

Early detection of Alzheimer's disease: A comprehensive review of machine learning, EEG and multimodal approach

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ABSTRACT: Alzheimer's disease (AD) is a continuous increasing neurological disorder that is an important reason of dementia which is mostly in older adults. An early and accurate diagnosis of AD is necessary for timely detection and treatment. This survey review the techniques used in deep learning (DL) and machine learning (ML) for AD classification and detection. Mainly focused on brain network analysis to identify alterations in local and global connectivity and spectral and coherence investigations of EEG data to identify disturbances associated with AD, are two research strategies that have highlighted the mechanisms behind AD. Two examples of robust deep learning models that have achieved notable precision in identifying AD using neuroimaging datasets like MRI and EEG are conventional neural networks (CNNs) and ensemble learning. Using sleep EEG to detect mild cognitive impairment (MCI), research has demonstrated the utility of functional connectivity metrics. Furthermore, hybrid models that merge CNNs and ensemble learning have shown promise in both feature extraction and classification. Latest inventions, like gated graph convolutional networks (GGCN) for working with non-Euclidean data and transformer-based speech recognition models, have taken the explainable and multimodal diagnostic frameworks to the next level. This study review and gives summarize knowledge about techniques and methods used to detect Alzheimer, comparison of techniques used to detect and classify the unlabeled data, furthermore limitations of different work are discussed and give future search guide for new researchers.

Keywords: Electroencephalogram (EEG), mild cognitive impairment (MCI), and Alzheimer's disease (AD) Power Spectral Density (PSD)

1. Introduction:

Alzheimer's disease (AD) is continuously increasing neurological disorder that impacts behavior, memory, and cognition in an enormous ways [1]. The number of people diagnosed with AD is estimated to reach over 150 million globally by 2050 due to aging populations [2]. Increasingly prevalent in the aging global population, AD is not going to fade away any time soon. Consequently, the demand for accurate, early diagnoses has never been greater. AD cannot be cured. The best that can be hoped for is delaying the onset of some of the more severe symptoms.

According to Wang et al., when they used power spectral density (PSD) and coherence measures to analyze Alzheimer's EEG, they observed abnormalities in the inter-regional connectivity between the brains of AD patients [3]. Their research highlighted the loss of particular frequency bands (such as alpha and beta) as indicators of cognitive impairment and the significance of spectral properties in distinguishing AD from appropriate controls.

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S. Afshari and Jalili emphasized the importance of testing global and local connectivity in AD patients by using directed functional networks generated from EEG data as well as investigating global connectivity within the networks [4]. As a result of their study's notable abnormalities in directed network metrics, they have shown that there is a collapse in the structure of brain networks in Alzheimer's patients. In this study, we gained a better understanding of how directed information flows in the brain activity associated with AD.

As sleep disturbances are a major contributing factor to AD, EEG-based sleep staging is a promising diagnostic tool. K. et al., developed an effective EEG sleep stage classification model using preprocessing and machine learning techniques [5]. which set the stage for subsequent research aimed at diagnosing AD using sleep-related EEG features. Similarly, D. Geng et al., used a sleep EEG-based technique for detecting MCI, concentrating on neural patterns during sleep stages to distinguish MCI from healthy controls [6]

A.D'Atri et al. used integrated EEG-based methods to examine changes in oscillatory activity throughout several cognitive states (wake and sleep) in both MCI and AD patients, further examining EEG abnormalities during wakefulness and sleep [7]. Their results demonstrated how important it is to investigate dynamic EEG signals in different stages to make a reliable diagnosis of Alzheimer's. Recent developments in deep learning and machine learning have greatly expanded the diagnostic abilities of EEG analysis.. In order to evaluate Alzheimer's EEG data, D. Klepl et al., developed an adaptive gated graph convolutional network (AGGCN), which provides explanation for model predictions [8]. This graph-based approach showed how useful it is to record temporal and spatial data in neural networks for accurate and timely diagnosis of disease.

Different models have been included for AD evaluation with EEG signals. Zih-Jyun Lin et al., highlighted the improving function of speech data to enhance diagnostic frameworks for cognitive disorders that creates a dementia detection model that combines speech recognition and attention-based encoders [9]. In the meantime, Qin et al., offered transferable insights into EEG source analysis by expanding the use of directed brain network analysis to further applications, like tiredness detection [10]. Lastly, using functional connectivity metrics, H. Huang et al. investigated EEG-based sleep staging and showed how the characteristics of the EEG network during various sleep phases can help diagnose AD [11].

