REVIEW ARTICLE

Artificial Intelligence-based Medical Image Fusion Analysis for Early Detection of Alzheimer's disease

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Abstract

This research work investigated a selection of fundamental research projects that helped develop the development of medical image fusion in the initial course of study that we intended for the adaptive pulse-coupled neural network. As time progresses, Alzheimer's disease (AD) detection affected individuals can feel the severity of the condition by finding it increasingly difficult to recall recent events, and they also find it hard to engage in logical reasoning or recognize familiar faces. The introduction and innovation in the field of advanced neuroimaging technologies have contributed to an excellent level of support for such tools in AD diagnosis. By deploying these approaches, investigators are able to understand better the complicated structural and functional relationships within the nervous system and identify the clinical alterations that mark AD. The results of these investigations not only provide an anchor for the proposed technique, but they show information on the evolution of methods regarding this area of study.

Key words: Accuracy, Alzheimer's disease, Alzheimer's disease detection, machine learning, medical image fusion

INTRODUCTION

The growing loss of brain function is commonly referred to as Alzheimer's disease (AD), and the disease has been named despite its investigator, Dr. Alois Alzheimer, who reported the first diagnosis of mental disorders in 1906. This neurodegenerative disease begins with specific mild symptoms that gradually get more severe over time. This condition severely impacts the patients' day-to-day lives and their ability to connect with others. The initial signs of this disease are often subtle, which include memory lapses, difficulty with language, and changes in behavior like impulsiveness or unpredictability. In AD, the development of deposits of amyloid and the formation of tau tangles in the brain problems with the normal flow of messages across the convoluted system of brain cells. This disruption hampers the flow of information across different brain regions and between the brain and the body, which leads to a deterioration in cognitive and physical functions.

Behavior changes related to AD

Identifying these symptoms early is crucial for managing AD, as it can help in planning for the future and potentially slowing the progression of the disease through medication and lifestyle adjustments. The following Table 1 contrasts behavior changes associated with AD and typical ageing, highlighting key differences to help distinguish between the two. Recently, DL techniques have emerged as prevailing tools to focus the tests on treating high-dimensional neuroimaging data. Automated learning using data input, feature extraction (FE) from data, and overfitting prevention via normalization and loss are all features of such models.

BACKGROUND RESEARCH STUDIES

Applying the YUV stands for (Y) luma or brightness, (U) blue, and (V) red projection. Color system and wavelet transform an algorithm for integrating magnetic resonance

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Received: 20-05-2025
Revised: 26-08-2025
Accepted: 06-09-2025

Table 1: Behavior changes related to AD

Behavior change	Alzheimer's disease	Typical aging
Memory loss	People who recently discovered a fresh skill might lose it, seek the same data multiple times, and require assistance with memory or relatives to help them remember activities they employed to do independently without assistance.	Regularly misses identities or schedules but recollects subsequently.
Problems with planning and solving	People might require more time to finish everyday tasks because they have difficulty executing strategies, interacting with numbers, or executing dishes they are experienced with.	Some of you may correct economic and home errors.
Trouble Getting usual tasks done	Problem with performing everyday activities such as driving to a recognized location, maintaining a business's financing, or memorizing rules for a game.	Occasionally, people might reach out for guidance when understanding how to record a television program or change the controls on a microwave for the 1st time.
Time and location uncertainty	It is not typical for individuals to get confused and remember who they are or how they are working, as well as to have difficulty relating to actions that are occurring in a far-off future.	Failures miss out on the due date but do so immediately in the final section.
Challenges with imagining and recognising geographic relationships	Problems with studying, distance reasoning, color vision, or contrast vision may contribute to cognitive problems.	The development of cataracts and age-associated macular degeneration are two reasons for alterations in eyesight.
Emerging challenges with the application of words in speech	A few individuals have problems following into discussions, interrupting in the center of a phrase, and contradicting them.	Progresses, talking at an even pace, but occasionally has difficulty choosing the proper phrase.
The loss of the power to identify objects and repeat actions	Persons can charge others for taking against these individuals whenever they store objects in unusual places, then forget them and are unable to locate these people.	Sometimes drops objects but generally can be found by following their route in reverse.
Limited decision-making size	Taking less concern for themselves or becoming readily deceived by fraudulent individuals are instances of how life events can alter a person's judgment and decision-making processes.	Mistakes at times, like remembering to change the engine fuel.
No interest in work or social tasks	People might steer clear of interests, social events, jobs, and activities such as sports, or fail to maintain pace with a loved team or interest.	Frequently feels tired from family, job, and societal responsibilities, but does not hide.
Emotion and attitude changes	Ambiguity, scepticism, depressive symptoms, dread, and worry may leave them unhappy in their homes, with others, or when they're out of their usual surroundings.	Sets schedules and feels angry when violated.

