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Research Article

Advanced MRI-Based Alzheimer's Disease Classification with Hybrid Convolutional Neural Networks

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Abstract: The key to effective therapy and management of Alzheimer's disease (AD), a progressive neurological condition, is obtaining a prompt and precise diagnosis. Support Vector Machines (SVMs), Random Forest (RFs), and Gradient Boosting Machines (GBMs) are some of the most used traditional machine learning algorithms for Alzheimer's disease (AD) classification, but they struggle to deal with the complexity of medical imaging data. On the other hand, Convolutional Neural Networks (CNNs) are great at image classification and have shown impressive results in analyzing MRI scans for AD detection. Plus, combining CNNs with traditional machine learning techniques can enhance both accuracy and reliability. This study explores hybrid methodologies that integrate Convolutional Neural Networks (CNNs) with conventional machine learning techniques, such as the combination of CNN with Support Vector Machines (SVM), CNN with Gradient Boosting Machines (GBM), and CNN with Random Forest (RF).The study achieved notable classification performance, with the CNN-SVM model reaching an accuracy of 97% and the CNN-RF model achieving 83%. These results indicate that blending deep learning with conventional machine learning methods can enhance the ability of Alzheimer's disease (AD) diagnosis, promoting more reliable early detection and supporting the creation of effective intervention strategies

Keywords: Alzheimer's Disease, Random Forest (RF), Convolutional Neural Networks (CNNs), Magnetic Resonance Imaging (MRI), Support Vector Machines (SVM).

1.Introduction

An important and growing global health concern, Alzheimer's disease (AD) is characterised by memory loss and a progressive reduction in cognitive function. As the leading cause of dementia, AD impacts millions of people worldwide, with its prevalence growing as the population ages. Timely detection and precise classification are essential for effective treatment and management [1-4]. However, conventional diagnostic approaches, which largely rely on clinical evaluations and cognitive testing, often fall short in detecting the disease at its early stages.

The diagnosis of Alzheimer's disease (AD) could be greatly improved by recent developments in medical imaging, particularly Magnetic Resonance Imaging (MRI). Hippocampal shrinkage and cortical thinning are two minor alterations associated with AD disease that can be detected by clinicians with the use of MRI, which offers deep insights into brain anatomy. However, radiologists' manual MRI scan analysis is frequently subjective, time-consuming, and may not accurately detect early illness symptoms [5-7].

Recently, Convolutional Neural Networks (CNN) have become well-known as extremely powerful image processing tools, significantly influencing fields such as computer vision and medical imaging. CNNs are very good at automatically learn complex patterns from unprocessed picture data, doing away with the requirement for specialised subject knowledge or manually created features [8-11]. CNNs have shown remarkable results in tasks like object detection, picture segmentation, and classification by utilising deep learning techniques and massive datasets.

Using CNNs, this study aims to identify and detect Alzheimer's disease (AD) early from magnetic resonance imaging (MRI) scans. We want to create a reliable approach that can automatically identify structural alterations linked to AD pathology by training CNN models on an extensive dataset of MRI images from both Alzheimer patients and healthy people [12-16]. To further enhance diagnostic precision, we also investigate hybrid methods that integrate CNNs with normal machine learning models like SVM, GBM, and Random Forest (RF). Our results indicate that these combined approaches significantly boost classification accuracy.

Our primary objective in doing this research is to develop a trustworthy decision-support tool that can aid in the early detection and categorization of Alzheimer's disease (AD). This tool will allow for more prompt interventions and better patient outcomes [17-21]. Through comprehensive evaluation and validation, we strive to advance the application of CNN-based methods for AD detection as wwll as classification, effectively bridging advanced machine learning techniques with realworld healthcare practices. By integrating deep learning with traditional methods, this study contributes to ongoing efforts to lessen the significant impact of AD on individuals and society.

2.Related Works

Neuroimaging data, especially MRI scans, have been the subject of numerous investigations on potential approaches for the detection and classification of Alzheimer's disease (AD). More accurate diagnoses and earlier AD detection have been the goals of these research efforts, which have made use of both traditional machine learning and cutting-edge deep learning methods.