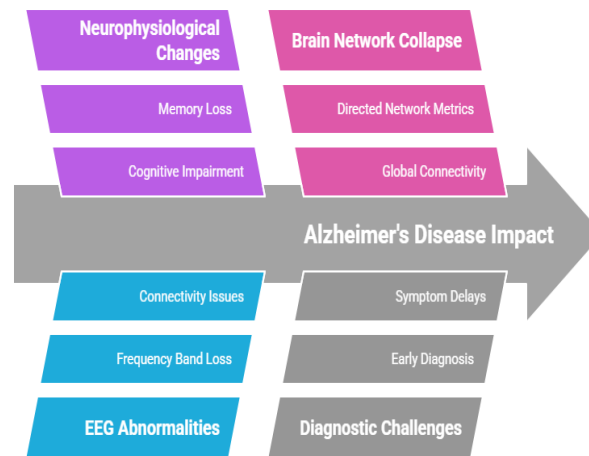


Fig 1: Understanding Alzheimer 's disease Complexity

2. Related work

In this survey we have done a brief literature review, and addressed analytical developments and their contributions to diagnose and detect Alzheimer's. This study summarizes important findings and suggests potential paths for employing EEG data in neuro-degenerative research by Focusing on different analytical methods from spectrum and connectivity analysis to highly effective machine learning models. The monitoring of EEG data is a transparent technique for identifying AD and associated cognitive problems. Researcher have concentrated on Power spectral density, functional connectivity, sleep-based diagnostics and highly efficient machine learning models are some of the aspects of EEG analysis. This section summarizes significant findings from current research, emphasizing on the techniques that are used in previous studies and their role played in the diagnosis of Alzheimer's disease.

2.1 Power Spectral Analysis and Coherence:

Previous research has used coherence analysis and PSD signals to find neuronal patterns that are uniquely associated to AD. When Wang et al. Studies the coherence and power spectral aspects of EEG data, they found that AD patients had a decrease in particular frequency bands, during sleep times, namely alpha and beta [3]. This study showed major differences in how different brain regions connect in people with Alzheimer's disease compared to healthy people brain. It proved that Power Spectral Density (PSD) and coherence are helpful tools for detecting Alzheimer's, as they can effectively differentiate patients from healthy people based on brain activity.

2.2 Functional Connectivity and Network Analysis:

Connectivity measures give useful observations into how brain networks are damaged in Alzheimer's disease (AD). Afshari and Jalili (2017), in their studies, used EEG recordings

to create directed functional networks and studied both local and overall brain connections in AD patients [4]. Their findings showed that the brain's information flow was troubling, which affect the network's structure. This approach helped us better understand how Alzheimer's affects brain activities and daily routine life. Similarly, Qin et al. explains that directed brain network analysis is flexible when using it on EEG source data for tasks like detecting fatigue [10].

2.3 Sleep-Based EEG Analysis:

Researchers have also explored how Alzheimer's disease (AD) is linked to sleep problems. Aboalayon et al. used EEG signals to create a machine learning system that could classify different sleep stages, and how this sleep pattern effect brain functions, starting important work in this area [3]. Later, Geng et al. found unique brain patterns during different sleep stages and used them to develop a method for detecting mild cognitive impairment (MCI) with sleep EEG data of healthy and unhealthy people [4]. D'Atri et al. went further by studying how EEG signals change during both sleep and wakefulness in people with AD and MCI, showing how these signals can describe cognitive issues [5] and leads to AD. All Together, these studies show that a sleep-related EEG analysis is important for AD research.

2.4 Machine Learning and Deep Learning Applications:

More reliable analysis of EEG signals is now possible because to recent developments in machine learning that classify these sleep signals into patterns. Klepl et al. in 2023 [6] presented an AGGCN for transparent Alzheimer's diagnosis utilizing EEG data. This approach provided clarity for predictions of Alzheimer while successfully capturing temporal and spatial aspects within neural networks. In addition, Lin et al. Promised the promise of multimodal techniques for early mild cognitive impairment diagnosis by proposing a speech-based dementia detection model that integrates an attention-based encoder with EEG data [7].

2.5 Functional Connectivity in Sleep Staging:

Huang et al. studied how brain connections during sleep, using EEG, that how sleep disturbance effect brain activities and they also could help to improve the diagnosis of Alzheimer's disease (AD) [9]. They showed that looking, how different parts of the brain connect during sleep can reveal small changes linked to MCI and AD. The studies discussed in this survey show that EEG is becoming a powerful tool for detecting AD. These studies use different methods like checking brain wave patterns, analyzing brain networks, studying sleep, and applying machine learning. Together, they provide a strong base for understanding how EEG changes in AD and help guide future research in early detection.

