Republic of Iraq
Ministry of Higher Education
and Scientific Research
University of Diyala
College of Science
Computer Science Department

An EEG-Based Machine Learning Approach for Early Detection of Alzheimer’s Disease in Iraq

A Dissertation Submitted to the
University of Diyala / College of Science / Department of Computer Science, in partial Fulfillment of the Requirements for the Degree of Doctor of Philosophy in Computer Science

By

Nigar M. Shafiq Surameery

Supervised by

Prof. Dr. Abdulbasit Kadhim Shakur Alazzawi

2025 A.D. Diyala 1447 A.H.

ABSTRACT

Alzheimer's disease (AD) presents one of the most significant challenges in neuroscience due to its progressive effects on memory and cognition, coupled with the urgent global need for accurate early diagnosis. While there have been advances in medical imaging and clinical tests, non-invasive and cost-effective methods for detecting AD remain underexplored. Electroencephalogram (EEG) signals offer a promising avenue, but their complexity and sensitivity to noise have hindered widespread adoption.

This dissertation addresses the challenge of developing reliable EEG-based diagnostic tools for AD by focusing on robust classification across different stages of the disease. The project introduces a Hybrid Transformer deep learning (DL) model, which integrates temporal and spatial features from EEG data to enhance accuracy and interpretability compared to conventional machine learning (ML) and recurrent or convolutional architectures.

A locally collected EEG dataset from 40 individuals, including healthy controls and patients at Mild, Moderate, and Severe stages of AD, was recorded using the international 10–20 system, marking the first dataset of its kind in Iraq. Results indicate that the proposed Hybrid Transformer model outperformed baseline models, achieving an accuracy of 93.7%, along with consistently high precision, recall, and F1 scores across different stages. These findings highlight the model's potential as a practical, non-invasive tool for supporting the clinical diagnosis of AD.

This dissertation makes several key contributions: it presents the first EEG dataset for AD diagnosis in Iraq, identifies EEG patterns that characterize disease progression, applies advanced signal processing to improve data quality, emphasizes model interpretability for clinical adoption, and introduces the Hybrid Transformer model as the most effective method for early stage AD detection.

Chapter One

General Introduction and Literature Review

Chapter One

General Introduction and Literature Review

1.1 Overview and Motivation

Dementia is a syndrome characterized by a progressive decline in cognitive abilities that interferes with daily activities, impacting memory, thinking, and behavior. It has significant health, social, and economic consequences worldwide, ranking as the seventh leading cause of death and a major contributor to disability among the elderly. Currently, over 57 million people live with dementia globally, with approximately 10 million new cases diagnosed each year. The prevalence of dementia is expected to rise sharply as populations age. More than 60% of individuals with dementia reside in low- and middle-income countries, and the economic burden of dementia reached $1.3 trillion in 2019. Informal caregivers, mostly women, provide the majority of care in these settings. [1].

AD is the most common form of dementia, accounting for 60–70% of dementia cases worldwide. The growing burden of AD presents urgent challenges for healthcare systems and families, particularly in low- and middle-income countries such as Iraq. [2]

Early and accurate diagnosis of AD is crucial to improving treatment outcomes, enabling timely interventions, and supporting informed decision-making for patients and their caregivers. However, diagnosis is often challenging, especially during the mild cognitive impairment (MCI) stage, when interventions are most effective. Many cases go underdiagnosed or misdiagnosed, highlighting the need for more accessible diagnostic tools. [3]

Currently, several techniques are employed for diagnosing AD, including Magnetic Resonance Imaging (MRI), Computed Tomography (CT), and Positron Emission Tomography (PET). While these neuroimaging methods provide valuable structural and functional insights, they are costly, time-consuming, and not feasible for routine or large-scale screening. Additional methods, such as cerebrospinal fluid (CSF) analysis and genetic testing, can provide diagnostic information but come with challenges related to invasiveness, cost, and ethical considerations. These limitations are particularly pronounced in developing countries, where access to advanced medical infrastructure is often limited. [4]

EEG presents a promising alternative for AD diagnosis. It is low cost, non-invasive, portable, and widely available, with the added benefit of high temporal resolution. Research has shown that abnormalities in EEG frequency bands can indicate the presence of AD and MCI, which positions EEG as a potential early biomarker for the disease. However, EEG data can often be noisy and susceptible to variability caused by muscle movement, fatigue, or medication. This variability necessitates advanced signal processing techniques, along with robust ML or DL methods, to extract clinically meaningful patterns from the data. [5].

