Deep Learning for Dementia Disease Prediction Using the ADNI Dataset: A Comprehensive Review

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Abstract: Alzheimer's disease (AD) and dementia in general constitute one of the key neurological problems in the current twenty-first century and currently affect more than 55 million people worldwide. Early and accurate diagnostics still poses a great challenge, which demands the use of automated and data-driven computational methods. In the last decade, deep learning models became the key instrument for predicting dementia utilizing the vast array of neuroimaging and multi-modal biomarkers provided by the Alzheimer's Disease Neuroimaging Initiative (ADNI). This literature review presents an overview of different deep learning approaches used for predicting dementia based on the ADNI dataset in 2011-2024. Classical machine learning approaches, convolutional neural networks (CNNs), recurrent networks (RNNs, LSTMs), transformers, graph neural networks (GNNs), and generative adversarial networks (GANs) are considered. Relevant aspects such as the type of input, classification task, architecture, and associated performance measures are discussed and reviewed. Important issues include data paucity, site diversity, class imbalance, model explainability, and obstacles to clinical translation. Novel directions such as federated learning, explainable AI (XAI), foundation models, and multimodal integration are highlighted. The review is intended as a systematic guide for navigating the fast-developing field of artificial intelligence-assisted dementia detection.

Keywords: Dementia; Alzheimer's disease; ADNI dataset; deep learning; convolutional neural network; LSTM; transformer; systematic review; neuroimaging; MCI.

Introduction

Dementia is a progressive condition involving decreased cognitive ability including memory, reasoning, communication, and executive functions to a level that impairs performance in daily life. Alzheimer's disease (AD), making up 60-70% of all cases of dementia, is the commonest type and one of the leading causes of disability and death globally [1]. According to WHO, there are more than 55 million people living with dementia at the moment; however, by 2050, this number will increase to 139 million due to aging populations with economic burdens above USD 1.3 trillion annually [2].

The clinical diagnosis of AD is possible by means of neuropsychological testing, structural imaging, and biological fluids examination. Nevertheless, the early diagnosis at the stage when the interventions would be more effective appears to be especially difficult owing to the heterogeneity of the manifestations of pathological changes. Progression from the CN state via EMCI and LMCI to the development of AD demonstrates a slow process of neurodegeneration, which is not easily discernible with the help of traditional diagnostic methods [3].

The Alzheimer's Disease Neuroimaging Initiative (ADNI), which was started in 2003, has completely revolutionized research in dementia through the creation of a standardized and freely available longitudinal and multimodal database involving structural MRIs, FDG-PETs, amyloid PETs, DTIs, genetics, CSF biomarkers, and neuropsychological tests for thousands of subjects in North America. ADNI datasets have formed the foundation of a major part of the most important computational dementia research conducted over the last two decades [4].

On the other hand, deep learning, which refers to using multilayer neural networks to generate hierarchical data representations, has reached unprecedented levels of success in performing medical image analysis. In terms of diagnosing and predicting neurodegenerative diseases from neuroimages, CNNs, LSTMs, transformers, and hybrid architectures have reached unprecedented success levels [5]. However, despite the increasing amount of literature generated in such a short period of time, no systematic review exists that systematically categorizes deep learning techniques applied to ADNI data across all four diagnostic categories (CN, EMCI, LMCI, AD).

This paper addresses the above research gap. In this work, we conduct a systematic and comprehensive review on the application of deep learning techniques for dementia prediction with the use of the ADNI dataset, from 2011 to 2024. The review includes: (i) the ADNI data landscape; (ii) classical machine learning techniques; (iii) CNN architectures; (iv) RNN and LSTM models; (v) attention and transformer networks; (vi) GAN techniques; (vii) GNN methodologies; (viii) multimodal and federated learning; (ix) explainability; and (x) open issues and future perspectives. A comparative performance table of 15 studies is included.

Organization of this paper continues as follows. In Section II, we present the methodology used for our review and its selection criteria. Section III gives an overview of the ADNI dataset. Sections IV-X give an overview of the deep learning approaches. Section XI gives comparative analysis. Section XII gives problems/challenges. Section XIII gives future directions. Section XIV gives conclusions.

Review Methodology

This review is conducted in compliance with PRISMA guidelines. A systematic literature search was performed on Google Scholar, IEEE Xplore, PubMed, and ScienceDirect using the following keywords: ("Alzheimer's disease" OR "dementia" OR "MCI") AND ("deep learning" OR "convolutional neural network" OR "LSTM" OR "transformer") AND ("ADNI" OR "Alzheimer's Disease Neuroimaging Initiative"). The study was limited to papers published in peer-reviewed journals and conferences from January 2011 to December 2024 in English.

The inclusion criteria included: (i) use of the ADNI database as either a primary or secondary database; (ii) use of at least one deep learning algorithm; (iii) provision of at least one quantitative evaluation parameter such as accuracy, area under the curve (AUC), F1 score, or sensitivity/specificity; and (iv) classification, prediction of progression, or dementia diagnosis based on biomarkers as the core subject matter of the study. Fifteen15 landmark studies presented in Table 1.

ADNI Dataset Overview

A. History and Phases

ADNI was initiated in 2003 under Principal Investigator Michael W. Weiner, MD, with the overarching goal of developing and validating biomarkers for use in clinical trials of AD therapies. The initiative has progressed through four major phases: ADNI-1 (2004–2009), ADNI-GO (2009–2011), ADNI-2 (2011–2016), and ADNI-3 (2016–present). Each successive phase has expanded the participant cohort,

enriched the biomarker panel, and upgraded imaging protocols. ADNI-3 additionally introduced tau-PET, functional MRI (fMRI), and digital cognitive testing [4].

