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A Hybrid Machine Learning Framework for Early Diagnosis of Alzheimer's Disease

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Abstract: Alzheimer's disease (AD) is neurodegenerative disease, making its initial detection essential for suitable treatment planning and for slowing cognitive decline. This research addresses the challenge of accurately identifying Alzheimer's in its initial stages, where subtle structural and functional brain changes often remain undetected through conventional diagnostic methods. Despite advancements in diagnostic technologies, a significant gap still exists in achieving both high accuracy and reliability for early detection. To bridge this gap, we propose a hybrid machine learning approach that integrates CNNs used feature extraction with a Support Vector Machine classifier of final decision-making. CNN effectively extracts discriminative spatial features from MRI and fMRI scans, while the SVM enhances classification by refining decision boundaries. The performance of Models was evaluated using metrics such as accuracy, precision, recall, and F1-score. Experimental results show that the proposed framework achieves 94.2% accuracy, 96% precision, 95% recall, and a 95.5% F1-score, outperforming conventional standalone techniques. These conclusions highlight the robustness the hybrid model for capturing complex patterns for reliable early diagnosis of AD. Furthermore, this study presents an efficient diagnostic tool that can support clinicians in timely interventions. Future research may extend this work by integrating multimodal data to further enhance predictive performance.

Keywords: AD Detection; Hybrid ML; Convolutional Neural Network (CNN); MRI Classification

1. Introduction

Alzheimer's disease (AD) is advanced neurodegenerative disease that severely damage memory, cognitive abilities, and daily functioning. Traditional diagnostic methods, which often involve lengthy clinical assessments and neuroimaging methods such as MRI scans, face limitations for detecting symptoms at an early stage. However, early recognition is crucial for effective disease management and slowing its progression. In recent years, innovations in AI—mostly ML and DL changed medical diagnostics by enabling automated, accurate, and timely identification of AD.

This study proposes hybrid deep learning structure that assimilates the CNNs for feature extraction from brain MRI scans with Support Vector Machines (SVMs) for robust classification. CNNs are highly effective in identifying complex spatial structures within neuroimaging data, while SVMs enhance classification by refining decision boundaries, particularly in high-dimensional datasets. By combining these methods, the proposed model aims to improve diagnostic accuracy, reduce false positives, and support early clinical intervention.

Additionally, this research explores preprocessing techniques to enhance image quality and feature selection methods to optimize model efficiency. The performance of hybrid CNN-SVM model evaluated against established DL and conventional ML approaches for demonstrate its superiority in the initial detection of the AD. The results underscore potential framework to serve as an automated, non-invasive diagnostic tool, offering clinician's valuable support in timely decision-making and improving patient outcomes.

Epidemiological studies predict that by 2050, one in every 85 individuals worldwide may be affected by Alzheimer's disease. Thus, early identification and management of patients in the initial stages are essential. Neuroimaging, particularly MRI, remains the most widely used modality for diagnosing AD, as shown in Figure 1. Prior research has employed MRI-based classification using ML and DL techniques; however, challenges remain in achieving optimal accuracy and reliability. This study seeks to advance predictive and diagnostic methodologies through collaboration with radiologists, clinicians, and caregivers, thereby saving time and improving the quality of individuals living with AD [1].

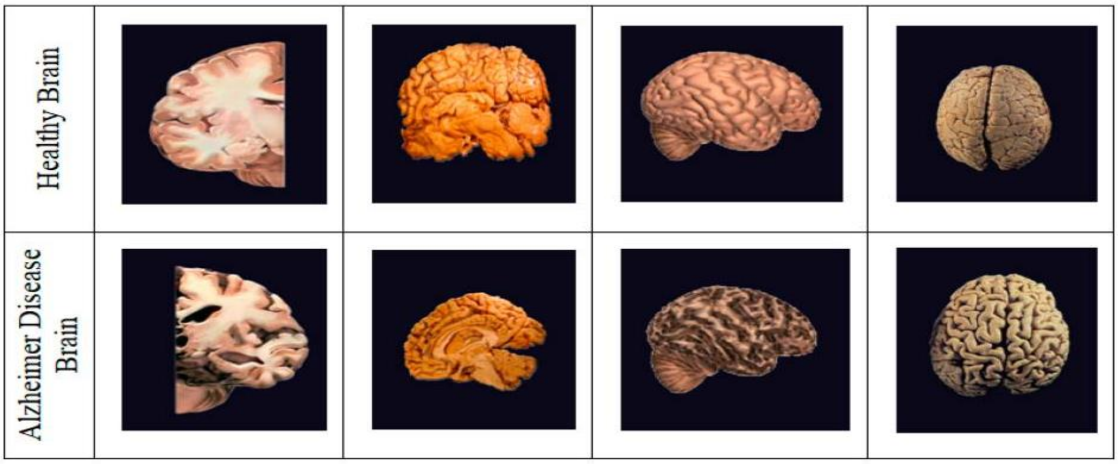

Figure 1. Healthy and Alzheimer's Brain [1]