Table 1. Comparison of different ML and DL techniques using different Data-set

Reference	Dataset	Classifier / Methods	Limitations	Specificity	Sensitivity	Accuracy
Wang et al. [3]	EEG dataset (private)	Power Spectral Density and Coherence Analysis	Small dataset; lacks deep learning methods	Not Reported	Not Reported	88%
Afshari & Jalili [4]	Directed functional network	Graph-based methods to assess connectivity measures	High computational cost; limited generalizability	86%	85%	85%
Klepl et al. [8]	Open EEG data (TUH EEG)	Adaptive Gated Graph Convolutional Network	Requires large annotated datasets for better performance	89%	91%	90%
Syed et al. [13]	Dementia Bank dataset	Bag-of-Deep-Features combined with Model Ensembling	Limited speech data; cannot generalize well to other modalities	88%	87%	89%
Zhu et al. [14]	ADNI dataset	Deep Transfer Learning (using CNN and pre-trained models)	Transfer learning methods require fine-tuning; domain-specific performance optimization needed	92%	94%	93%

3. Overview of Deep Learning and Machine Learning

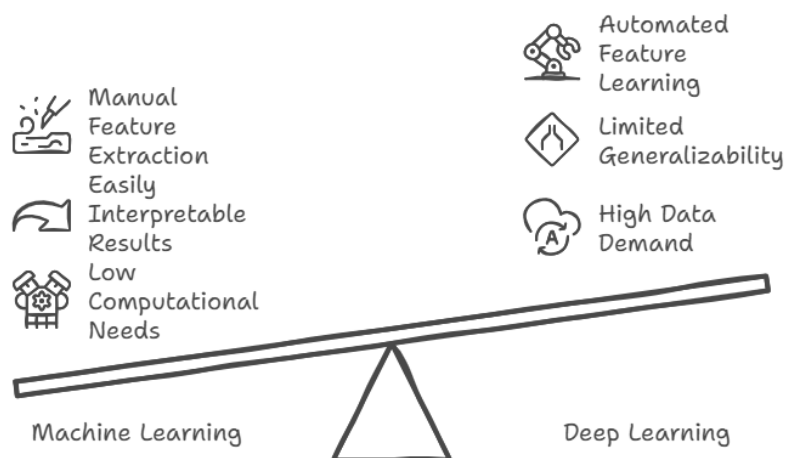
Over the past two decades, machine learning—a sub-field of artificial intelligence—has grown significantly in popularity and usefulness. An algorithm that can figure out the

connection between the input and the output is fed data by machine learning. A subset of ML, which is an algorithm that can learn without explicit programming, is deep learning. The process of making a machine function and behave like a person is known as artificial intelligence. This survey presents findings from a comparison of machine learning and deep learning techniques utilized in articles.

In machine learning approach H. Huang et al. [11] proposed EEG-based functional connectivity analysis methods that Applied traditional statistical methods to analyze sleep EEG data for Alzheimer's detection, which has Low computational requirements; interpretable results, but there are also Limited performance on large-scale datasets, unable to capture nonlinear relationships effectively. S. Khalighi et al. [16] used a method that combined feature engineering with basic machine learning models like Support Vector Machines (SVM) and Random Forest to study sleep stages and detect Alzheimer's disease using PSG signals. They focused on picking and using important features manually, which were then used by these models. This technique worked good for smaller datasets because it was simple and easy to understand and needs manually. But, since it depends a lot on manual feature selection, it had difficulty in finding more complex patterns in the data and didn't work good as compared with larger or more advanced problems.

S. Syed et al. [13] used a deep learning methods to detect Alzheimer's using a model based on bag of deep-features approach. They combined features from CNNs with ensemble methods to improve model's accuracy and performance. They got strong and reliable results by using pre-trained deep learning models and various classifiers. Though, the method had some problems, it didn't work as good as compared with other types of data and needed a large amount of labeled data to perform its best. These issues made it harder to scale the method or apply it to different real world scenarios.

For sleep staging and Alzheimer's detection using PSG signals, Khalighi et al., [16] used a classical machine learning approach that involved feature engineering and traditional classifiers, like Support Vector Machines (SVM) and Random Forest. Their method involved extracting handcrafted features from the data, which were then fed into these classifiers for analysis. This approach gave interpretable results, making it accessible and effective for targeted applications, but it had major drawbacks such as a heavy reliance on manual feature selection, which required domain expertise, and a lack of scalability for capturing more complex patterns present in larger or high-dimensional datasets.