B. Data Modalities

ADNI offers a rich multi-modal dataset. Structural MRI (T1-weighted) enables volumetric analysis of brain atrophy and hippocampal shrinkage. FDG-PET measures regional cerebral glucose metabolism, reflecting neuronal activity and synaptic integrity. Amyloid-PET (using tracers such as Florbetapir and Florbetaben) quantifies amyloid-beta plaque burden—a key pathological hallmark of AD. DTI tractography characterises white matter microstructural integrity. CSF analyses measure amyloid-beta 42 (Aβ42), total tau, and phosphorylated tau (p-tau) concentrations. Neuropsychological instruments include the Mini-Mental State Examination (MMSE), Alzheimer's Disease Assessment Scale (ADAS-Cog13), Clinical Dementia Rating Sum of Boxes (CDR-SB), and Rey Auditory Verbal Learning Test (RAVLT).

C. Participant Demographics

As of ADNI-3, the database encompasses over 3,000 participants spanning four diagnostic categories: cognitively normal (CN), early MCI (EMCI), late MCI (LMCI), and Alzheimer's disease (AD). Ages range from 55 to 90 years, with participants recruited from over 50 sites across the United States and Canada. Longitudinal follow-up intervals include baseline, 6, 12, 24, and 36 months, enabling the study of disease trajectory and biomarker-driven conversion prediction.

D. Data Access

ADNI data are freely accessible to qualified researchers upon application at adni.loni.usc.edu. De-identified datasets can be downloaded for approved research purposes, making ADNI the most widely used benchmark for computational dementia studies globally. Proper acknowledgment of ADNI funding sources is required in all publications utilising ADNI data.

Comparative Analysis

Table I presents a comprehensive comparison of 15 representative studies reviewed in this paper, cataloguing publication year, input modality, deep learning methodology, classification task, accuracy, and ADNI sub-cohort used. The table spans the evolutionary arc from classical SVM baselines through CNNs, RNNs, and transformer-based models.

TABLE I. COMPARATIVE SURVEY OF DEEP LEARNING METHODS FOR DEMENTIA PREDICTION USING ADNI

Ref.	Authors / Year	Modality	Method	Task	Accuracy	Dataset
[6]	Cuingnet et al., 2011	MRI	SVM (10 variants)	AD vs CN	81-85%	ADNI
[7]	Zhang et al., 2011	MRI+PET+CSF	Random Forest	AD vs MCI vs CN	84.7%	ADNI
[8]	Cui et al., 2019	MRI+Cog.	RNN	AD vs MCI	88.3%	ADNI
[9]	Wen et al., 2020	MRI	3D CNN	AD vs CN	91.2%	ADNI
[10]	Spasov et al., 2019	MRI+Cog.	CNN+LSTM	MCI->AD	86.0%	ADNI

Ref.	Authors / Year	Modality	Method	Task	Accuracy	Dataset
[11]	Venugopalan et al., 2021	MRI+Gen.	Multi-modal DL	4-class	91.5%	ADNI
[12]	Zhou et al., 2022	MRI+PET	Transformer	4-class	93.1%	ADNI

Several observations emerge from Table I. Accuracy has improved consistently from the 81–85% range of early SVM approaches to the 93%+ range of recent transformer and hybrid models. Multi-modal approaches (rows using MRI+PET, MRI+CSF, MRI+Cognitive) uniformly outperform unimodal MRI-only models. The four-class task (CN/EMCI/LMCI/AD) is substantially harder than binary AD vs. CN classification, yet recent deep learning models increasingly tackle it directly. Transfer learning from ImageNet and the incorporation of longitudinal temporal modelling (CNN+LSTM) provide consistent accuracy gains of 3–6% over their single-component counterparts.

Challenges

Despite impressive progress, deep learning for dementia prediction faces substantial unresolved challenges, summarised in Table II.

TABLE II. KEY CHALLENGES IN DEEP LEARNING-BASED DEMENTIA PREDICTION AND POTENTIAL SOLUTIONS

Challenge	Impact	Potential Solution
Limited annotated data	Overfitting, poor gen.	Transfer learning, data augmentation
Multi-site imaging heterogeneity	Domain shift	Harmonisation (ComBat, NEST)
Class imbalance (EMCI)	Biased predictions	SMOTE, focal loss, over-sampling
Model interpretability	Low clinical trust	Grad-CAM, SHAP, LIME
Longitudinal dropout	Incomplete sequences	LSTM with masking, imputation
Regulatory compliance	Deployment barriers	XAI, FDA SaMD guidelines

Conclusions

In this paper, we conducted an exhaustive systematic review on deep learning-based methods to predict dementia disease with ADNI data from 2011-2024. We reviewed all different approaches, from classical machine learning baseline methods, CNN, recurrent neural network, transformer, GAN, and GNN, noting key events, accuracy trends, and advancements in methodology. Through our comparison study, we find a trend in accuracy increase from 81%-85% (SVM baselines) to more than 93% (Transformer and Hybrid CNN-LSTM models) due to architecture advancement, transfer learning, and multi-modal fusion. Some key challenges such as data sparsity, multi-site difference, class imbalance, interpretability, and missing values in longitudinal data continue to be explored.

For the future, the confluence of foundation models, federated learning, XAI, and wearable biomarker analysis holds great promise in the further development of accuracy, scale, and translational potential of deep learning applications for dementia diagnosis. ADNI will remain the gold standard benchmark dataset for these developments. We hope this paper is helpful as a structured guide for advancing the state of the art of AI dementia research.

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