2025 International Conference on Computational Innovations and Engineering Sustainability (ICCIES) | 979-8-3315-3669-5/25/$31.00 ©2025 IEEE | DOI: 10.1109/ICCIES63851.2025.11032751

# Neuroimaging empowered Multimodal Alzheimer's Disease Diagnostic model to enhance early detection and diagnostic for personalize treatment strategies

K. S. Sastry Musti,
*Namibia University of Science and Technology,*
Nambia, Africa
mks.sastry@gmail.com

K Sarada,
*Dept. Of EEE,*
*Koneru Lakshmaiah Education Foundation,*
Vaddeswaram. India,
saradak@kluniversity.in

Ankush Dadarao Sawarkar,
*Department of Information Technology,*
*Shri Guru Gobind Singhji Institute of Engineering and Technology (SGGSIE&T),*
Nanded, Maharashtra, 431606, India.
adsawarkar@sggs.ac.in

Vignesh A
*Research Scholar, Department of ECE,*
*Sri Eshwar College of Engineering,*
Coimbatore – 641202, Tamil Nadu, India.
vignesh.a.engg@gmail.com

Atul Thakare,
*MIT Arts Design & Technology University,*
Pune, India.
atul.thakare@mituniversity.edu.in

J Baskaran
*Professor, Department of EEE,*
*PSG Institute of Technology and Applied Research*
Coimbatore, India
baski11@gmail.com

***Abstract*—The neurodegenerative condition Alzheimer's disease (AD) has phenotypic alterations linked to genetic variations and imaging pathology. AD costs about $250 billion annually and affects 5.8 million Americans. Biomarker genomics, based on brain imaging, has been created to better the AD pathogenesis and early diagnosis. Therefore, effective ways to find AD biomarkers for early diagnosis and medication are needed. Conventional diagnostic methods, focused on post-mortem findings and clinical symptoms, struggle to understand genetic, molecular, and neuroanatomical interactions. This non-invasive, high-throughput technique addresses these issues by combining genomic data with multimodal imaging phenotypes. The proposed framework introduces Multimodal Alzheimer's Disease Diagnostic model (MADM) which integrates Neuroimaging, cognitive assessments, and genetic data to enhance early detection, improve diagnostic accuracy, and personalize treatment strategies. The MADM system analyzes multimodal data, finds illness biomarkers, and predicts progression using powerful AI and ML. This paradigm's thorough and systematic Alzheimer's disease diagnosis includes cognitive test scores, MRI, PET, and genetic indicators including APOE and SNP genotyping. Consolidating data sets is key to precision medicine. This enables targeted therapy and better patient outcomes. Multimodal dementia ratings outperformed MRI and PET scan dementia ratings in predicting MADM progression in healthy control participants, according to ADNI data. In contrast to relying just on genetic data, a combination of neuroimaging, cognitive test scores, and genetic markers was found to be a more effective way to detect patients with stable moderate cognitive impairment. Classification accuracy in the remaining stratified groups was enhanced by combining multimodal data.**

***Keywords—Alzheimer's Disease, Integrating Neuroimaging, Cognitive Assessments, Genetic Data, Multimodal Alzheimer's Disease Diagnostic model.***

## I. Introduction

Many people worldwide suffer from dementia-related Alzheimer's disease (AD). Diseases like Alzheimer's are a form of dementia. Successful intervention requires early detection and detailed diagnosis. Since there is no treatment for the disorder, biomarkers that might detect at-risk persons before symptoms appear are of great interest. We collected and analyzed data from several modalities to identify biomarkers that can accurately diagnose early illness. Take MRI as an example. It is the gold standard for detecting dementia-related brain structural abnormalities. Another way to anticipate illness risk before pathological changes occur is to utilize genetic information. The APOE allele and other genetic risk factors cause twenty to twenty-five percent of cases. Possible connections between single-nucleotide polymorphisms (SNPs) have been uncovered in genome-wide association studies. GWAS showed that most of the twenty genes linked to AD had moderate to mild impact sizes, despite suggesting stronger associations.

