A Review of Machine Learning Techniques for Early Detection of Alzheimer's disease

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Abstract

This review aims to discuss the use of AI and ML in diagnosing and managing neurodegenerative diseases, with particular emphasis on AD and MCI. Emerging innovations present in depth the effectiveness of using ML models such as SVM, random forests, CNNs, and new frameworks such as quantum-classical neural networks on data obtained from MRI imaging, EEG signals, genetic makers and sociodemographic data. Widely used research findings demonstrate that these tools offer seemingly higher detection rates, sensitivity, and specificity than traditional diagnostic techniques for identifying and diagnosing early-stage illnesses. Some of them are techniques based on analyzing EEG time-frequency bands, combining MRI and PET data integration approaches, and creating telemedicine services to overcome geographical barriers. Furthermore, interpretable AI models improve clinical relevance by providing decision and trust support among practitioners. While these achievements are notable, the following limitations need to be noted, thus making it easier to establish the generalizability of the results and ways of using datasets that are free from bias and difficulties associated with applying AI in clinical settings. There are pressing questions regarding patients' rights and privacy, the issue of homogenization and standardization of data, and the distribution and accessibility of AI tools across industries as well as within the same region. More studies should be conducted to expand AI applications, use a more diverse dataset, and promote cooperation between representatives of various fields of science to ensure that technological advancement meets clinical demands. It also includes new methods like Vision Transformers and Quantum Computing Enhanced Deep Learning to overcome diagnostic issues in time-consuming and multi-parametric data analysis. These gaps can be closed with the help of AI and ML to enhance diagnostic accuracy, select the right treatment strategy, and risk assessment for the long-term management of NDs. In conclusion, this review similarly reaffirms how stunning AI's role is in improving future neurodegenerative disease care. For this reason, the deployment process must be done sensibly to enhance the patient's value most appropriately.

Keywords: Artificial Intelligence; Machine Learning; Neurodegenerative Diseases; Alzheimer’s Disease; Mild Cognitive Impairment; Diagnostic Technologies

1. Introduction

Neurodegenerative diseases, such as Alzheimer's disease (AD), are increasing health hazards around the world. These diseases' growing incidence and implications for individuals and society make them an urgent target for novel approaches. Traditional diagnostic methods have many shortcomings, but advances in artificial intelligence (AI) and machine learning (ML) are promising to improve early detection, diagnosis,

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and treatment. It is through AI's ability to analyze vast amounts of complex data that the landscape of neurodegenerative disease management is about to change for the better.

- **The Growing Challenge of Neurodegenerative Disorders**

Alzheimer's disease (AD) and other neurodegenerative diseases remain a primary global concern because of their increasing lethality and social and economic costs. Alzheimer's disease is the most prevalent type of dementia, being a degenerative pathology that results in progressive impaired cognition, memory, thinking and judgment. Poor reasoning and judgment are also indicative of Alzheimer's disease, which is the most common type of dementia. Unfortunately, early diagnosis has not improved in recent years. It remains a significant challenge today mainly due to the failure in the early detection of diseases, hence the early application of therapeutically relevant measures. As people living in the developed world are aging, Alzheimer's and related disorders' impact grows, making diagnostic and management innovations needed even more [1].

Recent studies bring out the disguised rise of Alzheimer's disease and related dementias, as over 55 million are presently struggling from them worldwide, and this is predicted to reach 82 million by 2030. The latest version of the World Alzheimer Report 2024 focused on the call for a less discriminant and more tolerant society for dementia sufferers3. In addition, the efficacy of new drugs for Alzheimer's disease has been witnessed early in clinical trial data; antibodies targeting amyloid beta (Aβ) fibrils and neurofibrillary tangles (NFT) may help halt the disease progression [2], [3].

Future work to enhance early identification continues with the development of new cognitive tests, biochemical markers, and various behavioral and lifestyle modifications. NIH remains the driving force of the United States' dementia research directions, including identifying the multifactorial origins of Alzheimer's and other dementias, recognizing the biomarkers of the diseases, and designing the most efficacious treatments4. These are important in countering the emotional, physical, and financial OR social costs of neurodegenerative diseases in patients' families and communities [4].