Comparing ML and DL in Alzheimer's

Fig: 2. Definitions of Deep Learning (DL), Machine Learning (ML), and Artificial Intelligence (AI)

3.1 Overview on Diagnosis of Alzheimer's Disease:

In computer science, classification is a significant field based on the quantity of newly published articles. Figure 2 illustrates the several steps that the AD diagnosis process goes through in order to identify and categorize the illness. In this study, K. A. I. Aboalayon et al.[5] concentrate on how EEG can effectively categorize sleep stages, which is essential for locating early AD biomarkers. The authors extracted important characteristics linked to different stages of sleep by using frequency-domain analysis of EEG signals. Machine learning models were then used to classify these data, giving rise to a fundamental understanding of how changed sleep patterns can indicate cognitive impairment. Despite the method's outstanding results in differentiating between sleep stages, it was not directly applied to the diagnosis of Alzheimer's disease and did not integrate with other physiological signals to improve diagnostic accuracy.

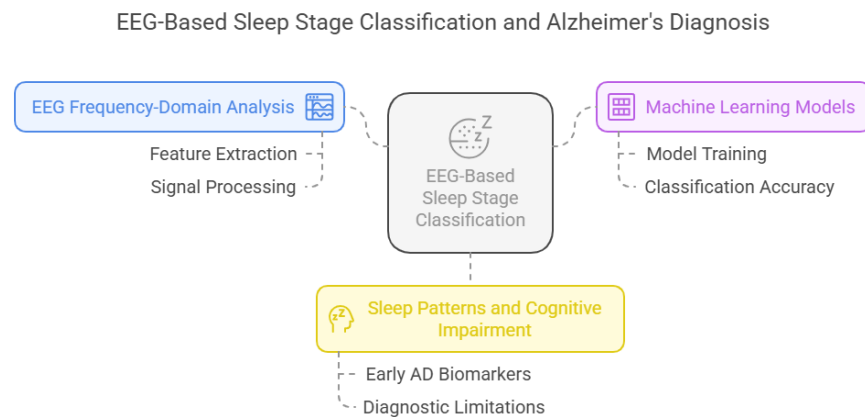


Fig. 3. Process of AD diagnoses

Geng et al. Investigated diagnostic potential of sleep EEG data for identifying MCI, that leads to Alzheimer's disease [6]. The study used complex processing techniques to find changes in EEG rhythms in signals during sleep of person, that concentrate on characteristics like decreased spindle density and changed slow-wave motion. When it came to differentiating MCI patients from healthy controls, these biomarkers showed great promise. But the strategy was constrained by its reliance on high-quality sleep EEG data and the absence of cross-population validation, underscoring the need for more extensive datasets and broadly applicable algorithms.

In another study D'Atri presented thorough examination of EEG signal changes in wakefulness and during sleep for individuals with MCI and Alzheimer's [7]. This study found some specific abnormalities such as decreased in alpha power and increased in theta activity during waking Along with disturbed sleep architecture. The study highlighted the possibility of EEG as a painless method for AD early detection by combining these findings. Meanwhile, issues including inter-subject variability and the requirement for an ongoing study were also present, which have limited the results of useful properties.

Klepl et. al., [8] presented an innovative technique for diagnosing Alzheimer's disease through analyzing EEG data using AGGCN. By identifying crucial EEG regions that contribute to the classification, this deep learning system integrated explain-ability. The method outperformed conventional models in capturing temporal and spatial relationships in EEG signals. The study emphasized the necessity of large-scale labeled data-sets to maintain robustness and generalization, especially across various demographics, despite its high accuracy and intractability.

In their work, L. Lias and D. Askounis [12] used transformer networks to analyze the trends in research associated to dementia that were providing an explicable framework for diagnosing Alzheimer's disease earlier. The approach offered highly detailed observations about cognitive decline by focusing on linguistic variables. However, its efficacy, the approach was restricted to textual data and did not allow for multimodal integration with physiological signals such as EEG or MRI data for a more thorough diagnosis. For Alzheimer's disease identification, Syed et al. [13] suggested a deep learning-based method that combines model assembling with bag-of-deep-features. This technique achieved great accuracy and robustness by using characteristics that were taken from CNNs that had already been trained. But for best results, it needed large labeled data sets and was less flexible for modals other than imaging, such as voice recordings or EEG.

