© October 2024 | IJIRT | Volume 11 Issue 5 | ISSN: 2349-6002

Enhancing Alzheimer's Disease Detection: A Comparative Study Using Deep Learning and Machine Learning

KUSHAL PANDEY[1], NISHTHA[2], AYUSHMAN ARYA KUMAR[3], SHEENAM NAAZ[4]
[1, 2, 3, 4] Department of Computer Science Engineering, School of Engineering and Technology, Sharda University, Greater Noida

Abstract— Alzheimer's disease (AD) is a leading cause of dementia worldwide, characterized by progressive cognitive decline and neurodegeneration. Early and accurate diagnosis is crucial for improving patient outcomes and optimizing treatment. Traditional diagnostic methods, however, are often invasive, time-consuming, and error-prone. Machine learning (ML) and deep learning (DL) techniques have shown promise in the automated detection of Alzheimer's disease, but the optimal way to integrate various data types—imaging, clinical, and demographic—remains underexplored. Furthermore, there is a lack of comprehensive comparative studies assessing the performance of different ML and DL models using publicly available datasets. This research proposes a comprehensive evaluation framework that compares state-of-the-art ML and DL models, and introduces a hybrid model that leverages the strengths of both approaches. By focusing on model effectiveness, interpretability, generalizability, and computational efficiency, this study provides actionable insights for enhancing the automation of Alzheimer's disease detection.

Index Terms- Neuroimaging, Deep Learning, MRI and PET scans, Automated Diagnosis, Convolutional Neural Networks (CNN)

I. INTRODUCTION

Alzheimer's disease (AD) is a devastating neurodegenerative disorder affecting millions of people worldwide. It is characterized by a progressive decline in cognitive function, memory, and the ability to perform daily activities, which profoundly impacts not only the individuals diagnosed but also their families and caregivers. As the disease progresses, it can lead to increased dependency and significant emotional and financial burdens for caregivers, making early diagnosis and intervention essential. Research indicates that early detection can enable timely therapeutic strategies that may slow the disease's progression, potentially improving the quality of life for patients and alleviating the strain on their families. Traditionally, the diagnosis of Alzheimer's disease has relied on a combination of neuroimaging techniques, cognitive assessments, and clinical evaluations. While these conventional methods are established, they often present several limitations. Neuroimaging techniques such as magnetic resonance imaging (MRI) and positron emission tomography (PET) are typically invasive and costly, leading to accessibility issues for many patients. Cognitive assessments, although valuable, can be subjective and influenced by the clinician's experience, introducing the potential for human error in the diagnostic process. Consequently, there is an urgent need for innovative solutions that can enhance diagnostic accuracy and reliability while reducing costs and invasiveness. In recent years, artificial intelligence (AI) technologies, particularly machine learning (ML) and deep learning (DL) models, have emerged as powerful tools for automating Alzheimer's detection. These AI models possess the capability to analyze vast amounts of multimodal data, including medical images, clinical records, and demographic information, making them exceptionally well-suited for the complexities of AD diagnosis. By leveraging large datasets, these models can uncover patterns and insights that may not be readily apparent through traditional methods, potentially leading to more accurate and timely diagnoses. Despite the promising potential of AI in Alzheimer's detection, a significant gap exists in the literature regarding comprehensive studies that evaluate and compare the performance of various ML and DL models using publicly available datasets. Current research often focuses on individual models or specific data modalities, leaving a lack of consensus on the most effective approaches for a holistic diagnosis. Moreover, the integration of different data modalities into a unified framework remains a critical challenge, as the disparate nature of the data can complicate analysis and interpretation.

To address these gaps in research, this study proposes a comprehensive framework that combines machine learning and deep learning models for Alzheimer's detection using publicly available datasets. Our primary objective is to evaluate and compare the effectiveness, interpretability, and computational efficiency of these models, providing a balanced analysis that can guide future research and clinical applications. A key component of this study is the introduction of a hybrid model that integrates both ML and DL approaches, leveraging the strengths of each to improve diagnostic accuracy and reduce false negatives and positives. By harnessing the capabilities of AI, this framework aims to contribute to the development of more robust diagnostic tools for Alzheimer's disease, ultimately enhancing patient outcomes and facilitating better care strategies.