In order to identify neurodegenerative diseases using magnetic resonance imaging (MRI) scans, Selvaganesh and Ganesan (2022) suggested a method that combines segmentation with classification. Their method combined region-based and edge-based segmentation techniques followed by classification using machine learning models. Similarly, S¸ener et al. (2024) investigated the classification of different AD stages using deep learning, evaluating various CNN architectures through statistical validation methods [22]. Their study emphasized the importance of stage-specific classification for personalized treatment strategies.

Automatic diagnosis and categorization of Alzheimer's disease (AD) was proposed by Bhadrashetty and Kulkarni (2023) using a convolutional neural network (CNN). With remarkable sensitivity and accuracy, their algorithm was able to extract unique features from MRI scans. Similarly, Y et al. (2021) developed an automated classification system using a CNN built on the AlexNet architecture, showcasing the effectiveness of deep learning in feature extraction for accurate AD classification [23-25].

In addition, researchers have investigated the use of functional MRI (fMRI) data for Alzheimer's disease (AD) diagnosis. To differentiate early cases of Mild Cognitive Impairment (MCI) from healthy controls, Zamani et al. (2022) used evolutionary optimization of graph metrics obtained from resting-state functional magnetic resonance imaging (fMRI). Performing a comprehensive analysis, Zhao et al. (2023) contrasted and discussed the benefits and drawbacks of deep learning and conventional machine learning approaches to Alzheimer's disease diagnosis. Their study highlighted the capability of deep learning models to improve diagnostic accuracy.

Researchers have also focused on creating lightweight and efficient deep learning models for practical clinical use. Abd El-Latif et al. designed a highly effective deep learning model for detecting Alzheimer's disease (AD) through MRI scans, demonstrating its practicality for real-world clinical applications [26-27]. Likewise, Altwijri et al. (2023) proposed a sophisticated deep learning architecture for automated AD diagnosis, demonstrating strong accuracy and reliability. Basavaraj et al. (2023) concentrated on early dementia detection by utilizing deep learning and image processing techniques to detect subtle brain structural changes associated with neurodegeneration.

Following on from these results, this study explores the possibility of combining Convolutional Neural Networks (CNNs) with more conventional machine learning techniques for the purpose of early AD detection using MRI data [28]. These techniques include Random Forest, Convolutional Neural Networks (CNNs), and Support Vector Machines (SVMs). When compared to conventional models, CNNs outperform them in terms of classification accuracy when it comes to distinguishing between AD patients and healthy individuals.

All of these findings show that people are starting to pay more attention to using machine learning algorithms to diagnose Alzheimer's disease (AD). While some researchers emphasize creating innovative deep learning architectures, others concentrate on combining multiple data modalities or refining existing algorithms to boost diagnostic accuracy. Building on these advancements, our research explores hybrid approaches to enhance early detection and classification precision, ultimately supporting better clinical decision-making and intervention strategies for AD.

3.Proposed Method

3.1 Data set

This study's dataset, which comprises MRI scans that were categorized into four groups, was received from the Kaggle website: www.kaggle.com/code/yashborude/alzheimerclassification-2-cnn-svm-hybrid/notebook. Decline from Mild to Moderate to Very Mild to Non-Demented. As illustrated in Figures 1, 2, 3, and 4, respectively. The dataset includes MRI scans categorized into two groups: individuals diagnosed with Alzheimer's disease (AD) and healthy subjects.

The dataset employed in this research shown in fig 1 consists of MRI images organized into four separate categories based on the Seriousness of Alzheimer's disease:

- Mild Demented – This category encompasses individuals showing initial signs of cognitive decline, including mild memory impairment and challenges with complex tasks. Although they can largely maintain independence, MRI scans might uncover minor structural alterations in the brain.

- Moderate Demented – Patients in this group experience more noticeable cognitive impairment, including difficulty with language, problem-solving, and daily activities. MRI scans reveal significant structural brain changes, like hippocampal shrinkage along with cortical thinning.