These all above mentioned studies collectively demonstrate a most choose-able approaches for Alzheimer's diagnosis, from basic machine learning to advanced deep learning techniques. Each study offers unique understandings and methodologies and has contribution to a more comprehensive understanding of this complex disease while addressing different aspects of data availability, model complexity, and clinical applicability.

3.2 Preprocessing techniques:

Images in particular may have distortions and noise in them. The most common causes of radiography noise include variations in the detector's sensitivity, low contrast (i.e., the object's reduced light), photographic constraints, and spontaneous fluctuations in the radiation signal. Preprocessing is therefore necessary to improve the data's quality or to maximize its geometric and intensity patterns. Preprocessing enables researchers to focus on a particular area of the brain and emphasizes the most important details needed for the classification process.

Wang et al. utilized power spectral density and coherence analysis as preprocessing techniques on EEG signals to detect disruptions associated with Alzheimer's disease. Their proposed approach pays attention on the importance of EEG signal pre-processing, providing insights into abnormalities in brain activity. However, the study is limited by its focus only on EEG data, as it does not integrate information from other modalities such as MRI, which could enhance the robustness of the analysis. [4] conducted directed brain network analysis using EEG data to construct functional networks, aiming to detect disruptions in local and global connectivity in Alzheimer's patients. Their research demonstrates how functional network analysis can be used to find disease-related connectivity deficits. However, the method's scalability is limited since it might not be able to effectively manage bigger datasets, which is essential for more extensive clinical applications.

4. Classification

A subfield of machine learning (ML) called deep learning (DL) is more sophisticated than conventional ML techniques since it automatically pulls significant characteristics from data. DL also employs "end-to-end learning," in which the network processes tasks and raw data directly. The majority of studies have concentrated on detecting Alzheimer's disease from MRI images using Convolutional Neural Networks (CNNs). However, other DL methods have also been investigated for this purpose, including Deep Belief Networks, Auto encoders, Recurrent Neural Networks (RNNs), and Deep Neural Networks (DNNs).

4.1 Deep neural network (DNN)

Deep Neural Networks (DNNs) have shown great potential in helping to study brain images and diagnose Alzheimer's disease (AD). For example, Basaia et al. [28] used DNNs in their work to detect Alzheimer's and mild cognitive problems from just one MRI scan, doing so with high accuracy and low cost. Pan et al. [29] used a mix of learning methods and CNNs to make Alzheimer's detection more reliable and useful for different cases. Helaly et al. [30] also used deep learning to find Alzheimer's early by carefully picking important features from MRI scans.

additionally, Liu et al. [31] created a deep neural network (DNN) model that works well on different types of brain MRI data. This technique helped to solve problems that caused by changes between different datasets. Their results show that DNNs are flexible and effective at finding complex patterns linked to Alzheimer's disease as compared to other methods. The model worked even better when good pre-processing methods were used to pick out useful features from the brain images.

4.2 Adaptive Gated Graph Convolutional Network:

The Adaptive Gated Graph Convolutional Network (AGGCN) is a strong method used to study speech and brain imaging data to find signs of dementia and Alzheimer's disease (AD). It creates graphs that show how different parts of the data are connected, and then adjusts those connections as needed. This technique helps the model to find detailed patterns in EEG and MRI data. For example, Lin et al. [9] used a similar method with adaptive attention to recognize Mandarin speech, showing that AGGCNs can be useful for picking out important features in tasks that check memory and thinking skills.

In another study Qin et al. [10] evaluate EEG source data using directed brain network analysis, which is comparable to how AGGCN may represent both local and global brain connections. Additionally, AGGCNs align with explainable AI trends, and Ilias and Askounis [12] underlined the importance of interpretable models for dementia diagnostics. Studies like Huang et al. [11] have shown that AGGCNs can effectively evaluate multi-modal data, which makes them adept for modelling functional connectivity analysis. All things considered, AGGCNs combine explain-ability,

adaptability, and the ability to work with a range of datasets, which is a significant step forward in the detection of AD and in accordance with the needs identified in many recent studies [30–33].

4.3 Hybrid classical-quantum neural network

Hybrid classical-quantum neural networks (HCQNNs) are machine learning model that combines strength of classical neural network with quantum computing techniques, have evolved as a state-of-the-art technique in the research of Alzheimer's disease (AD). This technique works as good to increase the effectiveness and accuracy of disease detection. Classical neural networks are good at handling large amounts of brain scan data like MRI and EEG. However, they struggle with very complex or high-dimensional data to overcome this problem, Hybrid Classical-Quantum Neural Networks (HCQNNs) use quantum computing methods. These include quantum entanglement and superposition, which help them explore large number of features more quickly and efficiently.