This dissertation is motivated by the urgent need for practical, affordable, and reliable diagnostic methods for AD in resource limited settings. It aims to enhance AD diagnosis using EEG data by developing advanced ML and DL models capable of classifying various stages of the disease while improving interpretability for clinical adoption. A major contribution of this work is the creation of the first locally collected EEG dataset for AD in Iraq, recorded from healthy controls and patients across mild, moderate, and severe stages, using the internationally recognized 10–20 system. Rigorous preprocessing techniques, including noise reduction and artifact removal, were applied to ensure data quality.

By combining this novel dataset with state of the art models, including a proposed Hybrid Transformer architecture, the dissertation advances EEG-based diagnosis as a scalable, interpretable, and cost effective tool. This research addresses current gaps in both data availability and model performance, with the ultimate goal of improving early detection and care for individuals affected by AD.

1.2 Related works

Numerous studies have explored the classification of AD using ML / DL techniques. Below is a summary of key works in this area:

Rad et al. [6] (2021) introduced a novel method for diagnosing AD in patients at mild stages. They analyzed three-channel EEG signals recorded from the Pz, Cz, and Fz locations under four different conditions: closed eyes, open eyes, recall, and stimulation. Various features were extracted from the preprocessed EEG signals, revealing that stimulation affects both the amplitude and latency of the P300 component related to age and stages of AD. In patients with mild AD, the initial changes observed in brain signals included increased theta band activity, decreased beta band activity, and reduced alpha band activity. Subsequently, feature selection approach were applied to the subjects for classification using Linear Discriminant Analysis (LDA), Elman Neural Networks (ENN), and CNN. Among the extracted features, two of the most discriminative variables were the Pz channel and the stimulation condition. The overall classification accuracy achieved with LDA was 59.4% for the recall mode and 66.4% for the stimulation mode. For the ENN, the accuracy reached 92.3% and 94.1% in the same modes, while CNN demonstrated remarkable performance, achieving a recall of 97.5% and an accuracy of 99% during stimulation. The study highlighted that appropriate feature selection of both linear and nonlinear features can significantly improve classification performance, with CNN outperforming both LDA and ENN due to its enhanced ability to represent the dynamics of brain signals.

Amini et al. [7] (2021) presented a method for the early diagnosis of AD using EEG signals, which can help in identifying biomarkers related to early symptoms. Their analysis utilized time dependent power spectrum descriptors to examine EEG data from three groups: patients with MCI, Alzheimer's patients, and healthy individuals. They applied various traditional classification algorithms, including K-Nearest Neighbors (KNN), Support Vector Machine (SVM), and LDA, all of which yielded results. Notably, they proposed a CNN architecture for classifying Alzheimer's patients, achieving an accuracy of 82.3%. This model proved to be particularly effective, detecting 85% of MCI cases and diagnosing 89.1% of Alzheimer’s cases, while correctly classifying 75% of healthy individuals. The CNN outperformed the other classification methods, with KNN being the second-best approach. In contrast, LDA and SVM resulted in relatively lower area under the curve values.

Araújo et al. [8] (2022) proposed a system for classifying the stages of AD using EEG signals. This study focused on three stages of AD: MCI, Mild to Moderate AD (ADM), and Advanced AD (ADA). The researchers also included healthy controls (C) for comparison. To analyze the EEG data, nonlinear multi-band analyses were performed using Wavelet Packet decomposition, from which various features were extracted for each group. The classifications were carried out using both ML and DL techniques. The classification results yielded the following accuracies: 78.9% for C versus MCI, 81.0% for C versus ADM, 84.2% for C versus ADA, 88.9% for MCI versus ADM, 93.8% for MCI versus ADA, and 77.8% for ADM versus ADA. The overall classification accuracy for distinguishing all groups was 56.8%. Notably, this approach achieved a 2% improvement over previously reported techniques for differentiating MCI from ADM, indicating an increase in the abnormality of central and parietal brain regions as AD progresses.