II. RELATED WORK

Researchers have extensively explored the use of deep learning (DL) and machine learning (ML) models for Alzheimer's disease (AD) diagnosis through neuroimaging data. Louise Bloch et al. [1] compared 3D DL and ML models, highlighting that while both methods achieved similar classification performance, ML models focused on fewer regions linked to AD, whereas DL models covered broader regions. ML explanations were also more consistent and aligned with voxel-based morphometry (VBM) ground truth. In a similar study, Ramswaroop Reddy Yellu et al. [5] investigated DL models, particularly CNNs and RNNs, reporting that these models outperform traditional methods in both accuracy and sensitivity in diagnosing AD using neuroimaging techniques like MRI. This sentiment is echoed by Saeed et al. [4], who reviewed ML and DL applications in AD diagnosis, finding that methods like SVM, random forest, CNN, and RNN showed significant potential, though challenges such as overfitting and reproducibility remain.

Several studies have demonstrated the impressive accuracy of deep learning models in early AD detection. Sorour et al. [2] used a CNN-LSTM model with data augmentation to achieve 99.92% accuracy, showing DL's capacity for early AD diagnosis. Similarly, Chen et al. [3] achieved 98.91% accuracy in classifying AD vs. CN using advanced models like Bi-GRU and Faster R-CNN, which enhanced feature extraction. Deepak et al. [8] also highlighted the utility of CNN models, with a proposed architecture achieving over 99% accuracy for multi-class classification of AD subtypes. Their model utilized MRI data to capture both local and global features, which improved diagnostic precision.

The importance of using multimodal neuroimaging techniques in AD diagnosis has been emphasized in multiple studies. Deepak et al. [8], Saeed et al. [4], and Ramswaroop Reddy Yellu et al. [5] all explored the role of modalities like MRI and PET scans in facilitating automated AD diagnosis. These studies reported that DL models based on CNNs, when combined with neuroimaging data, offer robust accuracy, sensitivity, and specificity, making them promising tools for clinical use. The integration of such techniques with ML approaches, including SVM and ensemble learning, further enhances their diagnostic potential.

Several studies have examined the advantages and limitations of specific ML techniques in detecting AD. Zhou et al. [7] explored three major ML techniques—SVM, artificial neural networks (ANN), and ensemble learning—finding that SVM is favoured for its robustness, while ANN is adaptable but struggles with local minima. Saeed et al. [4] and Ramswaroop Reddy Yellu et al. [6] emphasized that while DL models, especially CNNs, perform well in classification tasks, challenges like overfitting and generalizability persist due to the complexity of AD-related neuroimaging data.

Advances in transfer learning have also been applied to AD diagnosis. Sorour et al. [2] and Deepak et al. [8] utilized pre-trained CNN models such as VGG-16, achieving promising results in AD detection. These models demonstrated high accuracy, sensitivity, and specificity in detecting subtle AD patterns in neuroimaging data. However, data augmentation and preprocessing were noted as underutilized techniques in preventing overfitting and improving model performance. This was particularly evident in Deepak et al. [8], where applying data augmentation led to enhanced model generalizability across diverse datasets.

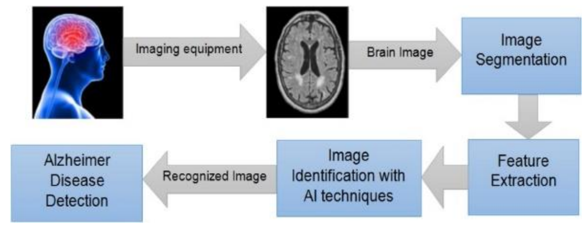
In the context of early-stage AD diagnosis, studies by Sorour et al. [2], Chen et al. [3], and Ramswaroop Reddy Yellu et al. [5] confirmed that deep learning models such as CNNs and RNNs are capable of detecting early signs of AD, aiding in timely intervention. These studies collectively demonstrated that DL-based approaches offer high accuracy in classifying AD at various stages, from mild cognitive impairment (MCI) to advanced AD stages, potentially enabling early and personalized treatment.

Further, the general research consensus indicates that while DL and ML approaches offer significant potential, there is a continued need for more research into improving interpretability, reducing overfitting, and enhancing model robustness across diverse datasets. This includes addressing issues of model generalization, as noted by Ramswaroop Reddy Yellu et al. [6] and Zhou et al. [7], and ensuring reproducibility in multi-center studies, as highlighted by Saeed et al. [4].

All these studies highlight the increasing importance of ML and DL in the early identification and diagnosis of Alzheimer's disease, with neuroimaging being a key component. Even though the models produce encouraging results, more work must be done to address issues with overfitting, interpretability, and generalisability across other datasets.