- **Advancements in Artificial Intelligence for Healthcare**

The advancement in artificial intelligence, machine learning, or AI and ML, has transformed multiple fields, including healthcare. These technologies provide solutions never seen before for handling large data sets, fusing multiple modalities, and providing accurate predictions and analytical tools1. AI can perform data mining of neuroimaging, genes, and clinical data sets to pursue early indicators of disease progression in neurodegenerative diseases. Machine learning predictors as basic as support vector machines and as complicated as deep learning neural networks have been helpful for early diagnosis and prognosis of Alzheimer's disease [5].

In recent years, Applied AI has significantly enhanced crucial healthcare processes, particularly in the diagnosis stage. This paper illustrates how AI-based technologies transform the healthcare sector, making services more efficient, safer, and manageable. For instance, AI can predict the actions of a drug's direct target, thereby enhancing clinical and patient outcomes. In clinical trials, AI is employed to select the target population and trial design, choose patients, and predict trial success [6] accurately.

For instance, AI can be used to reduce the number of human healthcare workers due to shortages around the world by assisting them in undertaking mundane tasks and helping them make decisions. The World Economic Forum recognizes that in delivering more stable, effective, and fair healthcare solutions, the application of AI 1. Therefore, AI must be adopted, used, developed, advanced, improved, applied and implemented positively, legally, ethically, reasonably and incredibly efficiently to achieve maximum benefits and optimally reduce the impacts associated with it [7].

- **Objective of the Review**

Current research utilizing the application of machine learning and AI methodologies is moving forward leaps and inches to the initial detection, diagnosis, and prognosis of Alzheimer's disease. Although these studies expose the strengths and limitations of using different data modalities such as neuroimaging, electroencephalogram (EEG), genetic features, and clinical records, they collect those features into data. Neuroimaging techniques, including MRI and PET scans, are well suited for observing structural and

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functional brain changes. Neurochemical data, especially that of EEG, reveal patterns of electrical brain activity associated with cognitive decline. Genetic markers give information regarding the genealogical part, while clinical records reflect complete histories of patients available to machine learning models. Analysis algorithms such as support vector machines, random forests, and cutting-edge deep learning architectures such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs) are promising in handling large datasets and extracting meaningful patterns. Data heterogeneity, interpretability, and ethical issues remain significant concerns. Solutions to these issues are essential in actualizing AI in contemporary clinical practice to ensure transparency and ethics. The collaborative research will further develop into fully extracting AI potentialities and, hence, more effective diagnostic tools for Alzheimer's.

- **Structure of the Review**

The review discusses comprehensively AI applications in Alzheimer's diagnostics, concentrating first on neuroimaging and genetic data, where deep learning techniques have taken the lead in biomarker identification and interpretation. It then explores how physiological and clinical data could be used in innovative frameworks such as EEG-based solutions or self-reported cognitive assessments that are valid at picking up subtle physiological and cognitive changes. This review also underscores multimodal approaches, which integrate different types of data to combine neuro-imaging, genetics, physiology, and clinical data into a more consolidated and, thus, solid diagnostic system for validating detection accuracy. Finally, it will deal with the challenges and future perspectives of the integration of machine learning for application in clinical practice concerning neurodegenerative diseases, with a focus on data heterogeneity, model interpretability, and ethical issues, thereby recognizing the need for continuous research and collaboration to achieve such objectives and fully exploit AI potential in clinical settings.

AI and ML can potentially transform neurodegenerative disease diagnosis, treatment, and patient care. By leveraging these technologies, researchers could explore the underlying mechanisms of these disorders and their early pathophysiology markers to develop better-targeted therapies. However, challenges still abound, including quality of data, interpretability of models, and ethical issues. These need to be explored critically to establish responsible and beneficial applications of AI in healthcare. Research and collaborations should continue to realize the complete promise of AI and ML for treating neurodegenerative disorders in affected individuals.