Several Studies like Wang et al. [18] and Mehmood et al. [26] have described the value of deep learning models for early AD diagnosis. HCQNNs excel this by offering superior feature extraction and classification performance. Likewise, Zhang et al. In their research [21] on regional attention in MRI described how HCQNNs optimize complex data analysis. Additionally, as Rahim et al. [24] point out advancements in multimodal data fusion techniques increase HCQNNs' ability to integrate a range of data sources, such as time-series data and imaging biomarkers. As Fouladi et al. [25] and Goenka et al.[22] explain in their work that has networks not only boost processing efficiency but also pave the way for explainable AI in AD research. Thus, the application of HCQNNs is a breakthrough step in addressing the challenges related to Alzheimer's detection and classification, and it gives new perspectives for diagnosing accurate and flexible systems.

4.4 Autoencoder (AE)

Autoencoders (AEs) have shown considerable promise in the early diagnosis and analysis of Alzheimer's disease (AD) due to their ability to learn compact representations of high-dimensional data in an unsupervised manner. AEs are designed to reduce the dimensionality of data while preserving important qualities by first encoding input data into a latent space and then recovering it. Avci et al. [19] used 3D deformable autoencoders to perform robust unsupervised feature extraction in order to assess Alzheimer's disease from neuroimaging data like MRI. This technique enables the detection of refined changes in the brain's structure, which is crucial for early AD diagnosis. Rahim et al. [24] also emphasized the importance of AEs in integrating multimodal data, including MRI and biomarkers, to improve prediction performance and allow explain-ability in disease progression models.

Zhang et al. [21] demonstrated the value of AEs in capturing regional grey matter features in MRI, which could aid in the early detection of neurodegeneration. Arafa et al. [27] also pay attention on the use of AEs to enhance the quality of MRI data pre-processing and feature learning that is leading to a more accurate categorization of AD and MCI. These results demonstrate how flexible AEs are at combining various data modalities and identifying significant characteristics, which makes them essential for developing expendable and successful AD diagnostic systems.

Table 2. Comparative study of different studies

Study	Preprocessing Techniques	Methodology	Advantages	Performance
Klepl et al. [8]	EEG signal preprocessing and adaptive feature extraction	Adaptive Gated Graph Convolutional Network for EEG data analysis	Explainable model for Alzheimer's diagnosis using EEG data	High accuracy in Alzheimer's diagnosis with explainable insights
Lin et al. [9]	Speech normalization and Mandarin speech preprocessing	Attention-based speech recognition encoder for dementia assessment	Tailored to Mandarin speakers, effective for linguistic dementia detection	Achieved promising results for dementia diagnosis from speech data
Basaia et al., [28]	MRI preprocessing and normalization	Deep neural networks for Alzheimer's and mild cognitive impairment classification	Utilizes a single MRI for accurate classification	High classification accuracy for Alzheimer's and mild cognitive impairment
Pan et al., [29]	MRI preprocessing and ensemble techniques	Combination of CNNs and ensemble learning for early Alzheimer's detection	Improved robustness and generalizability	Achieved significant performance improvements for early Alzheimer's detection

Shahwar et al., [32]	MRI preprocessing and quantum feature representation	Hybrid classical-quantum neural network for Alzheimer's detection	Novel integration of quantum computing for enhanced feature extraction	Moderate accuracy with unique contributions to hybrid quantum-classical learning
Hazarika et al., [33]	MRI preprocessing and feature extraction	Improved LeNet-based deep neural network for MRI Alzheimer's classification	Optimized architecture for better performance	High classification accuracy with optimized performance for brain MRI analysis

Based on above discussed studies, various deep learning and hybrid techniques have been explored to enhance the diagnosis of Alzheimer's disease (AD), each bringing unique strengths and limitations. Deep Neural Networks (DNNs) are widely appreciated for their ability to automatically extract significant features from complex MRI data. These models offer high diagnostic accuracy and cost-efficiency but often rely heavily on preprocessing and large datasets to generalize effectively across different populations. Simultaneously, other technique Adaptive Gated Graph Convolutional Networks (AGGCNs) shows prominent results for their ability to capture both local and global brain connectivity patterns from EEG and MRI data. However, the complexity of graph construction and training makes these models computationally intensive and less straightforward to deploy clinically in real world scenario. On another hand, Hybrid Classical-Quantum Neural Networks (HCQNNs) offer promising advancements by integrating quantum computing to manage high-dimensional data with enhanced speed and precision. While they demonstrate potential in feature fusion and multimodal integration, the quantum component remains largely theoretical or limited by current hardware constraints. Lastly, Autoencoders (AEs) have proven highly useful for unsupervised feature learning, especially in capturing subtle structural brain changes. Their ability to reduce dimensionality without supervision is a notable advantage, however, they may fail in classification performance when used alone and often require work with other models for notable results. Overall, while each approach contributes meaningfully to the field, a critical balance between accuracy, interpretability, computational cost, and data availability remains essential in selecting the most effective method for Alzheimer's diagnosis.