Alessandrini et al. [9] (2022) proposed an EEG-based approach for diagnosing neurodegenerative diseases, including AD, using ML methods. They emphasized the advantages of ML over traditional manual diagnostic techniques, highlighting improved reliability and accuracy in recognizing patterns within large datasets. However, they also acknowledged the challenges that arise when the accuracy decreases due to incomplete or compromised data, necessitating the use of effective preprocessing methods. To address this issue, the authors developed an automated classification method utilizing a Recurrent Neural Network (RNN) capable of processing EEG data affected by artifacts. The RNN is first trained on EEG data that has undergone conventional Principal Component Analysis (PCA) processing. It is then tested with corrupted data that has been filtered using Robust PCA (RPCA). The results demonstrated that even with up to 20% of the data missing, RPCA improved detection accuracy by around 5% compared to the baseline established by PCA. With optimal hyperparameters, the RNN achieved an accuracy of over 97% on the test data. The algorithms proposed in this study have the potential for a wide range of applications, including the classification of various neurodegenerative disorders and assessing the contributions of different brain regions to these conditions.

Komolovaite et al. [10] (2022) proposed a deep CNN approach for classifying visual stimuli using EEG signals collected from healthy subjects and patients with AD. Their method utilizes several CNN models, including *EEGNet*, *EEGNet SSVEP*, and *DeepConvNet*, all of which are designed to learn discriminative features from raw EEG data. To address the issue of limited EEG sample sizes, the researchers employed techniques such as Generative Adversarial Networks (GAN) and Variational Autoencoders to generate synthetic EEG signals for model pretraining. The best validation performance achieved in classifying emotional and facial inversion stimuli was 50.2% with the pre-trained *EEGNet SSVEP* model. However, the accuracy for the oldest subject in the control group was only 32.75%, while for Alzheimer's patients, it was 24.41%. This indicates poor generalization capabilities with a notable accuracy gap of 17.5%. The model struggled to differentiate between cognitive and emotional features; for familiarity stimuli, the validity accuracies were 43.25% and 30.23% in the control group, while for Alzheimer's patients, it was merely 27.72%. Analysis revealed that the model performed best in classifying both upright and inverted stimuli, suggesting it could effectively learn the face-inversion effect. Additionally, extending the *EEGNet SSVEP* model with L1 and L2 regularizations resulted in an average training performance improvement of 1%. However, the influence of pre-trained weights derived from the synthesized data was negligible.

Fouladi et al. [11] (2022) introduced two distinct DL architectures designed to classify individuals with AD, Mild MCI, and healthy control (HC) subjects, utilizing scalp EEG recordings. This study employed a modified CNN alongside a Convolutional Autoencoder (Conv-AE) for the classification process. To extract features from the EEG signals, the researchers used a time-frequency representation achieved through Continuous Wavelet Transform (CWT), specifically employing the Mexican hat function as the mother wavelet. The adapted CNN achieved an average accuracy of 92%, while the Conv-AE network reached an accuracy of 89%. Overall, the two proposed DL architectures demonstrated a 10% improvement in classification performance compared to similar studies and significantly outperformed traditional ML techniques. The results underline the effectiveness of DL models in processing EEG data, particularly in addressing inaccuracies, inconsistencies, and missing information, thereby providing significant advancements in the diagnosis of AD.

Latsiou et al. [12] (2022) proposed a novel method for diagnosing AD and MCI using EEG signals processed by Time Delay Neural Networks (TDNNs). The study aimed to classify patients into three categories: Healthy, MCI, and AD. The dataset consisted of 54 participants, with 18 individuals in each category. The data were pre-processed using filtering and Fast Fourier Transform (FFT) techniques. The TDNN model was trained using two approaches: "by segment," where the data were divided into 2-second segments, and "by sample," where each patient's data formed a single input. The TDNN model achieved an accuracy of up to 99% in some experiments, representing an innovative approach to classifying EEG data for cognitive impairment and Alzheimer's detection. This research highlights the effectiveness of EEG-based medical diagnosis, particularly in the context of cognitive disorders, where high accuracy is essential for early diagnosis and intervention.

Miltiadous et al. [13] (2023) proposed a new architecture called the data network, which utilizes a convolution transformer for detecting AD using EEG signals. This architecture combines Recurrent Back Propagation (RBP) and a Spatial Consistency Constraint (SCC) to process the EEG data through two parallel layers: one for convolution and another for transformer encoding. Compared to several state of the art algorithms, this model showed impressive performance in classifying AD patients versus healthy controls, achieving an accuracy of 83.28% using the Leave One Subject Out (LOSO) method. This approach is significant as it effectively captures both spectral and temporal relationships, leading to substantial improvements in the diagnosis of AD using EEG signals.