2. Literature Review

This literature review explores the use of machine learning and artificial intelligence approaches to the problem of early diagnosis and management of neurodegenerative diseases, using Alzheimer's disease as a case example. The analyzed studies focus on applying various methods ranging from conventional machine learning techniques to deep learning methods in handling different types of data, like neuroimaging, genetic, and clinical data. These sophisticated approaches aim to identify novel biomarkers for improved diagnostic discrimination, more accurate prognosis, and meaningful interventions for these paralyzing disorders.

As outlined in [8], mild cognitive impairment (MCI) presents significant challenges in early diagnosis and intervention, with underdiagnoses contributing to the economic and social burden associated with dementia. Machine learning (ML) techniques have emerged as promising tools to address these complexities by managing large datasets and improving predictive accuracy for MCI and dementia. This study employed the Korean Longitudinal Study of Aging (KLOSA) dataset to evaluate ML models, including random forest, xgboost, and others, in predicting cognitive decline. Sociodemographic and health-related variables such as pain, living arrangements, exercise habits, and education levels were identified as significant predictors, highlighting the importance of integrating multifaceted data for early detection and intervention.

As outlined in [9], Alzheimer's disease (AD) represents the most prevalent form of dementia, characterized by its progressive nature and lack of adequate preventative or curative measures. The study developed an algorithm leveraging electroencephalogram (EEG) signals to address these challenges and differentiate between early-stage AD, moderate AD, and healthy controls. By utilizing a balanced EEG dataset and extracting 43 time-frequency features from 1-second segments, the study achieved 100% accuracy in distinguishing control groups from MCI and AD. These findings demonstrate the promise of EEG-based methods for early AD diagnosis, though the study emphasizes the need for larger datasets to improve result generalizability.

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As discussed in [10], neurodegenerative diseases such as Alzheimer's, Parkinson's, and Huntington's present significant diagnostic challenges due to their progressive nature and overlapping symptoms. Artificial intelligence (AI) offers transformative potential in improving early diagnosis by analyzing complex datasets with remarkable precision, including imaging, genetic, and clinical data. Techniques like convolutional neural networks (CNNs) for imaging, natural language processing (NLP) for clinical records, and ensemble methods for multimodal data integration have shown significant advancements in detecting early neurodegeneration. These innovations enhance diagnostic accuracy and support risk stratification and personalized treatment planning, fostering better disease management. Despite challenges like data standardization and ethical concerns, AI's evolving capabilities promise substantial benefits in reducing the healthcare burden of neurodegenerative diseases.

As outlined in [11], neurological diseases such as Alzheimer's, Parkinson's, and multiple sclerosis are progressive and often challenging to diagnose in their early stages due to their subtle initial symptoms. Early detection is critical to delay disease progression and improve treatment outcomes. AI-based methods, including machine learning, deep learning, and natural language processing, offer significant promise in addressing these challenges by analyzing complex datasets such as neuroimaging, health records, and speech patterns. These systems excel in identifying minute changes in brain function or behavior that clinicians might miss, thus enhancing diagnostic accuracy and enabling personalized treatment strategies. The integration of AI into clinical practice has the potential to revolutionize neurological diagnostics and management, driving advancements in patient care.

As detailed in the paper [12], integrating physiological signals with advanced AI algorithms has significantly enhanced clinical applications such as diagnosing speech disorders, estimating cognitive status, and monitoring brain states. Despite these advancements, the opaque nature of raw physiological signals and the complexity of AI model architecture pose challenges for clinical interpretation and adoption. This necessitates the development of interpretable AI models tailored for healthcare settings. By incorporating features like interpretable bottleneck layers in neural networks, this research facilitates the joint learning of meaningful acoustic features alongside classification labels, enhancing both diagnostic accuracy and clinical insight. Additionally, innovative approaches such as machine learning-based metrics and unsupervised EEG channel selection frameworks have been proposed, enabling early detection of subtle cognitive changes and identification of active brain regions. These methods underscore the potential of interpretable AI in bridging the gap between advanced analytics and clinical applicability, fostering greater trust and utility in healthcare practices.