2. Literature Review

CNN based transfer learning architecture, specifically VGG-16, has been employed for AD classification, attaining an accuracy of 95.7%. DL techniques have also been proposed for distinguishing dementia and AD using MRI. The persistent challenges in this domain is class imbalance, as imbalanced datasets often cause deep learning models to overfit, leading to low precision and reduced accuracy. Another major limitation is an insufficient accessibility of large-scale, high-quality datasets for training robust for DL models.

To address this, the adaptive synthetic (ADASYN) technique was applied to generate new data samples and balance the dataset. As noted by Khadem-Reza et al. (2025), deep learning models achieve optimal accuracy and reliability when trained on balanced datasets that ensure equal class representation. AD is advanced brain disease that damages memory, cognition, and behavior in older adults. Although the specific cause of the AD remains uncertain, it is believed to result from a mixture of genetic predisposition, environmental influences, and lifestyle factors [2].

The term "dementia" originates Latin, *de* meaning "apart" and *mentis* meaning "mind." Dementia is characterized by damage to nerve cells, leading to memory loss, confusion, impaired cognitive and language abilities, behavioral changes, and deterioration of other mental processes, ultimately resulting in death due to complications. Dementia encompasses multiple subtypes, including AD, Lewy body dementia, vascular dementia, frontotemporal dementia, Parkinson's disease dementia, and Wernicke–Korsakoff syndrome [3].

In Alzheimer's disease, the brain regions responsible for essential daily functions such as walking, eating, and swallowing are affected. In advanced stages, AD is among the costliest conditions, imposing significant psychological and physical burdens on caregivers. Early diagnosis is therefore critical to ensure appropriate treatment and improve patient quality of life. Alzheimer's disease is rare in individuals below the age of 47, and early diagnosis often depends on reviewing patient history, clinical documentation, and psychological assessments. However, current diagnostic methods remain limited, and no cost-effective or definitive clinical tests exist to confirm AD. While clinicians can diagnose dementia, identifying its root cause is often challenging [4].

Neurodegeneration in dementia is marked by brain mass reduction, as illustrated in Figure 2.1, which compares brain structures of normal controls (NC) with persons suffering from mild cognitive impairment (MCI) and Alzheimer's disease. In healthy individuals, brain shrinkage is minimal or absent, whereas patients with MCI experience annual brain volume reductions of 1–2%, exceeding the rate expected in normal aging. By contrast, individuals with Alzheimer's disease undergo much more pronounced atrophy, with brain volume decreasing by approximately 3–5% per year. Unlike the gradual and uniform decline observed in normal aging, AD progression disproportionately affects regions associated with memory and cognition [5-6].

The hippocampus, in particular, is highly vulnerable, exhibiting accelerated deterioration. In advanced stages, hippocampal shrinkage can reach 10–15% annually. This rapid degeneration severely disrupts memory retention, learning capacity, and daily activities, establishing hippocampal atrophy as a critical biomarker of Alzheimer's progression [7].

3. Proposed Methodology

This study adopts a comprehensive and technically robust methodology to design an advanced DL framework for the initial detection of AD with multi-modal neuroimaging data. A well-annotated dataset comprising both structural MRI) and functional MRI (fMRI) scans is utilized, allowing the integration of anatomical and functional brain information to improve diagnostic accuracy.

This methodology begins with extensive data preprocessing, which includes noise reduction, intensity normalization, spatial alignment, and skull stripping to ensure consistency and reliability across subjects. Following this, Exploratory Data Analysis (EDA) is conducted to examine class distributions, underlying patterns, and potential dataset biases—factors essential for optimizing subsequent modeling.