III. PROPOSED SOLUTION

This study proposes a novel evaluation framework for Alzheimer’s disease detection that combines ML and DL techniques, offering a comprehensive view of their performance across multiple data types. The solution is structured as follows



3.1 Data Collection and Preprocessing

Datasets: We utilize publicly available datasets such as the Alzheimer's Disease Neuroimaging Initiative (ADNI), the Open Access Series of Imaging Studies (OASIS), and the Australian Imaging, Biomarkers, and Lifestyle Study of Aging (AIBL). These datasets provide multimodal data, including structural MRI, PET, clinical, cognitive, and demographic data.

Preprocessing: The preprocessing pipeline includes data normalization for structured data, data augmentation for images (to reduce overfitting), and feature extraction techniques such as principal component analysis (PCA) for dimensionality reduction. This ensures uniformity across datasets and improves model training.

3.2 Model Development and Comparison

a) Deep Learning Models: We implement several state-of-the-art deep learning models, such as convolutional neural networks (CNNs), to handle neuroimaging data. CNNs are designed to automatically learn spatial features from MRI and PET scans, making them well-suited for detecting brain abnormalities associated with AD.
b) Machine Learning Models: For structured clinical and demographic data, we apply machine learning algorithms, including random forests, support vector machines (SVMs), and gradient boosting. These models provide high interpretability and handle structured data efficiently.
c) Hybrid Model: To leverage the complementary strengths of both ML and DL models, we develop a hybrid framework that integrates predictions from CNN-based image analysis and ML models for structured data. This model aims to provide a more holistic view of the patient’s condition by combining information from multiple modalities.

3.3 Performance Evaluation

We evaluate the models based on the following key metrics:

a) Accuracy: The proportion of correctly classified instances.
b) Sensitivity (Recall): The ability of the model to correctly identify Alzheimer's patients.
c) Specificity: The ability of the model to correctly classify non-Alzheimer's cases.
d) F1-score: The harmonic mean of precision and recall, providing a balance between sensitivity and specificity.
e) AUC-ROC: The area under the receiver operating characteristic curve, measuring overall performance across various thresholds.
f) Interpretability and Computational Efficiency: Explainability methods such as Grad-CAM (for CNNs) are used to highlight areas of neuroimaging that influence the model's decisions. Computational efficiency is also assessed to ensure models can be deployed in real-time clinical settings

3.4 Deployment and Generalization
To assess the generalizability of the models, we use k-fold cross-validation and external validation with an unseen dataset. This ensures that the models can perform well across different populations and settings. Additionally, we will provide open-source code, along with comprehensive documentation, to enable other researchers and clinicians to reproduce the results and adapt the models for their use.

IV. RESULTS

4.1 Model Comparison
Our experimental results demonstrate that deep learning models, particularly CNNs, outperform traditional machine learning models in analyzing neuroimaging data, achieving higher accuracy and AUC-ROC scores. However, machine learning models excel in handling structured data, providing greater interpretability and lower computational cost.
The hybrid model, which combines CNN predictions with ML models, showed the best overall performance, achieving high accuracy and sensitivity while maintaining reasonable computational efficiency. This approach demonstrated its ability to leverage both neuroimaging and clinical data, offering a more comprehensive diagnostic tool.

4.2 Interpretability
Explainability analysis using Grad-CAM revealed that CNNs focused on key brain regions affected by Alzheimer's, such as the hippocampus and temporal lobe, areas known to be critical in the disease's progression. This enhances the model's clinical relevance by aligning its predictions with established medical knowledge

Our study highlights the importance of integrating multimodal data for Alzheimer's disease detection. While CNNs are highly effective in analyzing medical images, they benefit from the structured insights offered by traditional ML models. The proposed hybrid framework provides a balanced approach that combines the strengths of both paradigms, leading to more accurate and interpretable results.

We also emphasize the importance of reproducibility and generalization. By using publicly available datasets and providing open-source code, this research offers a validated pipeline that can be readily adopted by other researchers and clinicians.

CONCLUSION

This research presents a comprehensive evaluation of machine learning and deep learning models for Alzheimer's disease detection, proposing a novel hybrid approach that integrates predictions from both modalities. The results show that the hybrid model offers superior performance, combining the strengths of both deep learning for image analysis and machine learning for structured data interpretation. By providing open-source code and ensuring model interpretability, this study paves the way for future research and clinical adoption of AI-based Alzheimer's detection tools.