As discussed in [13], Alzheimer’s disease (AD) dementia and mild cognitive impairment (MCI) are significantly underdiagnosed in community settings, highlighting the need for accessible tools to facilitate early detection. FACEmemory®, the first self-administered online memory test with voice recognition, was evaluated for its neuropsychological validity and potential to discriminate between cognitively healthy individuals and those with MCI. Associations were identified between FACE memory sub-scores and traditional cognitive domains, such as memory ($\rho = 0.67$), executive functions ($\rho = 0.63$), and visuospatial abilities ($\rho = 0.55$), among others. An optimal machine-learning algorithm using FACE memory data achieved a sensitivity of 0.81 and specificity of 0.72 in distinguishing amnestic MCI, demonstrating its effectiveness as a diagnostic aid. These findings suggest FACE memory is potential to mitigate underdiagnoses in community settings and promote early intervention strategies for cognitive decline.

In the research presented in [14], early detection of cognitive impairment was addressed by integrating one-class classification with motor-cognitive tasks, aiming to develop a more efficient alternative to standard screening tools. Data from gait, finger tapping, cognitive, and dual tasks were analyzed using a method that modeled the behavior of healthy controls to detect abnormalities indicative of mild cognitive impairment. Gait features emerged as the most predictive in one-class classification, achieving a sensitivity of 87.5% and a specificity of 75.7%, outperforming traditional cognitive screening tests. Moreover, combining individual task models yielded better performance than feature-level integration, highlighting the potential of this approach for clinical application. These findings emphasize the promise of one-class classification in improving early detection while suggesting further validation in more extensive clinical cohorts.

In the article denoted as [15], late-onset Alzheimer’s disease (LOAD), which typically manifests after age 65, is explored through a systems biology perspective to understand its multifactorial progression. The study

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integrates genetic, epigenetic, metabolic, and environmental factors that modulate molecular networks and pathways affecting brain structure, functionality, and connectivity. Early biomarkers were identified as indicators of disease onset, while clinical-stage biomarkers reflected advanced disease manifestations. Additionally, the study reviews machine-learning methodologies, particularly the application of deep learning (DL) and convolutional neural networks (CNNs), in Alzheimer's diagnosis using biomarker data. It also highlights the utility of generative AI and the Synthetic Minority Oversampling Technique (SMOTE) for enhancing data representation, underscoring the potential of advanced AI technologies in improving diagnostic accuracy and addressing research gaps in biomarker efficacy.

Alzheimer's disease, diagnosed by symptoms of neurodegeneration, remains the most complex to diagnose and treat in the early stages. Investigations using non-invasive techniques like brain Magnetic Resonance Imaging (MRI) have the potential to identify early structural changes in the brain that mark the development of Alzheimer's. However, such analyses can be very complex in obtaining minute changes that characterize the disease. According to the report cited in [16], deep learning methods have been identified to enhance the accuracy and sensitivity of MRI analysis with special emphasis on Vision Transformers (VITS). Since self-attention mechanisms enable patterns across any region in the sequence, self-attention-based VITS could better identify complex patterns in the MRI-scanned human brain, which tends to be hardly detectable using conventional models. This has boosted research-involving VITS in the classification of Alzheimer's disease because these models perform well in light of the challenges posed by medical images. As a result, VITS' benefits become a guiding beacon for early diagnostics to build on by other researchers.

Magnetic resonance imaging (MRI) and positron emission tomography (PET) as multimodal imaging data are instrumental for Alzheimer's disease (AD) diagnosis. In the research performed in [17], authors have noted that most current deep learning methods have been shown to depend on patch-based extraction from these neuroimaging data and result in a lower accuracy level. This is because such methods must combine the information to facilitate comprehensive observation of the structural reorganization in the brain. In addition, these approaches still tend to concatenate multimodal data without checking the possibilities of modality interactions, which sometimes make up discrimination regions crucial in precise AD identification. In order to overcome these disadvantages, the study designed a novel work that is a multimodal, multi-scale deep learning model, which not only but also uses advanced fusion strategies, including multi-head self-attention and multi-head cross-attention. These mechanisms help improve the feature extraction and help in better interaction between different scales and modalities, leading to better classification stages of Alzheimer's. The performance of the proposed model has been evaluated on the publicly available dataset ADNI and proved to be outperforming the existing state-of-the-art methods.