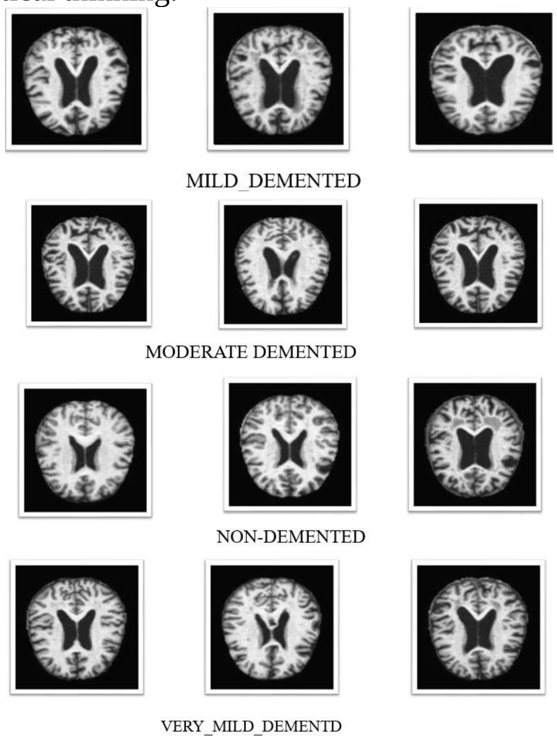

Figure 1: Dataset

- Non-Demented – This category represents healthy individuals without any signs of cognitive impairment. Their MRI scans serve as a control group, helping in differentiating normal brain structures from those affected by Alzheimer’s disease.
- Very Mild Demented – This phase is marked by mild yet noticeable cognitive decline, commonly known as Mild Cognitive Impairment (MCI). It signifies a transitional phase between regular aging and severe dementia, with subtle changes in MRI images suggesting the onset of neurodegeneration.

Classifications help with Alzheimer's disease progression analysis and machine learning model construction for stage recognition, which in turn promotes early detection and rapid intervention.

Clinicians and biomarker researchers have confirmed the diagnoses of patients with mild cognitive impairment (MCI), early-stage Alzheimer's disease (AD), and advanced AD, who comprise the AD group. People of similar ages who have never suffered from any kind of neurological disorder or cognitive impairment make up the control group.

To maintain consistency and enhance model performance, the MRI images were preprocessed through resolution standardization, intensity normalization, and non-brain tissue removal. Then, the processed dataset was split into training and test sets at random to make training and evaluating Convolutional Neural Network (CNN) models easier.

3.2 Algorithms:

Feature Extraction using CNN

Automatic extraction of critical structural and spatial characteristics linked to Alzheimer's disease (AD) is achieved by training a Convolutional Neural Network (CNN) model on MRI images. The convolutional layers detect key patterns, such hippocampus shrinkage and brain thinning, which are significant signs of Alzheimer's disease. To improve classification performance, the extracted feature maps are fed into conventional machine learning classifiers rather than a fully connected layer.

Classification combining CNN with SVM: Convolutional Neural Networks (CNNs) and Support Vector Machines (SVMs) together have shown to be very successful for early AD identification in MRI images. This hybrid approach can detect small brain changes associated with Alzheimer's disease (AD) pathology by combining deep feature extraction from MRI data with convolutional neural networks (CNNs). These extracted features, which reveal complex patterns in brain structures, are then fed into an SVM classifier, which enhances the classification process. The SVM identifies an optimal hyperplane to differentiate between classes. By combining the powerful feature extraction of CNNs with the strong classification performance of SVMs, this model achieves an impressive 97% accuracy, significantly surpassing traditional CNN-only models. This fusion of techniques improves the model's capability to detect early-stage AD, making it highly suitable for clinical applications where precision and early intervention are critical.

Classification using CNN with RF: The CNN-Random Forest (RF) model enhances AD classification by combining the feature extraction capabilities of CNNs with the collective learning power of RF. In this method shown in fig 2, CNNs analyze MRI images to extract deep features, capturing complex patterns and structural changes linked to AD pathology. These extracted features are then passed to an RF classifier, which comprises multiple decision trees trained on different data subsets.