Genetic data and Magnetic Resonance Imaging (MRI) offer unique properties that can enhance AD prediction algorithms. MRI scans provide tissue-level details and may indicate phenotypic brain abnormalities in early AD. In contrast, genetic data encodes genotype information of likely Alzheimer's disease progression even without brain changes. Combining genetic and phenotypic data may improve predictions. This may show patterns that are not obvious when using the two modalities independently. These methods rely on prior data, which may diminish the likelihood of uncovering new genetic risk factors. Due to the previous reliance on clinical examinations, neuroimaging, and cognitive testing, Alzheimer's disease is usually diagnosed later. In the early stages of AD, neuroimaging, genetic data, and mental evaluations can increase diagnostic accuracy and timeliness. This study advises developing and implementing a new paradigm that uses many data modalities to diagnose AD. Machine learning and artificial intelligence combine genetic biomarkers, neuroimaging data, and cognitive performance indicators into a prediction model to improve AD detection. Combining complementary information from both modalities improves diagnostic performance.

The proposed MADM uses neuroimaging, cognitive testing, and genetic information to improve Alzheimer's disease diagnosis and early detection. Unlike earlier diagnosis methods using clinical symptoms or biomarkers, MADM uses advanced machine learning (ML) algorithms to analyze multimodal data, unlike traditional clinical signs alone. This integration makes it possible to distinguish between stable Moderate Cognitive Impairment (MCI) and high-risk AD. Cognitive ratings derived from genetic data are a novel way to detect illness earlier than MRI and PET tests. Multiple

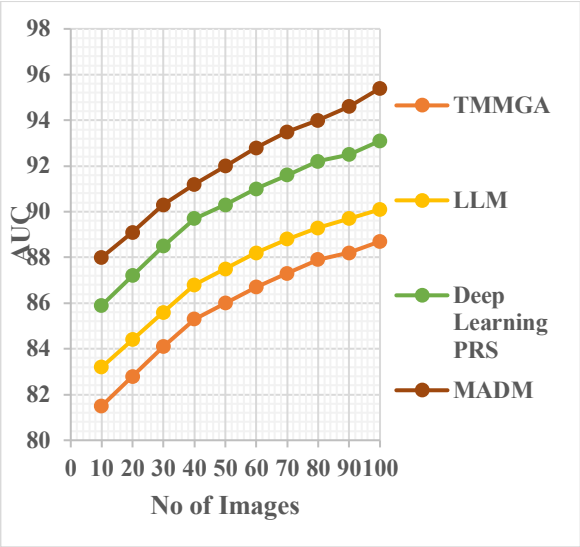


Fig 5. AUC (%) performance

## V. Conclusion

The suggested multimodal paradigm blends neuroimaging, cognitive testing, and genetic data to improve AD diagnosis. This framework outperformed unimodal techniques. MADM criteria effectively assess sample-wise modal in formativeness, enabling dynamic fusion across modalities. Experimental results indicated that the MADM works in AD categorization tasks. As shown, the biomarkers are linked to Alzheimer's disease. The model surpasses competitors with 92.5% accuracy, 91.3% F1-score, and 94.7% AUC after 100 iterations. The hybrid fusion strategy captures illness progression and biomarkers using CNNs for neuroimaging, LSTMs for cognitive data, and dense layers for genetic markers. However, this technique has several drawbacks. It requires plenty of computational power. Large, annotated datasets are another demand. Finally, dataset imbalances may cause biases. Future study should boost computing efficiency, use explainable AI methods for interpretability, and diversify the dataset's demographic samples to increase model generalization. Adding real-time clinical data and lightweight models for early detection can improve the framework's medical diagnostics application.

## References

[1] D. Nguyen, H. Nguyen, H. Ong, H. Le, H. Ha, N. T. Duc, and H. T. Ngo, "Ensemble learning using traditional machine learning and deep neural network for diagnosis of Alzheimer's disease," *IBRO Neuroscience Reports*, vol. 13, pp. 255–263, 2022.