It has been reported that Alzheimer's disease is closely related to the process of slow hippocampal volume reduction, and knowledge of the relationship between local morphometry and the extent of the disease is important to the early diagnosis of the disease. According to the study described in [18], using machine-learning algorithms was suggested to enhance the performance of detecting and estimating cognitive ability in the entire continuum of AD severity through SMRI of both bilateral hippocampi. The research drew data from high-resolution MRI scans of 120 AD dementia patients, 232 aMCI patients, and 206 HCs from the ADNI. Several pattern analysis methods, SVM and RVR, were employed to assess the classification performance and the cognitive pragmaticistic future possibility of considering the hippocampal volume. The results indicated that because of the feature selection process used in the current work, the presented SVM model reached high classification accuracy, which was 94.17% for discriminating between HC vs AD dementia, 80.85% for discriminating between HC and aMCI, and 70.74% for discriminating between aMCI and AD dementia. Moreover, the RVR model provided baseline and mean cognitive data with satisfactory accuracy over the year 3 follow-up data. The results were also replicable when analyzed using other methods of regrouping and another local dataset, further confirming the usefulness of the machine-learning model in differentiating AD severity and making the prognosis for future cognition.

In the third millennium, the rise in incidences of dementia makes it even more challenging to manage. In the research performed in [19], the OASIS (Open Access Series of Imaging Studies) program data, contributed from the University of Washington Dementia's Disease Research Center, were utilized for the Dementia predictive model creation. Cognitive impairment: Dementia is a long-term and gradually worsening disease that has received increasing attention in recent years, primarily as the affected population ages. For the imputation of missing data, data normalization and data transformation adopted in the present study included

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the following. Various Machine Learning models were used, viz., AdaBoost (AB), Decision Tree (DT), Exclusion Tree (ET), Gradient Boost (GB), K-Nearest Neighbor (KNN), Logistic Regression (LR), Naive Bayes (NB), Random Forest (RF), and Support Vector Machine (SVM). These algorithms were evaluated based on the complete set of features and the subset of features obtained with the LASSO technique. Comparing the results with reported accuracy, precision, etc., the values showed that the SVM model achieved % the highest accuracy of 96.77% when trained and tested on the complete set of features. Because of the high accuracy of the proposed method and the machine-learning algorithm having precise feature selection capability, there is a probability of an ideal early diagnosis of Alzheimer's disease (AD).

Alzheimer's disease (AD) is a chronic and nonreversible Neurodegenerative disorder characterized by a progressive cognitive impairment that begins with forgetfulness and ends with the patient being utterly helpless. As presented in [20], any traditional machine-learning model can fail to capture the underlying dependencies in various types of tabular data, specifically in case the missing data are imputed using standard methods. These limitations need to be corrected with lower accuracy and more generalization for the classification models of AD. To solve these challenges, the study presented ADXCLASS, a novel deep-learning framework that proposed multi-domain attention fusion to improve AD classification; the method developed also used data type-specific data imputation to deal with the tabular missing heterogeneous data. Thus, ADXCLASS increases classification model reliability by combining demographic, cognitive, genetic, and neuroimaging biomarkers. The framework was further tested on the ADNI dataset using a 5-fold cross-validation, which showed significant improvements in the classification compared to traditional methods.

In the work of Kobashi et al., recommended hospital visit rates of noncompliance were addressed through a methodologically sound approach that incorporated machine learning with the historical cohort design to conceive the effect of telehealth-supported physician advice. In the publication referred to as [21], the authors highlighted how telehealth guidance influenced adherence with patient characteristics, proving significant importance. Using the study findings, the need for enhancing telehealth technologies and the distribution of health resources fairly was discussed in terms of disparities concerning compliance with medical advice and healthcare services availability. Furthermore, the salient issues for unique populations, including older adults and the rate of those with behavioral health conditions that Telehealth systems have issues were revealed. The study also stressed how policy changes such as CMS 1135&id= and the CHRONIC Care Act could potentially improve telehealth access to Traditional Medicare beneficiaries and chronic disease solutions. Such results correspond with the related studies by Wang and colleagues that explored telehealth service preference and use among Medicare beneficiaries with and without ADRD. This research found service availability and use parity for these groups, but telehealth accessibility during the pandemic experienced demandingness fluctuations compared to before the pandemic.