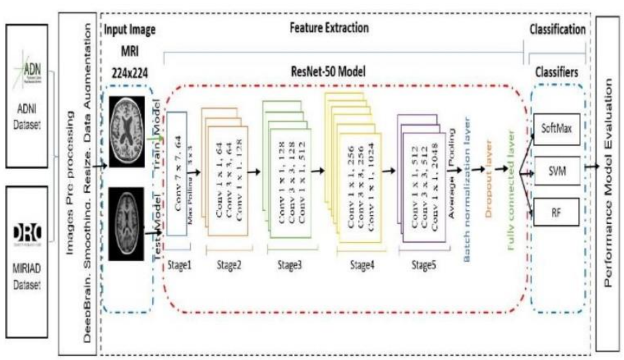

Figure 2: Using CNN Methods, MRI-Based Brain Analysis for the Diagnosis of Alzheimer's Disease.

Random Forest improves classification by aggregating predictions from individual decision trees, effectively reducing variance and preventing overfitting, which improves resilience to noise in medical imaging datasets. By combining CNNs' spatial learning benefits with RF's effective decision-making capabilities, this combination technique enhances the model's generalizability. Experimental findings reveal that the CNN-RF model attains 83% accuracy, showcasing its capability in differentiating various AD stages. While RF offers stability and interpretability, it may not always outperform gradient-based methods in optimizing classification boundaries.

Classification using CNN with GB: Combining the deep feature extraction capabilities of Convolutional Neural Networks (CNNs) with the boosting capacity of Gradient Boosting Machines (GBMs) helps enhance Alzheimer's disease (AD) categorization. The CNN automatically recognizes crucial patterns from MRI images using this strategy, such as hippocampal atrophy and cortical thinning, important indicators of AD progression. The extracted features are then fed into a GBM classifier, an ensemble learning approach that constructs multiple weak learners (decision trees) in a sequential manner, gradually improving the model's predictive accuracy.

GBM operates by progressively reducing errors, with each successive tree rectifying the inaccuracies of its predecessors. This methodology augments the model's capacity to identify intricate relationships within the data, thereby enhancing classification performance. By leveraging both CNN's feature extraction strengths and GBM's iterative optimization, this hybrid model achieves an accuracy of 85%, outperforming standalone classifiers. The ability of GBM to refine predictions through boosting makes it particularly effective in distinguishing between different AD stages with higher precision.

4.Experiments

For this research, we employed a magnetic resonance imaging dataset encompassing four classifications: Light, moderate, non-demented, and extremely mild are the four phases of Alzheimer's disease. To ensure a balanced assessment of the model's performance, the dataset was divided into two parts: a training set with 70% of the data and a test set with 30%. A variety of preprocessing methods were used to improve the input data quality. These included image standardization for consistent resolution, intensity normalization to improve contrast, and noise reduction methods such as skull stripping to remove non-brain tissues.

To implement the model, we trained and evaluated various approaches to achieve effective Alzheimer's disease (AD) classification. At first, we used a CNN, which automatically sorts MRI scans into various phases of Alzheimer's disease by extracting key information. To further increase classification accuracy, we integrated the CNN with traditional machine learning models. The CNN-SVM hybrid model leverages CNN-extracted deep features and classifies them using SVM, which optimally separates different AD stages with hyperplane-based decision boundaries. Similarly, the CNNRF model uses deep features as input to a Random Forest classifier, utilizing an ensemble of decision trees for robust classification. Additionally, the CNN-GBM model refines predictions by iteratively improving weak classifiers to achieve higher accuracy.

5.Results

Hybrid models combining CNN with traditional machine learning classifiers enhance Alzheimer's disease classification accuracy. The CNN-SVM model utilizes deep features extracted by CNN and classifies them using SVM's hyperplane-based approach, achieving 97% accuracy. The CNN-RF model leverages CNN-extracted features and classifies them using multiple decision trees in RF, reaching 83% accuracy. Meanwhile, the CNN-GBM model refines deep features through iterative boosting, achieving 85% accuracy. These hybrid approaches demonstrate the potential of integrating deep learning with machine learning to improve early AD detection and classification. Table 1 showing performance comparison.