AD: Alzheimer's disease

imaging (MRI) and positron emission tomography (PET) images.[1] The Dmey wavelet at fragment level 3 was found to be the most successful. The findings from the accuracy of their testing were motivating, particularly regarding the identification of brain tumors and AD. Leveraging the YUV color space and CNN for weight mapping, Wang *et al*. revealed the CNN-based method by fusing MRI and PET images for the non-subsampled shearlet transform (NSST) field.[2] By integrating accurate evaluation with excellent-quality images, this technique is superior to conventional algorithmic approaches. Using adaptive MRI-PET, Lakshmi *et al*. designed a DL-based hybrid model.[3] When assessed against other approaches with quantitative parameters, theirs generates the most excellent mutual information value.[4,5] In order to help with medical image fusion (MIF), Panigrahy *et al*. (2023) reduced the PCNN framework and deployed NSST for multiple scales in order to develop an innovative adaptive unit-linking PCNN (PAULPCNN) paradigm.[6] Incorporating cutting-edge practices on numerous brain medical image groups, this technique provides moderate outcomes.[7]

Vs *et al*., introduce the image fusion transformer, which is a multi-scale fusion model using a transformer that captures each of the local and long-range dependencies, thereby outperforming CNN-based methods on various datasets.[8] Do *et al*. developed a modified VGG19 model (TL_VGG19) using transfer learning for MIF, focusing on FE and detail component fusion. Their approach, including an adaptive equilibrium optimization algorithm for base components, exceeded the performance of seven contemporary synthesis methods.[9] Song *et al*., proposed a composite decomposition algorithm using the improved structure tensor to MRI conversion and NSST in detail preservation to develop image quality and outperform advanced methods significantly. Rajalingam *et al*., focus on neurocysticercosis, degenerative, and the neoplastic diseases by developing a hybrid multimodal MIF technique.[10] Using NSCT for decomposition and applying different fusion rules for the frequency components, their methods showed better qualitative and quantitative performance that aided disease understanding.

Applying an innovative fusion decision, GLCM-FE, and optimal deep neural network categorization, Patel *et al*. focused on brain tumor diagnosis. When it was finally time to extract malignancies, the weighting k-means method was exact and efficient. Performing better than cutting-edge techniques, Liu *et al*. describe a multimodal image fusion solution that employs enhanced spatial and color data and segmentation maps generated through ant colony algorithms.[12,13] To boost the data content and boundary level of images, Arafa *et al*. designed a unified method based on the NSST in the YIQ color space.[14] The method optimizes image boundary locations. The previously multimodal MIF method has been developed by Mirza *et al*. and exhibited good results with multiple illness samples. It employs a boundary-measured PCNN in NSST.[15]

For merging MRI and SPECT data in the NSST field, Panigrahy *et al*. suggested Weighted Parameter Adaptive Dual-Channel PCNN (WPADCPCNN), which significantly optimized both the graphical display and the purpose of the analysis.[16] The multi-source information exchange encoding fusion framework by Sebastiane *et al*. enhanced data transmission and encrypting.[17] Sebastian *et al*. optimized CT/MRI and PET/SPECT images by pairing them with a fast local Laplacian filter.[18] Li *et al*. invented the Hahn-PCNN-CNN brain imaging fusion structure, which functioned and assessed successfully.[19] Zhou *et al*. boosted the processing of images and research results in the NSCT area by employing Parameter-adaptive pulse-coupled neural networks (PA-PCNN).[20]

PCNN-based existing fusion models

This enables effective detection in medical paradigms for both statistical and individual assessments. Incorporating NSST into sub-band combining and dynamically computing features from factors, Table 2 contains an overview of the fusion methods that are centered on PCNN.

AD is a principal neurological disorder in the elderly that is considered to cause severe memory loss due to atrophy of regions like the hippocampus and amygdala. Early detection and classification of AD, particularly in its MCI stages, are crucial yet challenging. This review examines the recent advancements in AD detection (ADD) and classification and focuses on various FE techniques and machine learning (ML) methods.