An important feature of dementia is that accurate early diagnostic tests remain a critical problem in geriatric populations because the conventional methods of assessment obtain several false positives and false negatives at the first stages of the disease. Similarly, as described in [22], biomarkers like CSF are, by definition, intrusive, while neuroimaging techniques are generally expensive and not widely accessible. EEG is considered the most feasible solution due to its relatively low costs and incredible adaptability in the light of advancing technology. Among ERP, specifically P300, it was found that ERP might have the potential for supporting dementia assessment as a biomarker; however, their application in clinical practice or within daily-use technology products is still somewhat limited. A framework to fill these gaps was implemented to govern the three data flows in a federated style for both the EEG-based, passive P300 use-case and for the big data approach-using consumer EEG to monitor several subjects. The P300 application focuses on the effects of emotional stimulus on visual attention and from assessment of the P300 component through latency and amplitude with subsequent use of machine learning for discrimination of cognitive impairment. A cross-sectional study with older adults in Kraków, Poland, showed that it is possible to screen cognitive decline in the community using portable EEG, such as the MUSE. Artificial intelligence accurately recognized EEG responses and provided evidence for differentiating cognitive disorders and social applications of the assessment tools in non-specialized settings.

To this end, Kobashi et al. [23] conducted a machine learning study to analyze how compliance with physicians' recommendations of hospital visits was influenced by telehealth about relevant patient factors. It is vital to maximize telehealth delivery and equitably allocate resources to drive adherence and access and address disparities for all covered populations, especially elderly and behavioral health patients. Compared

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to the telehealth use among Medicare beneficiaries with and without ADRD, no disparities in use or availability were discovered during the COVID-19 pandemic; however, there has been increased usage during the pandemic, increasing existing disparity. An identified focus should be placed on the rural-urban gap for accessing digital technology to improve telehealth for the elderly and chronically ill patients. On this basis, Hernandez and his colleagues emphasized that it is necessary to ensure that such tools are culturally sensitive and achieve inter-organizational partnerships between healthcare providers, community organizations, and federal agencies to guarantee that disadvantaged telehealth groups have equal opportunities.

As explained in [24], DL offers enormous opportunities for artificial intelligence, not least when implemented with quantum computers in solving multidimensional problems. Quantum-deep-learning improves data mining activities and provides excellent opportunities for the preliminary accurate and non-intrusive diagnosis of grave diseases and ailments such as cancer, hepatotoxicity and neurodegenerative diseases. Parkinson's disease affects the human nervous system and behavior or motor function in general in the case of dementia. It outlines a machine learning-based system that identifies Parkinson's disease using speech signals with the help of a quantum-classical convolution neural network (QCCNN). Like how CNNs decode feature mapping, QCCNNs enhance the mapping processes by employing quantum computing. Preprocessing filters, such as the principal component analysis, are used for the preprocessed datasets to optimize the prediction accuracies. Using a standard dataset from the UCI machine-learning repository, I show that ensemble models have superior detection rates to other machine learning and deep learning techniques for Parkinson's disease.

The proposal of utilizing deep learning DL in conjugation with quantum computing for future complex or multidimensional-modeled solutions with healthcare diagnosis is discussed in the research done in [25]. Quantum deep learning raises data mining to a new level by using quantum computing to engage within large multidimensional domains, making early-stage non-invasive diagnostics of health disorders, including cancer, hepatotoxicity, and neurodegenerative diseases like Parkinson's. Parkinson's, associated with dementia, produces a decrease in the nervous system and changes interactions and patient behaviors. The study suggested a new quantum model that combined both quantum and classical convolutional neural networks or the QCCNN, which is inspired by CNN but tailored to quantum computations with the view of enhancing feature mapping. Preprocessed disease datasets were analyzed by applying dimensionality reduction methods, particularly PCA. Finally, applying ensemble models on a UCI repository dataset revealed better detection ability than the AM and DL algorithms, especially in detecting PD.