[2] X. Sheng, H. Cai, Y. Nie, S. He, Y. M. Cheung, and J. Chen, "Modality-aware discriminative fusion network for integrated analysis of brain imaging genomics," *IEEE Transactions on Neural Networks and Learning Systems*, 2024.

[3] A. Gamal, M. Elattar, and S. Selim, "Deep Feature Fusion Framework for Alzheimer's Disease Staging Using Neuroimaging Modalities," in *Meets Africa Workshop*, Cham: Springer Nature Switzerland, Oct. 2024, pp. 277–288.

[4] G. Castellano, A. Esposito, E. Lella, G. Montanaro, and G. Vessio, "Automated detection of Alzheimer's disease: a multi-modal approach with 3D MRI and amyloid PET," *Scientific Reports*, vol. 14, no. 1, p. 5210, 2024.

[5] M. Odusami, R. Damaševičius, E. Milieškaitė-Belousovienė, and R. Maskeliūnas, "Alzheimer's disease stage recognition from MRI and PET imaging data using Pareto-optimal quantum dynamic optimization," *Heliyon*, vol. 10, no. 15, 2024.

[6] K. M. Niyas and P. Thiyagarajan, "Improving Dementia Prediction Using Ensemble Majority Voting Classifier," *Annals of Data Science*, pp. 1–21, 2024.

[7] D. Pan, A. Zeng, L. Jia, Y. Huang, T. Frizzell, and X. Song, "Early Detection of Alzheimer's Disease Using Magnetic Resonance Imaging: A Novel Approach Combining Convolutional Neural Networks and Ensemble Learning," unpublished.

[8] J. Lyu, X. Chen, S. A. AlQahtani, and M. S. Hossain, "Multi-modality MRI fusion with patch complementary pre-training for internet of medical things-based smart healthcare," *Information Fusion*, vol. 107, p. 102342, 2024.

[9] Y. Zhang, K. Sun, Y. Liu, F. Xie, Q. Guo, and D. Shen, "A Modality-Flexible Framework for Alzheimer's Disease Diagnosis Following Clinical Routine," *IEEE Journal of Biomedical and Health Informatics*, 2024.

[10] M. G. Kwak *et al.*, "A Cross-Modal Mutual Knowledge Distillation Framework for Alzheimer's Disease Diagnosis: Addressing Incomplete Modalities," *medRxiv*, preprint, 2024.

[11] G. Dolci *et al.*, "An interpretable generative multimodal neuroimaging-genomics framework for decoding Alzheimer's disease," *ArXiv preprint*, arXiv:2406, 2024.

[12] S. Cong *et al.*, "Trustworthy enhanced multi-view multi-modal Alzheimer's disease prediction with brain-wide imaging transcriptomics data," in *2024 IEEE International Conference on Bioinformatics and Biomedicine (BIBM)*, Dec. 2024, pp. 1898–1904.

[13] Y. Feng, X. Xu, Y. Zhuang, and M. Zhang, "Large language models improve Alzheimer's disease diagnosis using multi-modality data," in *2023 IEEE International Conference on Medical Artificial Intelligence (MedAI)*, Nov. 2023, pp. 61–66.

[14] W. Ko, W. Jung, E. Jeon, and H. I. Suk, "A deep generative–discriminative learning for multimodal representation in imaging genetics," *IEEE Transactions on Medical Imaging*, vol. 41, no. 9, pp. 2348–2359, 2022.

[15] J. Bae, A. B. Sanjay, K. Nho, A. J. Saykin, V. Penchev, and L. G. Apostolova, "Chromosome 19 polygenic risk scores defined by deep learning model predict the rate of Alzheimer's disease progression," *Alzheimer's & Dementia*, vol. 19, p. e068204, 2023.

[16] "ADNI Dataset," *Papers with Code*. [Online]. Available: https://paperswithcode.com/dataset/adni. [Accessed: Mar. 22, 2025].