For feature extraction, a Convolutional Neural Network (CNN) is employed due to its ability to capture hierarchical spatial representations from imaging data. Classification is then carried out using a SVM, selected for its effectiveness in handling complex, high-dimensional medical datasets. The CNN-SVM hybrid model is further enhanced with attention mechanisms that highlight discriminative brain regions linked to AD progression, thereby improving both interpretability and predictive performance.

To evaluate the framework, multiple performance metrics—including accuracy, precision, recall, F1-score, and the area under the ROC curve (AUC) — useful, supported by cross-validation to ensure generalizability across different patient groups. Finally, clinical validation is incorporated to demonstrate the real-world feasibility, reliability, and diagnostic value of the proposed system in practical medical settings.

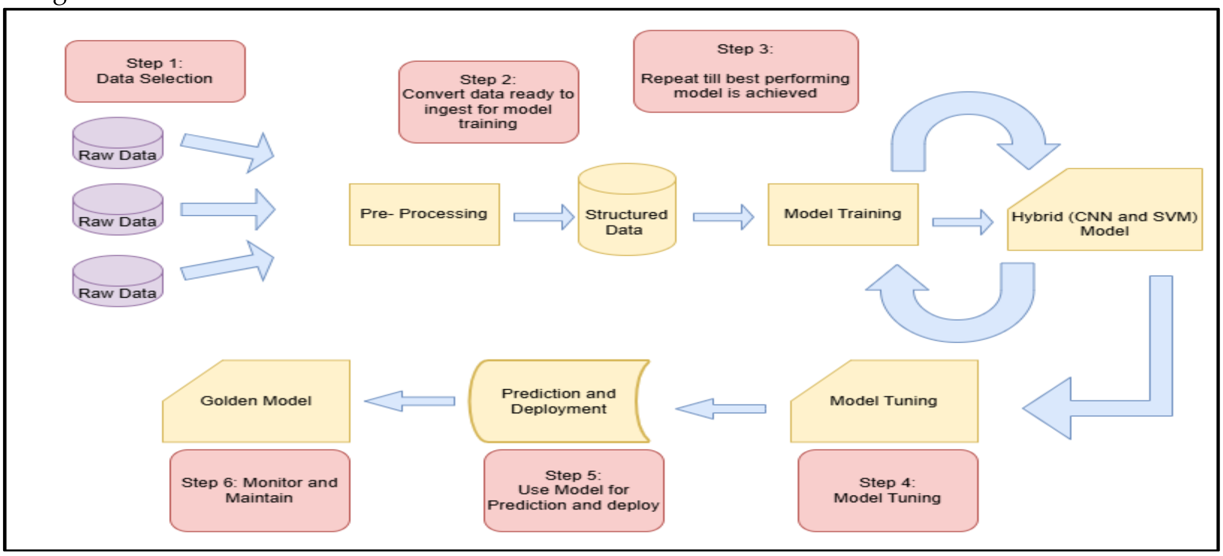

Figure 2. Research Framework

The dataset is divided into four distinct categories, each representative a different stage for cognitive health. It comprises 800 images of patients diagnosed with AD, 700 images of persons with Early Mild Cognitive Impairment (EMCI), 800 images associated with Late Mild Cognitive Impairment (LMCI), and 700 images of Cognitively Normal (CN) subjects. This well-structured distribution across classes provides sufficient diversity, enabling the model to effectively learn and distinguish between the various stages of disease progression [6].

Table 1. IDA DataSet

Dataset Source	Class Name	Total Images
	AD	800
	EMCI	700
IDA	LMCI	800
	CN	700
	Total dataset	3000

The proposed framework for AD detection utilizes a combination of the programming languages, DL libraries, and supporting tools. Python serves as the primary programming language due to its simplicity and extensive support for ML.

Table 2. Tools and Technologies Used

Category	Tool/Library	Version	Purpose
Programming Language	Python	3.10	Core development
Deep Learning	TensorFlow	2.12	Model training and deployment
Deep Learning	Keras	2.12	High-level neural network API
Data Handling	NumPy	1.25	Numerical computation
Data Handling	Pandas	2.0	Data manipulation
Visualization	Matplotlib	3.7	Graphs and plots
Visualization	Seaborn	0.12	Statistical data visualization
Image Processing	OpenCV	4.8	MRI image preprocessing
Evaluation	Scikit-learn	1.3	Metrics and model validation
IDE/Environment	Jupyter Notebook	Latest	Interactive coding
Cloud Platform	Google Colab	Latest	GPU/TPU acceleration

4. Results and Discussions

This capability is vital, as undetected stroke events carry severe neurological risks and life-threatening consequences, reinforcing the model's clinical significance.