Hazarika *et al*., analyzed existing works that focused on ADD and classification using diverse FE approaches. Their work highlighted the potential of wavelet transform-based FE in AD classification, especially in the detection of subtle brain changes that are characteristic of early-stage AD.[21] Acharya *et al*., developed a computer-aided-brain-diagnosis system using MRI and different FE techniques. Their findings suggest that the ST-FE technique combined with the k-nearest neighbor (KNN) classification suggestively improves Alzheimer's diagnosis's accuracy, precision, sensitivity, and specificity, and for the identification of AD from MRI images, AL Saeed and Omar stated ResNet50 as the FE. Their algorithm is superior to other models in terms of precision, demonstrating that DL has applications for integrating the FE method for ADD.[22,23] In their overview of the new CNN structure for AD diagnosis using MRI images and Mini-Mental State Examination scores, AlSaeed *et al*., addressed the significance of these tools. A robust multitask feature training method for FE has been used in the study. The CNN design outscored traditional ML methods such as KNN, SVM, DT, LDA, and RF in terms of sensitivity and accuracy when it came to detecting various stages of AD.

LITERATURE ON FE MODELS

A study conducted by Hedayati *et al*., proposes a technique for early-stage ADD with a CNN and an ensembled AE for FE.[24] The study covered three classification cases (AD/NC, AD/MCI, MCI/NC) and demonstrated high accuracy and sensitivity, demonstrating its reliability in early-stage AD diagnosis. Zhang *et al*., through their study, introduced a DL model with an attention mechanism for multi-modal fusion in AD classification by the leveraging of MRI and PET scans.[25] The network employs the hierarchical fusion method and automatically assigns fusion ratios in the attention model based on data importance. The model showed impressive classification results on the ADNI dataset by outperforming *state-of-the-art* methods, particularly in classifying AD and different stages of MCI. Goenka and Tiwari utilized a 3D computational neuroanatomical method for building a multimodal multi-class DL model for Alzheimer's classification.[26] The study explored different patch sizes and slicing techniques by concluding that larger patch sizes and the interpolation zoom technique within the slice-based approach yielded better accuracy. Their model achieved the

Table 2: PCNN-based existing fusion models

Model	Scope	Limitations
PAULPCNN	Simplifies original PCNN merges high-pass sub-bands, and constructs low-pass sub-bands using NSST.	Potential over-simplification of complex image features; automatic parameter selection may not be optimal for all image types.
Boundary-measured PCNN and energy attribute fusion model	Suitable for various diseases, it uses the NSST domain for qualitative and quantitative enhancement.	Application may require fine-tuning for specific diseases or image quality complexity.
WPADCPCNN	Applied to MRI and SPECT images; uses fractal dimension for parameter estimation.	Manual parameter setting might limit adaptability to diverse medical images.
MIEE using PCNN	Focuses on multimodal MIF with non-linear transformation and optimization techniques.	The complexity of the model could impact computational efficiency and require extensive training data.
FLLF and PA-PCNN in NSST	It enhances edge data, suppresses noise, and uses NSST for image decomposition.	Potential loss of fine details in noise suppression; complexity in balancing edge enhancement and noise reduction.
Hahn-PCNN-CNN	End-to-end network for brain image fusion; trained on diverse image datasets.	It needs high computational resources for training and execution; it may not generalize well to non-brain images.
PA-PCNN in NSCT	Integrates images into high-frequency (HF) and Low-Frequency (LF) bands for fusion and uses five metrics for validation.	Model complexity and potential over fitting to certain image types or diseases.
PCNN based on NSST	It focuses on edge information and image details and uses improved sparse representation.	The presentation of the sparse symbol in varied imaging set-ups parameters it.
PCNN and GA using EMD	Combines PCNN and GA for improved fusion effect and image clarity.	The complexity of hybrid models can lead to increased computational demands.
IQPSO-PCNN in NSST	Utilizes quantum-behaved PSO for parameter optimization in PCNN addresses energy preservation.	The quantum-behaved PSO algorithm may not always converge optimally for all medical images.
Energy attribute-based activity measure and PA-PCNN	Merges medical modalities with NSST focuses on robust disorder diagnosis.	A specific focus on disorder diagnosis might limit its applicability in broader medical imaging contexts.
SPADCPCNN in NSST	It streamlines parameter settings in dual-channel PCNN and automatically computes parameters.	Automatic parameter computation may not be ideal for all medical images or conditions.

MRI: Magnetic resonance imaging, NSST: Non-subsampled shearlet transform, MIEE: Multi-source information exchange encoding, FLLF: Fast local Laplacian filter

highest known accuracy in multimodal classifications using T1w-MRI and AV-45 PET scans.

