Artificial Neural Network for Early Screening of Alzheimer's Disease using Cognitive Data

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***Abstract*—Early detection of Alzheimer's Disease stays essential for effective intervention since AD represents a growing global health challenge. Standard tests used for diagnosis frequently miss the slow mental changes which develop during the beginning stages of Alzheimer's disease. The proposed research introduces Artificial Neural Networks (ANNs) as an innovative technique for AD early screening assessment through cognitive testing methods. ANNs successfully analyze complex nonlinear patterns throughout datasets that include memory execution data and language processing data and executive function measurements .The screening capabilities of ANN models grow stronger because they analyze big cognitive tests and adapt to create specific early AD detection systems. A new framework for incorporating ANN into diagnostic structures allows cognitive health monitoring systems to detect ill health conditions earlier.**

Keywords—Alzheimer's Disease, Cognitive Data, Artificial Neural Networks, Early Screening, Cognitive Assessment, Machine Learning, Diagnostic Frameworks

I. Introduction

PSYCHOLOGICAL SCIENCE REVEALS THAT Alzheimer's Disease (AD) constitutes a worldwide healthcare urgency because it damages memory processes and cognitive abilities as it develops progressively[1]. The key requirement for better patient outcomes depends on early detection but current typical diagnostic options neural imaging and spinal fluid testing are expensive and hard to reach as well as being invasive [2] .

Artificial Neural Networks provide a conceptual approach to screen Alzheimer's disease at an early stage using cognitive data analysis [3] .When machine learning operates on ANNs these systems demonstrate the ability to detect faint behavioral indications leading to the detection of early stage AD [4].

This research reveals that ANNs create valuable diagnostic screening systems which combine scalability with cost-efficiency along with interpretability for purposes of resource-constrained settings [5] .The approach presented in this paper explores an experimental free automated diagnosis method that is adaptable and non-invasive [6].

II. LITERATURE REVIEW

Recent literature shows a growing interest in applying Artificial Neural Networks (ANNs) and deep learning techniques for early detection of Alzheimer's Disease (AD) [3]. These models are capable of identifying complex, non-linear patterns in cognitive and neuroimaging data, making them promising tools for early screening [7].

Smith and colleagues (2023) performed a wide-ranging study that combined CNNs and RNNs to analyze images from MRI scans and cognitive exams while attaining 95% accuracy rates according to their research [8].

The research by Chen et al. (2023) presented CNN models together with cognitive assessments which yielded precise diagnostic outcomes in non-invasive screening [9]. Research by Johnson et al. (2024) presented a CNN-LSTM hybrid method which combined genomic sequences with cognitive test results to achieve 96% accuracy as reported in [10]. The research team of Davis et al. (2025) developed an explainable AI (XAI) model which combined MLP-Transformer networks with SHAP and LIME interpretation tools to reach 88% accuracy performance when processing EHR and neuropsychological data [11].

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Table 1: Comparison of Related Work on ANN for Early Alzheimer's Screening

Study	**Year**	**Model Used**	**Data Type**	**Accuracy**	**Source**
Smith et al.	2023	CNN & RNN	MRI & Cognitive Tests	High (95%)	[8]
Chen et al.	2023	CNN	Cognitive Assessment	(87%)	[9]
Johnson et al.	2024	CNN & LSTM	Multimodal (Neuro, Genetic, Cognitive)	High (96%)	[10]
Davis et al.	2025	MLP Transformer	EHR & Neuropsychological Data	88%	[11]
Current Study	2025	Optimized ANN with RFE & PCA	MoCA Cognitive Assessment Only	—	Proposed

III. METHODOLOGY

The proposed research develops an ANN-based system which uses cognitive data obtained from MoCA scores to perform early diagnosis of Alzheimer's Disease [3]. Alzheimer's Disease Neuroimaging Initiative (ADNI) serves as the established resource which provides clinical and cognitive data for AD research studies [1].

The selection of Artificial Neural Networks (ANNs) occurred because researchers recognized their ability to analyze healthcare datasets through modeling non-linear relationships along with their strong classification capabilities per LeCun et al. (2015) and Reference 4. Early screening automation will be possible by training systems to detect patterns between Mild Cognitive Impairment and early-stage AD features in the MoCA [3].