5. Research challenges

In this survey two primary categories of research issues are highlighted the one is difficulties with the data and the other problem faced was difficulties with the classification issue. Below subsections explain briefly main difficulties faced in each category.

5.1 Overcoming data imbalance problem

Several studies described that data imbalance is still a big challenge in the field of Alzheimer's disease (AD) research. This problem arises when there are fewer samples for certain stages of the disease, which can affect machine learning and deep learning models performance, as models cannot learn and produce false results. To fix this problem, researchers proposed the methods like data augmentation and creating virtual data.

For instance, Basaia et al. [28] and Pan et al. [29] used techniques in their work like rotating, flipping, and cropping MRI scans to make their models stronger. Other than, Avci et al. [19] used autoencoders in unsupervised learning to learn key features from limited data. Also, Helaly et al. [30] applied class-weighted loss functions to give more importance to rare cases during training.

In order to improve accuracy with unbalanced data, Shahwar et al. [32] and Hazarika et al. [33] used hybrid and ensemble models in their work that combined classical and quantum neural networks to boost the efficiency. In the time where data imbalance is still a problem, researchers are finding smart ways to improve AD detection by using these creative solutions

5.2 Over-fitting problem

A notable issue in deep learning for diagnosing Alzheimer's disease (AD) is the over-fitting problem, which occurs when models perform surprisingly well on training data but not good result on unknown data. This problem was addressed in a number of studies using different techniques like regularization strategies including dropout layers were employed in the studies by Basaia et al. [28] and Pan et al. [29] to keep their conventional neural network (CNN) models from over-fitting. Data augmentation technique was used by Helaly et al. [30] to expand the training data and less the model's dependency on particular data-set trends.

In a similar work by Liu et al. [31], they improved the generalization of their models by using cross-validation during training to guarantee that they were exposed to various data splits. In order to combine model complexity and flexibility, Shahwar et al. [32] and Hazarika et al. [33] used hybrid techniques such as merging classical and quantum neural networks. These strategies highlight how it is necessary to reduce over-fitting in order to

guarantee a reliable and accurate diagnosis of AD, particularly when working with sparse or unbalanced data-sets.

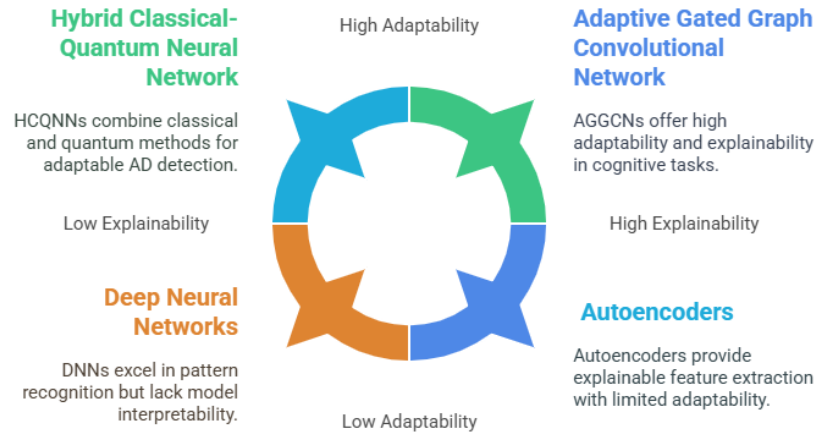


Fig 4: Comparative Analysis of AI Techniques in Alzheimer's Detection

Several studies in Biomedical engineering plays a vital role in the advancement of disease diagnosis by integrating engineering principles with medical and biological sciences to develop innovative diagnostic tools and systems. Studies like, microfluidic technologies [34], offer precise control of small fluid volumes. Similarly, the valve less pump design [35] demonstrates how fluid manipulation without mechanical valves can lead to compact, reliable devices suitable for continuous monitoring. In the context of vascular conditions [36-37] explored the design and fabrication of sinusoidal micro-channels for varicose vein implantation. Furthermore, the use of bio-compatible materials like PDMS [38], efficient diagnostic micro-devices. Collectively, these studies highlight how biomedical engineering bridges the gap between technology and health care to enable the creation of precise, less invasive diagnostic platforms that could be extended to the detection and monitoring of diseases including neurological disorders like Alzheimer's.

