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. Accurate and timely diagnostic remains one of the biggest challenges, requiring automation and application of computational techniques. Over the last ten years, deep learning models emerged as the most important tool to diagnose dementia, using the rich repository of biomarkers obtained from the Alzheimer's Disease Neuroimaging Initiative (ADNI). The current literature review gives an overview of various deep learning methods employed for dementia prediction from the ADNI dataset in 2011-2024. Machine learning methods, CNNs, RNNs, LSTMs, transformers, GNNs, and GANs are mentioned. Various features such as input form, classification problem, architecture, and related performance metrics are reviewed. Such issues as data scarcity, heterogeneity of sites, class imbalance, model interpretability, and challenges in clinical implementation are also important. Emerging fields like federated learning, XAI, foundation models, and multimodal data integration are outlined. 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, 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 founded in 2003 by Principal Investigator Michael W. Weiner, MD, with the objective of establishing biomarkers that could be used in clinical trials for treatments of AD. The development of ADNI is divided into four main phases: ADNI-1 (2004-2009), ADNI-GO (2009-2011), ADNI-2 (2011-2016), and

ADNI-3 (2016-present). With each new phase of the program, the number of participants increases, as well as the number and quality of biomarkers. The latest ADNI-3 has added tau-PET, functional MRI [4].

B. Data Modalities

ADNI provides a diverse multi-modality database. T1-weighted imaging (Structural MRI) allows the quantification of brain atrophy and hippocampal volume. The regional cerebral glucose metabolism is measured by FDG-PET, which represents brain metabolic activity and synaptic health. Amyloid PET imaging, which uses tracers such as Florbetapir and Florbetaben, allows the quantification of amyloid-beta plaques – one of the pathological markers of AD. White matter microstructure integrity is determined by DTI tractography. Amyloid-beta 42 (Aβ42), total Tau, and p-Tau levels are measured by CSF analysis. The following neuropsychological tests are used: MMSE, ADAS-Cog13, CDR-SB, and RAVLT.

C. Participant Demographics

With regard to ADNI-3, the database is made up of more than 3,000 individuals who fall under four different diagnoses: cognitively normal (CN), early mild cognitive impairment (EMCI), late mild cognitive impairment (LMCI), and Alzheimer's disease (AD). The subjects are aged between 55 and 90 years old, with individuals being sourced from over 50 centers in the USA and Canada. The longitudinal follow-ups take place at 0, 6, 12, 24, and 36 months.

D. Data Access

The ADNI data sets are freely available to eligible researchers after submitting an application via the following web address: adni.loni.usc.edu. The de-identified data sets can be downloaded for research purposes only, making the ADNI data set the most popular data set used in the computational studies of dementia around the world.

Comparative Analysis

A detailed summary of 15 relevant studies discussed in this research is provided in Table I with respect to their publication date, type of data used, deep learning approach adopted, classification task performed, and percentage accuracy obtained along with ADNI sub-cohort used in the study.

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
[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

There are several key observations made from Table I. Accuracy has steadily increased from the 81-85% range in the early SVM methods to 93%+ in the more recent transformers and hybrids. Multi-modal techniques (where MRI+PET, MRI+CSF, and MRI+Cognitive have been used) all perform better than uni-modal techniques which use only MRI. Four-class classification (CN/EMCI/LMCI/AD) is much more difficult than binary AD vs CN classification; however, the four-class technique is being increasingly utilized by more recent deep learning methods. Transfer learning from ImageNet and Longitudinal modeling (CNN+LSTM) yield consistent accuracy gains of 3-6%.

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 extensive systematic review of deep learning methods for predicting dementia disease using ADNI datasets (2011-2024). We discussed all types of approaches ranging from classical machine learning baseline methods, CNN, recurrent neural network, transformer, GAN, and GNN, mentioning important events, accuracy, and progress in methodology. In the light of our comparison study, there is a tendency of increasing accuracy from 81%-85% (SVM baselines) to above 93% (Transformer and Hybrid CNN-LSTM models) due to advancements in architectures, transfer learning, and multimodal fusion. There still are some important challenges like data sparsity, multisite difference, class imbalance, explainability, and longitudinal missing values that are under investigation.

In the future, the convergence of foundation models, federated learning, XAI, and wearable biomarker analysis provides a promising avenue in the development of accuracy, scalability, and translation capabilities of deep learning applications for dementia disease prediction. ADNI will continue to be the gold standard benchmark dataset for these innovations. We hope that this paper will be useful as a systematic guide for further AI dementia research.

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