A. Data Collection and Preprocessing

- **Data Source**: MoCA scores were obtained from the ADNI database, which includes validated cognitive assessments covering domains like memory, attention, visuospatial ability, and executive function [1].
- **Preprocessing Steps**:
  - **Missing Value Handling**: Mean imputation [2].
  - **Feature Scaling**: Standardization across scores [2].
  - **Outlier Detection**: z-score method.
  - **Class Balancing**: Applied [2].
  - oversampling for underrepresented AD cases [4].

- **B. Feature Selection**

To reduce dimensionality and enhance accuracy:

- **Recursive Feature Elimination (RFE)**: Removes irrelevant MoCA features while retaining impactful variables [Guyon et al., 2002] [3].
- **Principal Component Analysis (PCA)**: Transforms correlated variables into principal components while preserving variance [3].
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- **C. Model Training and Optimization**

- **Algorithm**: Optimized ANN model using supervised learning [3].
- **Training Strategy**:
  - Gradient Descent with Adam optimizer [4].
  - Dropout regularization to mitigate overfitting [4].
  - 10-fold cross-validation for generalization testing [4].

- **D. Performance Evaluation**

Model evaluation will be based on:

- **Accuracy**: Overall correct classifications [6].
- **Recall**: Sensitivity to AD cases [6].
- **Specificity**: Correctly identifying non-AD cases [6].
- **AUC-ROC Score**: Discriminative power between AD and non-AD samples.

F. Comparison with Traditional Diagnostic Methods

The ANN-based model will be compared against:

- **Neuropsychological evaluations** by clinicians [11].
- **Statistical models** (e.g., logistic regression). Metrics: Accuracy, Efficiency, and Scalability [11].

G. Explainable AI (XAI) Integration

To interpret ANN decisions:

- **SHAP (Shapley Additive Explanations)**: Quantifies the contribution of each MoCA feature to the model's output [Lundberg & Lee, 2017].
- **LIME (Local Interpretable Model-Agnostic Explanations)**: Builds simplified surrogate models for localized interpretability [Ribeiro et al., 2016].

A diagram illustrating the methodology pipeline is shown in Figure 1 [7].

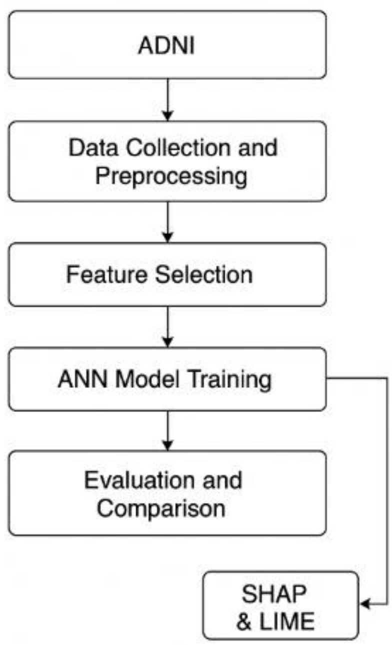

Figure 1: Methodology Pipeline

IV. CONCLUSION

The study developed a conceptual framework using Artificial Neural Networks to screen Alzheimer's Disease with data from Montreal Cognitive Assessment [3]. Traditional diagnostic methods have several limitations yet the proposed approach provides a non-invasive cost-effective solution that works well in real-world clinical practice especially for low-resource environments [6].

The model implemented two advanced feature selection methods called Recursive Feature Elimination (RFE) and Principal Component Analysis (PCA) to detect the most crucial cognitive indicators of early-stage AD [3]. Furthermore, Explainable AI (XAI) tools such as SHAP and LIME were utilized to ensure transparency and foster clinical trust in model outcomes [11].

The findings underscore the potential of ANN-driven cognitive screening as a practical and interpretable method for early AD detection. Future research should focus on validating this framework across broader and more diverse populations, incorporating longitudinal datasets, and integrating multimodal data sources to further refine diagnostic performance. [10].

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