6. Limitations

Every study has its strengths and weaknesses, and this one is no exception. Here are some limitations:

- We only covered the most common pre-processing techniques used with neuro-imaging, such as intensity normalization, contrast enhancement, noise reduction, brain extraction, and data augmentation.
- We focused on five deep learning (DL) techniques—DNN, ANN, CNN, AE, and DBN—even though many other methods exist. We chose the most commonly used ones for diagnosing Alzheimer's disease (AD).
- Machine learning (ML) was not discussed in as much detail as DL.

- We mentioned only four data sets, though there are more available, and this study is based on research from the past ten years.

7. Conclusion and future work:

In short, the above reviewed studies present differing approaches to diagnose Alzheimer's disease (AD), also highlight EEG signal analysis, deep learning techniques used to diagnose and experimental multi modal frameworks. From power spectral density and coherence analysis to functional network disruptions in Alzheimer's patients, these works provide important features into the neural and cognitive abnormalities that are linked to this disease. EEG-based methods, such as those leveraging sleep staging , proved the potential of sleep metrics as reliable bio markers. Advanced machine learning techniques, such as Adaptive Gated Graph Convolutional Networks and transformer-based language models , emphasize explain-ability and accuracy, offering adjustable solutions for early detection. Despite these solutions proposed there are some challenges such as limited dataset diversity, high computational demands, and the need for robust generalizability still present.

To improve diagnostic results and dependency of data, future studies should give special attention to the integration of multimodal data, integrating EEG, imaging, speech, and text-based techniques so that data imbalance can overcome. The development of models that are relevant in clinical settings and robustness to a variety of patient demographics should also be a first priority by using this approach current gaps will be filled and cross-study comparisons made possible by standardizing evaluation procedures and growing public databases. Additionally, developments in explainable AI and transfer learning have the capacity to produce diagnostic frameworks that are flexible and changeable. These methods have the potential to transform Alzheimer's diagnosis, opening the door to early intervention and better patient outcomes with sustained innovation and cooperation.

Recent progress in machine learning (ML) and deep learning (DL) has greatly improved how we detect and diagnose Alzheimer's disease (AD). These technologies help doctors identify the disease early, which allows for better and faster treatment. Researchers have tested many methods like convolutional neural networks (CNNs), ensemble learning, and hybrid models to deal with the complex nature of AD. For example, Pan et al. (2020) showed that using CNNs with ensemble learning on MRI scans can increase the accuracy of AD detection. Helaly et al. (2022) also focused on making deep learning models both accurate and efficient for early detection.

Even though these results are promising, some challenges remain. These include making sure the models work well on different datasets, reducing computing time, and combining different types of data (like MRI, EEG, etc.) for a complete analysis. The work of Liu et al. on generalizable models and Shahwar et al. on hybrid classical-quantum networks

highlights ongoing efforts to tackle these limitations. These advancements, coupled with future innovations, are expected to improve diagnostic precision, scalability, and real-world applicability of AI-driven tools for AD detection.

Using these cutting-edge methods and strategies several studies have added remarkable work to the research on AD detection. For MRI-based AD detection, Pan et al. presented a unique CNN and ensemble learning combination that showed good accuracy but also highlighted the need for robust scalability. This endeavor was advanced by Helaly et al., who focused on computationally effective deep learning techniques designed for early AD diagnosis. An enhanced LeNet-based deep neural network was proposed by Hazarika et al., resolving computational complexity concerns and improving performance for MRI data classification.

Furthermore, Liu et al. in their study created a deep learning model for structural MRI analysis that is applicable and highlighting the significance of flexibility across various data sets. In order to improve detection skills, Shahwar et al. presented a hybrid classical-quantum neural network architecture that included quantum computing and conventional machine learning. On the other hand, the model a lot of difficulties with computational resource requirements. Together, these all studies demonstrate the variety of techniques used to improve AD diagnosis while focusing on the common difficulties associated with heterogeneous data sets, high computational requirements and clinical translation. By overcoming these hardships and achieving the full potential of AI in Alzheimer's care would require ongoing studies and make significant differences.

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