Sibilano et al. [14] (2023) proposed a DL approach based on attention mechanisms to investigate Subjective Cognitive Decline (SCD) in individuals with MCI using resting state EEG signals. This approach leverages the self-attention component of the transformer architecture, enhancing the physiological interpretability of the model's decisions. The study employed a LOSO cross validation scheme using 10-second epochs of EEG data. Results demonstrated that the best performance was achieved using the delta and theta frequency bands. The transformer model achieved a classification accuracy of 67.4% on epochs and 76.2% on patient-level classification when analyzing delta band data. This study contributes not only by introducing a new transformer based method for the early diagnosis of cognitive impairments but also by highlighting the significance of specific EEG rhythms, such as delta and theta, in differentiating SCD from MCI.

Chen et al.[15] (2023), proposed a novel hybrid approach for diagnosing AD using EEG signals. This method combines CNN with Visual Transformers (ViT) to leverage the strengths of both architectures for feature extraction from complex and noisy EEG data. Their proposed Dual Branch Feature Fusion Network (DBN) employs CNNs to extract texture features and ViTs to model global semantic information. Additionally, Spatial Attention (SA) and Channel Attention (CA) blocks are incorporated to enhance the model's ability to identify abnormal patterns in EEG signals. The approach achieved an accuracy of 80.23% in classifying three categories: AD, Frontotemporal Dementia (FTD), and Normal Control (NC) subjects.

Khare and Acharya [16] (2023) proposed a new framework called *Adazd-Net* for the automated detection of AD using EEG signals. Given that EEG data are spontaneous and can change rapidly, the authors developed an adaptive, flexible analytic wavelet transform that adjusts according to variations in the EEG signals. Their research focused on finding the optimal number of features for accurate detection and identifying the most discriminative EEG channels. A key aspect of this work is explainability, which involves techniques for clarifying both individual predictions and the overall predictions made by the classifier model. The results demonstrated that the proposed method achieves an impressive accuracy of up to 99.85% in detecting AD, utilizing a ten fold cross validation strategy. Consequently, the *Adazd-Net* model appears to be highly accurate and robust for clinical applications, enabling clinicians to confidently and reliably detect AD while also facilitating further investigation into the neurological changes associated with the disease.

Khosravi et al. [17] (2023) proposed the Attention Time Aware Long Short Term Memory (ATLSTM) model for the classification of AD using EEG data. This study applies windowing techniques to non-stationary EEG signals and employs the ATLSTM model to enhance deep feature representation in the classification process. The model is designed to classify three types of AD by integrating EEG signals into a novel deep learning structure. The proposed approach was tested on a publicly available dataset from *Figshare*, which includes individuals with AD, MCI, and a control group. The ATLSTM model achieved an impressive accuracy rate of 95.23%, making it one of the most accurate methods for forecasting AD. Additionally, this approach facilitates the identification of both MCI and AD, addressing some limitations of previous systems that could only detect two classes. Various evaluation metrics, including the accuracy, sensitivity, specificity, and F1 score, demonstrated that the model is effective and can serve as a supportive tool in the diagnosis of AD.

Kumar and Saravanan [18] (2023), proposed a DL strategy for AD detection based on EEG signal analysis. They utilized EEG signals from online databases, which were decomposed into several wavelets using a 3-level Lifting Wavelet Transform (LWT). Temporal features were extracted using RNN, while spatial features were gathered from a multi-scale dilated CNN. The combined features were weighted based on optimal values determined through the Enhanced Wild Geese Lemurs Optimizer (EWGLO) algorithm. The final AD detection was performed using an Optimized Transformer based Attention Long Short Term Memory (LSTM) model, with further parameter optimization conducted via EWGLO. This proposed model achieved an accuracy of 96% and a Matthews Correlation Coefficient (MCC) of 98%, demonstrating superior performance compared to other state-of-the-art methods for AD detection.

Xia et al. [19] (2023) proposed a novel approach for diagnosing AD by classifying resting-state EEG data from subjects with AD, MCI, and HC. To address challenges related to a small dataset and overfitting, one-dimensional EEG data from 100 subjects (49 with AD, 37 with MCI, and 14 HC) were augmented using overlapping sliding windows. Classification was performed using a modified Deep Convolutional Neural Network (DPCNN). The model's performance was evaluated through 5-fold cross-validation, repeated five times. For the three class classification, the model achieved a mean accuracy of 97.10% and a mean F1 score of 97.11%. These results provide strong evidence that the DPCNN model is effective in classifying EEG data for the accurate detection of AD.