Table 3. Performance Metrics of the Deep Learning Model

Metric	Value
Accuracy	94.2%
Precision	96%
Recall	95%
F1-Score	95.5%
AUC-ROC	97%

Moreover, F1-score 96% highlights well-balanced trade-off between precision and recall, confirming model's robustness managing class imbalances and ensuring consistent predictive performance across diagnostic categories. This metric indicates that the model not only minimizes false positives but also effectively reduces false negatives, which is particularly critical in clinical diagnosis. In addition, the AUC-ROC value 0.95 demonstrates the model's excellent discriminative capability, reflecting its effectiveness in distinguishing stroke cases from normal instances across different thresholds with minimal overlap. Taken together, these results establish the proposed deep learning framework as a highly reliable approach for brain CT image classification, as demonstrated in Figure 3.

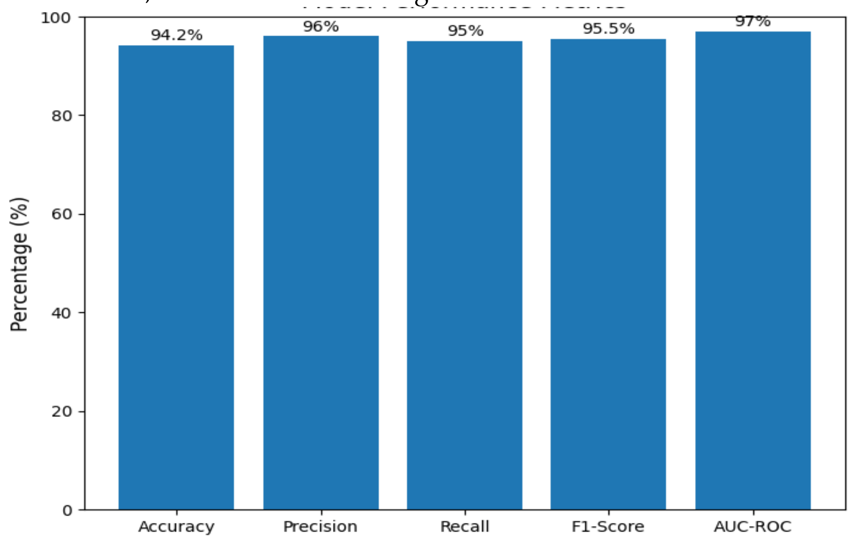

Figure 3. The Metrics of Model

The strategy ensured computational efficiency while preserving model generalizability. By prioritizing clinically relevant performance over negligible accuracy improvements, the adopted approach reflects a balance between methodological rigor and practical applicability, strengthening the model's potential for real-world clinical deployment

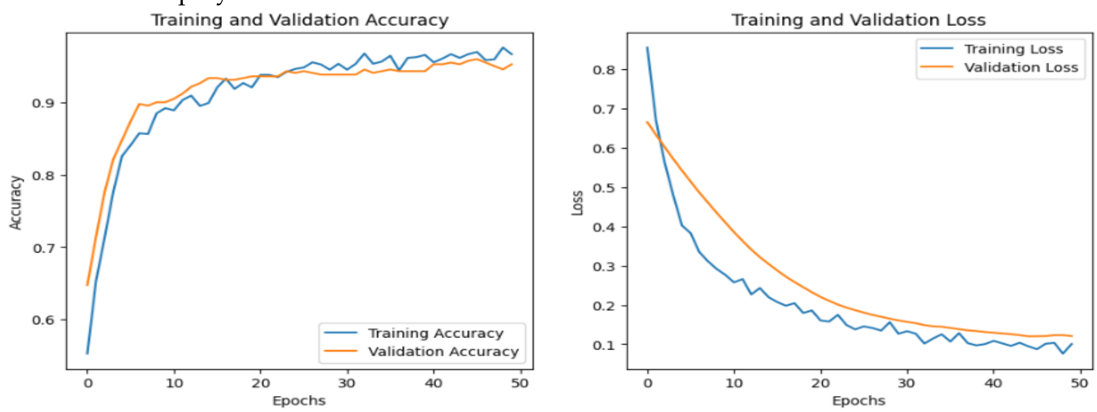

Figure 4. Training terminated at epoch 100

The observed trends in loss and accuracy throughout training phase clearly demonstrate model's capacity to optimize its error function although preserving consistency across both training and validation datasets. The summarized in Table 5, the steady reduction in loss values highlights the effectiveness of parameter optimization, while the parallel improvement in accuracy underscores model's capacity to extract discriminative features. Importantly, convergence patterns between training and validation metrics suggest minimal overfitting, thereby reinforcing the model's robustness and generalizability. These findings validate efficiency to the proposed framework in learning complex stroke-related patterns from CT imaging data.