Table 1: Performance Comparison

Algorithm	Accuracy (%)
CNN + SVM	97
CNN+Random Forest	83
CNN+ GBM	63

6. Conclusion

Combining the robust classification capabilities of conventional machine learning models with the feature extraction power of deep learning, the hybrid approach to MRI-based Alzheimer's disease detection has proven to be a highly effective strategy. The hybrid model improves diagnostic accuracy by combining CNN with classifiers like RF, SVM, and GBM. This enables earlier and more precise AD detection. This approach leverages deep feature learning while refining classification boundaries, resulting in improved performance compared to standalone models. Furthermore, the adaptability of hybrid models makes them suitable for various medical imaging applications, offering a scalable and efficient solution for complex neurodegenerative disease diagnosis. These findings highlight the potential of hybrid methodologies in advancing AI-driven healthcare solutions, Laying the foundation for more precise and dependable diagnostic tools.

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References

[1] S. Alqahtani, A. Alqahtani, M. A. Zohdy, A. A., Alsulami and S. Ganesan, “Severity Grading and Early Detection of Alzheimer's Disease through Transfer Learning,” *Information*, vol.14, no.12, pp. 646, 2023.

[2] F. Ambily and I.A. Pandian, “Early detection of Alzheimer's disease using local binary pattern and convolutional neural network,” *Multimedia Tools and Applications*, vol.80, no.19, pp. 29585-29600, 2021.

[3] D.A. Arafa, H.E. Moustafa, A. Ali-Eldin, and H.A. Ali, “Early detection of Alzheimer's disease based on the state-of-the-art deep learning approach: a comprehensive survey,” *Multimedia Tools and Applications*, vol.81, no.17, pp. 23735-23776, 2022.

[4] S.S. Verma, A.D.P. Arya, T. Chakrabarti, A.A. Elngar, A. Kamali and M. Nami, "A systematic review on machine learning and deep learning techniques in the effective diagnosis of Alzheimer's disease," *Brain Informatics*, vol.10, no.1, pp. 17, 2023.
[5] S.S. Bamber and T. Vishvakarma, "Medical image classification for Alzheimer's using a deep learning approach," *Journal of Engineering and Applied Science*, vol.70, no.1, pp. 54, 2023.
[6] A. El-Assy, H.M. Amer, H.M. Ibrahim and M.A. Mohamed, "A novel CNN architecture for accurate early detection and classification of Alzheimer's disease using MRI data," *Scientific Reports (Nature Publisher Group)*, vol.14, no.1, pp. 3463, 2024.
[7] S. Fouladi, A.A. Safaei, N.I. Arshad, M.J. Ebadi and A. Ahmadian, "The use of artificial neural networks to diagnose Alzheimer's disease from brain images," *Multimedia Tools and Applications*, vol.81, no.26, pp. 37681-37721, 2022.
[8] A. Francis and I. Alex Pandian, "Ensemble learning approach for multi-class classification of Alzheimer's stages using magnetic resonance imaging," *Telkomnika*, vol.21, no.2, pp. 374-381, 2023.
[9] F. Hajamohideen, N. Shaffi, M. Mahmud, K. Subramanian, A. Al Sariri et al., "Four-way classification of Alzheimer's disease using deep Siamese convolutional neural network with triplet-loss function," *Brain Informatics*, vol.10, no.1, pp. 5, 2023.
[10] R. Ibrahim, R. Ghnemat and Qasem Abu Al-Haija, "Improving Alzheimer's Disease and Brain Tumor Detection Using Deep Learning with Particle Swarm Optimization," *AI*, vol.4, no.3, pp. 551, 2023.
[11] A. Irshad, H.S. Muhammad, F.A. Sultan and A.A. Ziyad, "Improving Alzheimer's Disease Classification in Brain MRI Images Using a Neural Network Model Enhanced with PCA and SWLDA," *Healthcare*, vol.11, no.18, pp.2551, 2023.
[12] W.N. Ismail, P.P. Fathimathul Rajeena and M.A.S. Ali, "MULTforAD: Multimodal MRI Neuroimaging for Alzheimer's Disease Detection Based on a 3D Convolution Model," *Electronics*, vol.11, no.23, pp. 3893, 2022.
[13] M. Odusami, R. Maskeliunas and R. Damaseviˇ Cius, "Pixel-Level Fusion Approachˇ with Vision Transformer for Early Detection of Alzheimer's Disease," *Electronics*, vol.12, no.5, pp. 1218, 2023.
[14] V. Patil, M. Madgi and A. Kiran, "Early prediction of Alzheimer's disease using convolutional neural network: a review," *The Egyptian Journal of Neurology, Psychiatry, and Neurosurgery*, vol.58, no.1, 2022.
[15] B. Selvaganesh and R. Ganesan, "A hybrid segmentation and classification techniques for detecting the neurodegenerative disorder from brain Magnetic Resonance Images," *Multimedia Tools and Applications*, vol.81, no.20, pp. 28801-28822, 2022.
[16] A. Bhadrashetty and S. Kulkarni, "Detection and Classification of Alzheimer's Disease by Employing CNN," *International Journal of Intelligent Systems and Applications*, vol.15, no.2, pp. 14, 2023.
[17] N.F. Y, I. Wijayanto, N.K.C. Pratiwi, F.F. Taliningsih, S. Rizal and M.A. Pramudito, "Automated Classification of Alzheimer's Disease Based on MRI Image Processing using