Hong et al. [20] (2023) proposed a low-cost quantitative EEG-based diagnostic method for Alzheimer's Disease Dementia (ADD) using a comprehensive set of quantitative EEG features. In this study, EEG data from 594 non-ADD (NADD) subjects and 137 ADD participants were analyzed after preparing artifact-free data through Independent Component Analysis (ICA) and the rejection of problematic epochs. Absolute and relative power spectra were calculated at the channel level, while source level power spectra were obtained using low resolution standard cerebral electromagnetic tomography. These features, along with the brain's functional networks, served as the foundation for deep neural architectures and a tree-based ML algorithm. The deep neural networks (DNN) achieved a classification accuracy of 85.3% for absolute power spectra and 86.5% for relative power spectra. Meanwhile, the tree model based on source-level features reached an accuracy of 87.7%. A combined model that integrated predictions from the previous two methods demonstrated an accuracy of 88.5%. These results highlight the potential of EEG-based AI models to enhance diagnostic procedures for neurodegenerative diseases by utilizing various independent EEG features.

Tawhid et al. [21] (2023) proposed a new strategy for detecting MCI through the analysis of frequency sub-bands based on the characteristics of EEG signals. Their approach involved pre-processing the signals to reduce noise, followed by segmentation into different frames. Sub-band extraction was performed in addition to analyzing the complete frequency range. CNNs were employed for classification. The proposed methodology demonstrated impressive accuracy, achieving an overall classification rate of 99.03% for dataset 1 and 100% for both versions of dataset 2. In terms of specific sub-bands, the beta band reached an accuracy of 97.04% for dataset 1, while in the balanced dataset 2, the alpha and delta bands achieved high classification accuracy rates of 88.90% and 85.09%, and 99.74% and 100%, respectively. Overall, the full frequency band outperformed the sub-bands in terms of precision and sensitivity, indicating that this method was highly effective in detecting MCI.

Alvi et al. [4] (2023) proposed a new DL approach to detect AD and MCI using EEG data. The study utilizes LSTM networks and Gated Recurrent Units (GRU) to process the sequential and non-stationary nature of EEG signals. The preprocessing pipeline included noise removal and adaptive filtering techniques to ensure high quality data for classification. The GRU model achieved an impressive accuracy of 96.91%, with a sensitivity of 97.95%, specificity of 96.16%, and an F1 score of 96.39%. These results demonstrate the potential of DL models to provide accurate and computationally efficient solutions for EEG-based MCI detection. The study also introduced the structure of the Deep Recurrent Attention Model (DRAM), which achieved a classification accuracy of 96.66% for healthy volunteers, 98.06% for MCI, and 97.79% for AD, surpassing traditional ML methods. This work underscores the promise of EEG-based AI models in diagnosing neurodegenerative diseases, emphasizing the classification of different patient groups and computational efficiency.

Bravo-ortiz et al. [22] (2024) proposed a method called *Spectro CVT-NET* for classifying AD using EEG signals. These signals are pre-processed with Short-Time Fourier Transform to produce a spectrogram. The study utilizes the *Brainlat* database and introduces a convolutional vision transformer embedding architecture that employs channel attention mechanisms to capture both local and global dependencies within the generated spectrograms. The architecture consists of two parts: feature extraction and classification, which are integrated with the CVT module. This module combines local feature extraction with attention heads that analyze the global context. *Spectro CVT-NET* achieves a remarkable accuracy of 92.59 ± 2.3% in classifying AD, healthy individuals, and behavioral variant frontotemporal dementia (bvFTD), outperforming traditional methods in transfer learning. Additionally, *Grad-CAM* analysis has been conducted to identify which layers and frequencies contribute most significantly to the classification. Adopting this method will enhance the model's interpretability and may provide valuable insights for clinical diagnosis and management.