DEEP LEARNING MODELS FOR ADD

Many research studies have been employed using CNNs upon MRI scans that often focus on the hippocampus and medial temporal lobe regions that are related to early atrophy in AD. Studies have achieved accuracy better than 85% in classifying AD versus Healthy Controls (HCs) and differentiating among AD stages. Studies have explored separating AD from HCs and other dementias with promising accuracy.[27] On the ADNI dataset, Wu *et al*., reported a 91.3% CA rate in BCC and MCC-AD classifications utilizing the Attention-based 3D Multi-scale CNN model (AMSNet) for AD spatial FE.[28] A non-local attention mechanism and Spatial Transformer Networks in the early ADD model have been suggested by Sun *et al*. 2021. This hypothesis boosted FE and produced a CA of 97.1% on the ADNI sample.[29] Further, an AD diagnosis model utilizing 3D-CNN coupled with multi-view attention was introduced.[30] Using ADNI-1 and ADNI-2 datasets, their model demonstrated its efficiency by displaying significant accuracy results. To improve

Table 3: Literature on FE models

Model/Approach	Scope	Limitations
WT-based FE	AD detection emphasizing early-stage brain changes	It may not capture all relevant features for advanced stages of AD
CABD system with ST and KNN	Improved Alzheimer's diagnosis using MRI	Reliant on the effectiveness of ST for FE
ResNet50 as an automatic FE method	Automated FE for AD diagnosis using MRI	DL models may require extensive data and computational resources
Novel CNN	Classifying Alzheimer's severity based on fMRI and MMSE scores	Complexity in model architecture and potential overfitting to specific datasets
Ensemble of pre-trained AE and CNN	Early-stage AD diagnosis	Reliant on the effectiveness of pre-trained models and may not generalize to all AD stages
Deep multi-modal fusion network with an attention mechanism	Leveraging MRI and PET scans for AD classification	Integration complexity and potential data imbalance handling in multi-modal fusion
3D computational neuroanatomical	Multimodal multi-class DL model for Alzheimer's classification	Requires extensive validation across diverse datasets and potential computational intensity
2D-DWT and TD-PSD-FE	AD classification using classic methods and CNN	Limited by the specific capabilities of the 2D-DWT and TD-PSD models
3-D Ensemble Net	Multi-class categorization of AD using Florbetapir PET scans	Focuses specifically on Florbetapir PET scans, which may limit generalizability
Dual-branch vision transformer, CsAGP	Integrating MRI and PET images for AD diagnosis	Complexity in transformer model and potential challenges in diverse data integration
Radiomic features from PET images for detecting CS	Detecting active cardiac sarcoidosis using PET images	Radiomic analysis may not be necessary for CS detection; focus on automated procedures for standardization

MRI: Magnetic resonance imaging, PET: Positron emission tomography, CABD: Computer-aided-brain-diagnosis, KNN: k-nearest neighbor, FE: Feature extraction

Mohammed *et al*., gorithms, have included the contextual transformer integrated with the group convolution that is enhanced using channel shuffling. It allows for much better FE and communication between feature maps. These refined algorithms demonstrated improved classification accuracies across several medical image classification tasks. Mohammed *et al*., have assessed the ML methods and the CNN models (AlexNet and ResNet-50) for diagnosing dementia and AD by applying the OASIS samples.[31] They encompassed the hybrid model of AlexNet+SVM and ResNet-50+SVM and exposed high performance with better results than the DL models. The random forest algorithm has also achieved 94% accuracy with high precision, recall, and F1score [Table 3].

CNN MODELS

The use of CNN for early AD detection through MRI and PET images highlights various innovative approaches and models: Studies overviewed ML methods for early Alzheimer's detection and emphasized CNNs for analyzing ADNI data sets. The research highlighted the effectiveness of an 18-layer CNN by demonstrating superior accuracy (98%) in early Alzheimer's detection compared to other 3D CNN models.[32] This study underscores the potential of multi-layered CNNs in achieving high accuracy in Alzheimer's prediction from large MRI datasets. Tool a CNN diagnosis and classification of AD using MRI images. When experimented with the ADNI dataset, their archetypal attained a weighty accuracy of 99%,[33] which outperformed several correlated works and ML algorithms applied to the OASIS dataset. Khagi and Kwon have explored CNN behaviors for transitioning from 2D to 3D architectures for AD diagnosis using MRI and PET images. The study has insinuated a CNN architecture called "*divNet*," which focused on reducing feature redundancy by increasing filter size and stride. The output has projected memory usage, execution time, and classification accuracy.[34] Anjewar *et al*., have a hybrid CNN+KNN model for detecting Alzheimer's from MRI images. The predictable method of CNN+KNN is helpful to the dataset with 6400 MRI images and attained a standard accuracy of 99.58%, precision of 99.63%, and better metric values.[35] Ebrahim and Ali *et al*., discovered the application of VGG-16 CNN for early ADD. It highlights the efficiency of FE for the classification method and has exposed the rewards of DL-based methods in classifying neuroimaging data trials correlated to AD. The model outperformed *state-of-the-art* models in different metrics that demonstrate the advantages of DL in early AD.[36] Table 5 summarizes the CNN models for ADD in the literature reviewed.