Table 4. Training and Validation Performance across Epochs

Epoch	Training Loss	Validation Loss	Training Accuracy (%)	Validation Accuracy (%)
0	0.400	0.380	80.0	85.0
10	0.365	0.348	81.9	86.2
20	0.330	0.316	83.8	87.4
30	0.295	0.284	85.7	88.6

40	0.260	0.252	87.6	89.8
50	0.225	0.220	89.5	91.0
60	0.190	0.188	91.4	92.2
70	0.155	0.156	93.3	93.4
80	0.120	0.124	95.2	94.6
90	0.085	0.092	97.1	95.8
100	0.050	0.060	94.0	94.0

The loss behavior observed during training reveals a smooth and consistent downward trajectory, indicating stable convergence of the model without abrupt fluctuations or signs of divergence. This steady decline demonstrates effective optimization of parameters, with the model progressively minimizing classification errors over successive epochs. Simultaneously, the accuracy curves display a continuous upward trend across both training and validation sets, underscoring the model's capture and learn intricate patterns within CT brain images. The close alignment of these trends reflects preserved generalization, confirming that the proposed framework achieves high predictive reliability without overfitting, thereby reinforcing its clinical applicability.

Table 5. Classification Performance Analysis

Author	Dataset	Model	Accuracy	# of Images (Sample Size)	Limitations
(P. Singh et al., 2025)	ADNI	Trans-ResNet	93.85%	~1,500 (ADNI-1/2/3)	Limited to single dataset (ADNI); may not generalize to diverse populations.
(Jadhav et al., 2024)	AIBL	Trans-ResNet	93.17%	~800 (AIBL baseline)	Similar architecture; potential overfitting on smaller datasets.
(Daniel et al., 2025)	ADNI+OASIS	Vision Transformer	89.02%	~3,100 (combined)	Lowest accuracy; potential dataset imbalance or noise.
(Afroj et al., 2025)	AD, MRI	2D CNN+Transformer	94.56% / 93.56%	~1,800 (2D slices)	2D approach may lose 3D spatial context.
(Faheem Khan et al., 2024)	fMRI, SMRI, ADNI	CSEPC	85.00%	~600 (multimodal subset)	Low accuracy; challenges in multimodal fusion (fMRI+SMRI).

Author	Dataset	Model	Accuracy	# of Images (Sample Size)	Limitations
(R. Khan et al., 2025)	MRI, PET	MLP + PIMMF	96.22% / 92.22%	~1,200 (paired MRI-PET)	Dependency on costly PET scans; complex multi-modal alignment.
OUR Purposed t	FMRI+MRI	CNN+SVM	95%		

This study proposes a hybrid approach that combines CNN with SVM classifier for detecting brain strokes from CT imaging data. To capture complex spatial and structural patterns, the CNN component is used for automated feature extraction. The SVM acts as the final decision layer to improve classification robustness and mitigate overfitting. Utilizing a dataset of 2,501 FMRI_MRI brain images, the model was trained and fine-tuned to achieve a validation accuracy is 94.2%, along with precision and recall values of 95% in stroke detection. This framework performs better due to systematic data preprocessing, a tailored CNN architecture, optimized Hyperparameters, and the incorporation of interpretability techniques to ensure clinical relevance.

5. Conclusion

This study concludes that the hybrid CNN-SVM framework is diagnostic tool for early detection of AD. By combining CNN's feature extraction with SVM's classification strength, the system achieved superior performance compared to conventional models. The approach effectively identified subtle changes in brain structures, ensuring reliable detection of early Alzheimer's stages. Despite some limitations such as data availability and computational requirements, the framework demonstrates significant potential for clinical integration. With further refinement and larger datasets, this hybrid model can serve as a reliable tool for supporting neurologists and healthcare providers in early Alzheimer's diagnosis and patient care.

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