Sibilano et al. [23] (2024) proposed a method for distinguishing between Subjective Cognitive Decline (SCD) and MCI using resting state EEG signals. Their study employed the self-attention component of the Transformer network, providing physiological interpretability for the decisions made by the model. Validation was carried out using a 5-fold cross validation scheme, and the optimal configuration was determined through extensive hyperparameter tuning. In this approach, EEG epochs were classified with an accuracy of 65.4%, while a hard voting method at the patient level achieved an accuracy of 65.7%. This research not only presents a Transformer based model for identifying cognitive impairment but also introduces an interpretability workflow that helps experts better understand the discriminative features utilized by the model.

Wang et al.[24] (2024) proposed a new Transformer based approach for classifying AD using EEG signals, called *ADformer*. Their method emphasizes the extraction of multi granularity temporal and spatial features from EEG time series. The approach combines self-attention mechanisms with patch and channel embedding techniques to effectively capture information at different granularities. They achieved an F1-score of 75.19% with a total of 65 subjects, which increased to 93.58% in an extended version involving 126 subjects. As a result, this method outperformed existing CNN based approaches and ML techniques, demonstrating the potential of Transformers in diagnosing AD through EEG. Furthermore, the study highlighted the advantage of using a subject independent configuration, which enhances the practical relevance of their methodology and integrates essential information, such as accuracy metrics, in the required format.

Vimbi et al. [25] (2024) conducted a systematic review of studies focused on the implementation of explainable AI techniques for the detection of AD. This review highlighted how Local Interpretable Model-Agnostic Explanations (LIME) and SHapley Additive exPlanations (SHAP) can improve the interpretability of ML models in a clinical context. The findings indicate that while traditional ML approaches, such as RF, are effective in detecting AD from EEG and other neuroimaging data, there remains a significant need for models that provide explanations of their decisions. This is particularly important for clinicians. LIME and SHAP were integrated into this context to offer deeper insights into model predictions by identifying the features that most significantly influence diagnoses. The paper also notes that many models achieve high classification accuracy for AD detection but are not adopted in clinical settings due to their "black-box" nature. The study concludes that explainable AI models hold promise for real-world AD detection, helping to bridge the gap between model performance and trust in clinical applications.

He et al.[26] (2024) proposed a new set of methods that employ neural oscillation state space modeling to evaluate AD neuropathology using sleep EEG. Their work addresses the challenges of EEG analysis in patients with AD, enhancing the interpretation of signals and improving the detection of disrupted neural activity. They introduced a probabilistic approach to identify sleep spindles and slow oscillations, which are key neural characteristics altered in AD. Their study demonstrated that sleep EEG could provide early insights into AD by identifying biomarkers that indicate the preclinical stages of the disease. The application of these state space models enabled more accurate temporal and spatial analyses of neural activity, advancing the potential for non-invasive, individualized assessments of neural changes related to AD. This research has significant implications for early diagnosis, offering a new tool for detecting alterations in neural integrity associated with AD pathology before clinical symptoms appear.

To enable a clearer comparison of recent studies on AD detection using EEG signals, Table (1.1) summarizes the methodologies, focus areas, accuracy performance, and notable features of various research works, including those that employ DL and ML techniques.

Table (1.1): Comparison of studies on AD detection using EEG signals

Ref.	Paper	Methodology	Focus	Accuracy/Performance	Notable Features
[6]	Rad et al. (2021)	LDA, Elman NN, CNN	Mild AD detection, P300 component analysis	99% (CNN, stimulation mode), 97.5% (CNN, recall mode), mode), 92.3% (Elman NN), 66.4% (LDA, stimulation	Theta, beta, alpha band analysis, channel Pz
[7]	Amini et al. (2021)	CNN, KNN, SVM, LDA	Early-stage AD, MCI detection	82.3% (CNN), 85% (MCI), 89.1% (AD), 75% (Healthy controls)	Time-dependent power spectrum descriptors
[8]	Araújo et al. (2022)	Wavelet Packet decomposition, ML and DL	Classifying AD stages (C vs MCI, C vs ADM, C vs ADA, MCI vs ADM, MCI vs ADA, ADM vs ADA)	78.9% (C vs MCI), 81.0% (C vs ADM), 84.2% (C vs ADA), 88.9% (MCI vs ADM), 93.8% (MCI vs ADA), 77.8% (ADM vs ADA), 56.8% (All vs All)	Wavelet-based multi-band EEG analysis
[9]	Alessandrini et al. (2022)	RNN, PCA, RPCA	Neurodegenerative pathologies, artifact handling in EEG	97% (RNN on test data)	Handling of corrupted data, RNN with PCA and RPCA
[10]	Komolovaite et al. (2022)	CNN models, GAN, VAE	Stimulus classification in AD patients	50.2% (EEGNet SSVEP, best validation performance)	Generative models for EEG data augmentation
[11]	Fouladi et al. (2022)	CNN, Conv-AE, Continuous Wavelet Transform	MCI, AD, HC classification	92% (CNN), 89% (Conv-AE)	Wavelet transform-based feature extraction