Convolutional Neural Network (CNN) with AlexNet Architecture," *Journal of Physics: Conference Series*, vol.1844, no.1, 2021.

[18] J. Zamani, A. Sadr and Amir-Homayoun Javadi, "Classification of early-MCI patients from healthy controls using evolutionary optimization of graph measures of resting-state fMRI, for the Alzheimer's disease neuroimaging initiative," PLoS One, vol.17, no.6, 2022.

[19] Z. Zhao, J.H. Chuah, K.W. Lai, C. Chow, M. Gochoo et al., "Conventional machine learning and deep learning in Alzheimer's disease diagnosis using neuroimaging: A review," *Frontiers in Computational Neuroscience*, 2023.

[20] A.A. Abd El-Latif, S.A. Chelloug, M. Alabdulhafith, and M. Hammad, "Accurate Detection of Alzheimer's Disease Using Lightweight Deep Learning Model on MRI Data," *Diagnostics*, vol.13, no.7, pp. 1216, 2023.

[21] O. Altwijri, R. Alanazi, A. Aleid, K. Alhussaini, Z. Aloqalaa, M. Almijalli, and A. Saad, "Novel DeepLearning Approach for Automatic Diagnosis of Alzheimer's Disease from MRI," *Applied Sciences*, vol.13, no.24, pp. 13051, 2023.

[22] M.P. Basavaraj, M.R. Raigonda, S. Anakal, and A. Bhadrashetty, "Early Detection of Dementia using Deep Learning and Image Processing," *International Journal of Engineering and Manufacturing*, vol.13, no.1, pp. 14, 2023.

[23] V.S. Gaikwad, S. Deore, G.M. Poddar, R.V. Patil, D.S. Hirolikar et al., "Unveiling Market Dynamics through Machine Learning: Strategic Insights and Analysis," *International Journal of Intelligent Systems and Applications in Engineering*, vol.12, no.14s, pp.388–397, 2024.

[24] S.K. Swarnkar and T.A. Tran, "A Survey on Enhancement and Restoration of Underwater Image," *Underwater Vehicle Control and Communication Systems Based on Machine Learning Techniques*, pp. 1–15, 2023.

[25] Suman Kumar Swarnkar, "Improved Convolutional Neural Network based Sign Language Recognition," *International Journal of Advanced Science and Technology*, 2019.

[26] S. Agarwal, J.P. Patra, and S.K. Swarnkar, "Convolutional Neural Network Architecture Based Automatic Face Mask Detection," *International Journal of Health Sciences*, no. SPECIAL ISSUE III, pp. 623-629, 2022.

[27] S.K. Swarnkar, G.S. Chhabra, A. Guru, B. Janghel, P.K. Tamrakar and U. Sinha, "Underwater Image Enhancement Using D-Cnn," *NeuroQuantology*, vol.20, no.11, pp. 2157–2163, 2022.

[28] S.K. Swarnkar, A. Guru, G.S. Chhabra, P.K. Tamrakar, B. Janghel, and U. Sinha, "Deep learning techniques for medical image segmentation classification," *International Journal of Health Sciences*, vol.6, no.S10, pp. 408–421, 2022.