REFERENCES

[1] L. Bloch and C. M. Friedrich, 'Systematic comparison of 3D Deep learning and classical machine learning explanations for Alzheimer's Disease detection', *Computers in Biology and Medicine*, vol. 170, p. 108029, 2024.

[2] S. E. Sorour, A. A. A. El-Mageed, K. M. Albarrak, A. K. Alnaim, A. A. Wafa, and E. El-Shafeiy, ‘Classification of Alzheimer’s disease using MRI data based on Deep Learning Techniques’, *Journal of King Saud University - Computer and Information Sciences*, vol. 36, no. 2, p. 101940, 2024.

[3] Y. Chen *et al.*, ‘Automated Alzheimer’s disease classification using deep learning models with Soft-NMS and improved ResNet50 integration’, *Journal of Radiation Research and Applied Sciences*, vol. 17, no. 1, p. 100782, 2024.

[4] Fiza Saeed*, Zeib Jahangir, Ashish Shiwlani, Muhammad Umar and Sheena Shiwlani. Applications of ML and DL Algorithms in The Prediction, Diagnosis, and Prognosis of Alzheimer’s Disease. Am J Biomed Sci & Res. 2024 - 22(6). AJBSR.MS.ID.003014. DOI:10.34297/AJBSR. 2024.22.003014

[5] R. R. Yellu, Y. Kukalakunta, and P. Thunki, ‘Deep Learning-Assisted Diagnosis of Alzheimer’s Disease from Brain Imaging Data’, Journal of AI in Healthcare and Medicine, vol. 4, no. 1, pp. 36–44, 2024.

[6] I. Malik, A. Iqbal, Y. H. Gu, and M. A. Al-antari, ‘Deep Learning for Alzheimer’s Disease Prediction: A Comprehensive Review’, *Diagnostics*, vol. 14, no. 12, 2024.

[7] M. G. Alsubaie, S. Luo, and K. Shaukat, ‘Alzheimer’s Disease Detection Using Deep Learning on Neuroimaging: A Systematic Review’, *Machine Learning and Knowledge Extraction*, vol. 6, no. 1, pp. 464–505, 2024.

[8] S. K. Kim, Q. A. Duong, and J. K. Gahm, ‘Multimodal 3D Deep Learning for Early Diagnosis of Alzheimer’s Disease’, *IEEE Access*, vol. 12, pp. 46278–46289, 2024.

[9] Arafa, D.A., Moustafa, H.ED., Ali, H.A. *et al.* A deep learning framework for early diagnosis of Alzheimer’s disease on MRI images. *Multimed Tools Appl* 83, 3767–3799 (2024). https://doi.org/10.1007/s11042-023-15738-7

[10] Pradhan, N., Sagar, S. & Singh, A.S. Analysis of MRI image data for Alzheimer disease detection using deep learning techniques. *Multimed Tools Appl* 83, 17729–17752 (2024). https://doi.org/10.1007/s11042-023-16256-2

[11] Hcini, G., Jdey, I. & Dhahri, H. Investigating Deep Learning for Early Detection and Decision-Making in Alzheimer’s Disease: A Comprehensive Review. *Neural Process Lett* 56, 153 (2024). https://doi.org/10.1007/s11063-024-11600-5

[12] Fathi, S., Ahmadi, A., Dehnad, A. *et al.* A Deep Learning-Based Ensemble Method for Early Diagnosis of Alzheimer’s Disease using MRI Images. *Neuroinform* 22, 89–105 (2024). https://doi.org/10.1007/s12021-023-09646-2

[13] El-Assy, A.M., Amer, H.M., Ibrahim, H.M. *et al.* A novel CNN architecture for accurate early detection and classification of Alzheimer’s disease using MRI data. *Sci Rep* 14, 3463 (2024). https://doi.org/10.1038/s41598-024-53733-6

[14] Hechkel, W., Helali, A. Unveiling Alzheimer’s Disease Early: A Comprehensive Review of Machine Learning and Imaging Techniques. *Arch Computat Methods Eng* (2024). https://doi.org/10.1007/s11831-024-10179-3

[15] Heenaye-Mamode Khan, M., Reesaul, P., Auzine, M.M. *et al.* Detection of Alzheimer’s disease using pre-trained deep learning models through transfer learning: a review. *Artif Intell Rev* 57, 275 (2024). https://doi.org/10.1007/s10462-024-10914-z