[12]	Latsiou et al. (2022)	Time Delay Neural Networks (TDNN)	AD, MCI, HC classification	99% (TDNN, segment method)	Time-frequency representation with continuous wavelet transform
[13]	Miltiadous et al. (2023)	Convolution-transformer, RBP, SCC	AD detection	83.28% (CNN-Transformer, LOSO)	Convolution-Transformer hybrid architecture
[14]	Sibilano et al. (2023)	Attention-based DL with Transformer	SCD vs MCI detection	67.4% (epoch-level classification), 76.2% (Patient-level classification)	Self-attention mechanism
[15]	Chen et al. (2023)	CNN with Visual Transformers, Spatial and Channel Attention	AD, FTD, NC classification	80.23% (CNN+ViT)	Fusion of CNN and ViTs for feature extraction
[16]	Khare and Acharya (2023)	Adaptive flexible wavelet transform, Explainability	Wavelet transform and CNN for AD detection	99.85% (Adazd-Net)	Adaptive filtering, explainability
[17]	Khosravi et al. (2023)	Attention-time-aware LSTM (ATLSTM)	MCI, AD classification	95.23% (ATLSTM)	Windowing for non-stationary EEG signals
[18]	Kumar and Saravanan (2023)	RNN, CNN, Transformer-based attention LSTM	EEG signal analysis with CNN, RNN, LSTM	96% (Transformer-based attention LSTM)	Feature extraction and classification using ATLSTM
[19]	Xia et al. (2023)	Lifting Wavelet Transform, RNN, CNN	EEG feature extraction, multi-class classification	97.10% (mean accuracy), 97.11% (F1 score)	Decomposition of EEG data with Lifting Wavelet Transform, DPCNN, sliding windows for small dataset and overfitting
[20]	Hong et al. (2023)	Low-cost quantitative EEG-based diagnosis, ICA, bad epoch rejection, DNN, tree-based machine learning	EEG features for ADD and cognitive disorders	85.3% (Absolute power spectra), 86.5% (Relative power spectra), 87.7% (Source-level tree model), 88.5% (Ensemble model)	ICA and bad epoch rejection, power spectra at channel and source levels, DNN, tree-based model, ensemble model
[21]	Tawhid et al. (2023)	CNN, frequency sub-band analysis	MCI detection using frequency sub-bands	99.03% (Dataset 1), 100% (Dataset 2, both versions) for full band; Beta band: 97.04% (Dataset 1), 100% (Dataset 2, unbalanced); Theta band: 92.58% (Dataset 1), 100% (Dataset 2); Alpha and Delta bands: 88.90% and 85.09% (Dataset 1), 99.74% and 100% (Dataset 2)	High classification accuracy for sub-bands using CNN
[4]	Alvi et al. (2023)	LSTM, GRU, noise removal, adaptive filtering	AD and MCI detection using EEG data	96.91% (GRU), sensitivity: 97.95%, specificity: 96.16%, F1 score: 96.39%; DRAM-Net: HV: 96.66%, MCI: 98.06%, AD: 97.79%	Multi-class classification using LSTM, GRU, and DRAM-Net framework
[22]	Bravo-Ortiz et al. (2024)	SpectroCVT-Net (STFT, CVT with channel attention)	Classifying AD, Healthy Controls, bvFTD	92.59% ± 2.3% (Transfer learning accuracy)	CVT architecture, Grad-CAM analysis, increased interpretability

[23]	Sibilano et al. (2024)	Transformer-based model with self-attention	Distinguishing SCD from MCI	65.4% (Epoch-level), 65.7% (Patient-level)	Self-attention mechanism, interpretability in decision-making
[24]	Wang et al. (2024)	Attention mechanism and cross-validation	AD classification with temporal and spatial EEG features	93.58% (Extended version)	Attention mechanism and cross-validation
[25]	Vimbi et al. (2024)	Explainable AI	Explainability in AD detection using AI	Not explicitly provided; focused on explainable models	LIME, SHAP, explainable AI models
[26]	He et al. (2024)	State-space modeling of neural oscillations in sleep EEG	Detecting AD neuropathology via sleep EEG, focusing on sleep spindles and slow-wave activity	Not explicitly provided; focused on model development and application	Early biomarkers for AD using sleep EEG analysis

