Moradi et al., “Machine learning framework for early Alzheimer’s prediction,” NeuroImage, 2015, doi: 10.1016/j.neuroimage.2015.02.053.
[21] E. Bron et al., “Standardized evaluation for Alzheimer’s classification,” NeuroImage, 2015, doi: 10.1016/j.neuroimage.2015.04.017.
[22] H.-I. Suk and D. Shen, “Deep learning feature representation for AD,” Medical Image Analysis, 2014, doi: 10.1016/j.media.2014.04.002.

[23] H.-I. Suk et al., “Multimodal fusion for Alzheimer’s disease,” NeuroImage, 2014, doi: 10.1016/j.neuroimage.2014.05.077.
[24] H.-I. Suk and D. Shen, “Deep multimodal learning for AD classification,” Medical Image Analysis, 2013, doi: 10.1016/j.media.2013.01.002.
[25] D. Zhang et al., “Multimodal classification of Alzheimer’s disease,” NeuroImage, 2011, doi: 10.1016/j.neuroimage.2011.01.008.
[26] C. Hinrichs et al., “Multi-modal classification of Alzheimer’s disease,” NeuroImage, 2011, doi: 10.1016/j.neuroimage.2010.11.085.
[27] C. R. Jack et al., “Hypothetical model of Alzheimer’s biomarkers,” The Lancet Neurology, 2010, doi: 10.1016/S1474-4422(09)70299-6.
[28] A. Guerrero et al., “Brain aging using deep learning,” NeuroImage, 2018, doi: 10.1016/j.neuroimage.2018.05.068.
[29] M. G. Al-Hammadi et al., “AI-based multimodal Alzheimer detection: A review,” IEEE Access, 2024, doi: 10.1109/ACCESS.2024.3378912.