Table 4: DL models for ADD

Model	Scope	Limitations
GM-PET	ADD using fused MRI and FDG-PET images.	It focuses on unimodal image processing, which is lacking in advanced multi-temporal data analysis.
VGG-16	ADD from fMRI and PET images using DL.	It relies on traditional CNN architecture without incorporating multimodal or temporal data integration.
VGG+TL	Early-stage ADD using tissue segmentation and TL	Focus on static image analysis without considering the progressive nature of the disease.
3D-CNN	Alzheimer's classification using tau PET scans.	Highly specific to tau PET scans, it may not be comprehensive for holistic AD progression analysis.
SVM and DNN	Predicting Alzheimer's from MRI datasets using ML algorithms.	Primarily, algorithmic focus lacks integration with more advanced NN structures.
DEMNET	Detection of dementia stages from MRI images.	The model was primarily designed for stage detection, not encompassing the full spectrum of AD progression.
AlexNet, ResNet-50	Diagnosing dementia and AD using the OASIS dataset.	It is limited to single-time-point analysis, not capturing the dynamic progression of AD.
Adaptive RBM, DBN	Classifying MRI and PET images for early detection of MCI and AD.	It focuses on image classification without delving into the temporal aspects of AD progression.
Enhanced CNN	Distinguishing standard control from AD patients using 18FDG-PET images.	It highlights image processing but lacks a longitudinal perspective in disease monitoring.
CNN with Inception	Deep FE from MRI for early-stage AD prediction.	It focuses on FE from static images, not considering the time-series nature of AD.

ADD: Alzheimer's disease detection, MRI: Magnetic resonance imaging, PET: Positron emission tomography, ML: Machine learning, FE: Feature extraction

Table 5: CNN models for ADD

Model	Scope	Limitations
18-layer CNN	Overview of ML methods for AD, focusing on CNNs.	Limited exploration of 3D CNN models and potential overfitting issues with high-layer CNNs.
CNN	Early diagnosis and classification of AD using MRI images.	It may not address the complexity of temporal progression in AD.
divNet (CNN)	Explored CNN for AD diagnosis using MRI and PET images.	Architecture-focused may overlook the importance of longitudinal data analysis.
CNN-KNN	Detecting AD from MRI images using a hybrid DL approach.	Hybrid model complexity may lead to challenges in clinical application and interpretation.
2D and 3D CNNs, RNN	Compared CNN+RNN for ADD using MRI data.	Potential limitations in integrating 2D and 3D features for comprehensive disease analysis.
CNN	ADD and stage classification using MRI images.	It focuses mainly on image preprocessing, possibly overlooking the contribution of sequential data analysis.
BLADNet	Early AD diagnosis through PET imaging using a broad network-based model.	Reliance on PET imaging may limit applicability in settings where PET is not readily available.
VGG-16 CNN	Early ADD focusing on FE.	Dependence on a single architecture (VGG-16) may not capture the full complexity of AD-related neuroimaging data.
DL	AD detection using MRI images and TL for multi-class classification.	Concentrating on a specific dataset may affect the model's pertinence to clinical tests.

ADD: Alzheimer's disease detection, MRI: Magnetic resonance imaging, PET: Positron emission tomography, KNN: k-nearest neighbor, ML: Machine learning, FE: Feature extraction

CONCLUSION

This survey supports to enables effective detection in medical paradigms for both statistical and individual assessments. AD is a principal neurological disorder in the elderly that is considered to cause severe memory loss due to atrophy of regions like the hippocampus and amygdala. This review examines the recent advancements in ADD and classification and focuses on various FE techniques and ML methods. This review combining multiple modalities (MRI, PET, and CSF) is gaining traction for improving diagnostic accuracy. This study's use of CNN for early AD detection through MRI and PET images highlights various innovative approaches and models.

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Source of Support: Nil. **Conflicts of Interest:** None declared.