1.3 Problem Statement

AD poses a growing global health challenge, and early detection is crucial for improving patient outcomes. Although advanced techniques like MRI and PET scans are available, they are often costly, time consuming, and not easily accessible in low and middle income countries such as Iraq. EEG is a widely accessible and non-invasive diagnostic tool with significant potential for early diagnosis. However, its use remains underutilized in clinical practice. This dissertation addresses this important gap by developing an EEG based diagnostic framework specifically designed for the early stage diagnosis of AD. This framework is supported by the first dataset collected locally from healthcare organizations in Iraq.

1.4 Aim and Objectives

The aim of this dissertation is to enhance automated EEG analysis techniques by developing a reliable and interpretable diagnostic tool capable of distinguishing healthy individuals from patients at various stages of AD. Early detection is crucial because brain degeneration often occurs before clinical symptoms manifest, and timely intervention can significantly slow the progression of the disease. This work also tackles the shortage of advanced diagnostic tools in Iraq by providing a non-invasive, scalable solution. A major contribution of this dissertation is the creation of the first locally collected EEG dataset, which includes healthy individuals and AD patients at different stages. This dataset will be used to train and evaluate the proposed models.

The specific objectives of this dissertation are:

1. To collect a comprehensive EEG dataset that includes healthy controls and patients at various stages of AD (mild, moderate, and severe) for effective model training and analysis.
2. To design an interpretable EEG-based model for AD detection, ensuring a balance between accuracy and interpretability for clinical use.
3. To apply preprocessing techniques to EEG signals, thereby improving data quality and identifying key features associated with AD.
4. To explore EEG-derived features as potential biomarkers for early-stage AD, assisting in timely diagnosis and treatment planning.
5. To develop an economical, clinically relevant model with the potential for scalable deployment in healthcare settings.

1.5 Contributions

This dissertation makes significant contributions to the advancement of AD diagnosis by:

1. Collected the first EEG dataset for AD diagnosis from Iraq, enhancing both local and global understanding of AD and providing valuable data for model training and disease progression research.
2. Identified the stages of disease progression in AD, which is crucial for early detection and intervention, improving patient outcomes and potentially delaying the advancement of the disease.
3. Applied advanced signal processing techniques to enhance EEG signal quality and feature extraction, ensuring better diagnostic

accuracy and effectiveness in distinguishing between healthy individuals and those with AD.

4. Emphasized the importance of model interpretability to facilitate clinical adoption and increase trust in AI-based diagnostic tools, making these systems more accessible and reliable for healthcare providers.
5. Developed and validated an innovative method for early-stage AD diagnosis using deep learning. Extensive evaluations identified the Hybrid Transformer as the most effective approach, improving both diagnostic precision and interpretability compared to existing methods.

These contributions are expected to enhance early diagnosis, reduce the burden of AD, and improve healthcare outcomes both locally in Iraq and globally.

1.6 Outlines of The Dissertation

This dissertation is organized into five chapters as follows:

Chapter One: General Introduction and Literature Review

This chapter introduces the background and motivation for the project, reviews related works, and states the research problem. It also presents the aim and objectives, highlights the main contributions, and outlines the overall structure of the dissertation.

Chapter Two: Theoretical Background

This chapter reviews the theoretical foundations of AD and its progression, as well as the basics of EEG signals. It also discusses data preprocessing techniques, ML and DL approaches, and evaluation metrics relevant to EEG-based AD diagnosis.

Chapter Three: Proposed System Implementation

This chapter describes the design and implementation of the proposed system. It covers data acquisition, preprocessing pipelines, feature extraction, data augmentation methods, and the classifiers employed for AD detection.

Chapter Four: Experimental Results and Evaluation

This chapter presents the experimental setup, including dataset description, preprocessing outcomes, and classification results. It compares the performance of different models, analyzes interpretability aspects, and evaluates the effectiveness of the proposed system.

Chapter Five: Conclusions and Future Work

This chapter summarizes the key findings of the research, draws conclusions from the results, and outlines potential directions for future work in EEG-based diagnosis of AD.