As described in [26], the current study was the first to investigate the effects of parental psychological abuse on symptoms of psychological disorders in TMGY subgroups – including transgender women, transgender men, and genderqueer individuals. The symptoms investigated in the study-included depression, anxiety, self-harm risk, and suicidal risk in 1293 transgender and genderqueer adolescents and adults from across China based on the 2017 Chinese National Transgender Survey. These were in addition to a measure of parental abuse that included neglect, forced conformity, and verbal insults. In the network analysis, suicidal risk and self-harm were found to correlate with parental neglect and avoidance, and node centrality produced a moderate effect size for low self-esteem (r^2 = 0.25, 0.17, 0.31) for all subgroups. Abuse and psychopathological symptoms were significantly higher in pre- to post-transition MTF transgender women than in their male counterparts. Consequently, the results highlighted how parental psychological abuse should be considered as another type of family violence and how preventive measures in schools and neighborhoods should be offered to assist gender minority youth in managing mental health problems.

Comparing the results presented in [27], Alzheimer's disease insistently grows in populations, being ranked as one of the primary causes of disability and also taking the seventh place among cases of death according to WHO. This work proposed a novel explainable prediction model implemented on a clinical, MRI segmentation, and psychological dataset regarding natural limitations in diagnosing AD. A comparison of 9 machine-learning algorithms, such as RF, LR, and GB, found RF to be the most accurate, with a 10-fold cross-validation of accuracy of 98.81% in five AD-related classes. For interpretability, Shapley Additive explanations (SHAP) were used to detect important features and explain model judgments. This work can be considered a significant leap forward in multimodal classification, using the OASIS-3 database and designing a new patient management architecture for Alzheimer's patients.

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Table 1 shows that machine learning (ML), artificial intelligence (AI), and other advanced technologies have been comprehensively applied in diagnosing and managing neurodegenerative diseases and cognitive impairments, as summarized in Table 1. It considers various methodologies such as EEG analysis, MRI-based modeling, multimodal data integration, and new frameworks like quantum-classical neural networks. Early detection of Alzheimer's disease, Parkinson's disease, and mild cognitive impairment, together with accurate diagnosis and prognosis, is facilitated through the application of predictive models, feature extraction, and interpretable AI tools, with various studies focusing on EEG and MRI modalities to more novel and holistic approaches. Despite such promising results, the increased classification accuracy and precision in diagnosis—studies plead for more extensive databases, enhanced generalization potential and complicated/ethical incorporation of these systems into clinical workflows. All these efforts to ease inequalities in access to healthcare, such as telehealth provisions, indicate the multidimensional difficulties and possibilities in the outcome quality for patients through diagnosis innovation.

Table 1: Summary of Literature Review

Study	Focus Area	Key Methodology/Model	Key Findings	Limitations/Future Directions
[8]	MCI diagnosis and intervention	ML techniques (Random Forest, xgboost) on the KLOSA dataset	Significant predictors include sociodemographic and health-related factors, highlighting ML's role in early detection	Integration of multifaceted data is emphasized; underdiagnosis remains a challenge
[9]	Early-stage AD diagnosis	EEG signals; extraction of 43 time-frequency features	Achieved 100% accuracy in differentiating AD stages from controls	Larger datasets are needed to improve generalizability
[10]	Neurodegenerative diseases	AI techniques (CNNs, NLP, ensemble methods)	Enhanced early detection and personalized treatment; integration of multimodal data	Challenges include data standardization and ethical concerns
[11]	Early diagnosis of neurological diseases	AI (ML, DL, NLP) applied to imaging and health records	Identified minute brain changes for personalized treatments	Adoption limited by dataset complexity and interpretation challenges
[12]	AI in healthcare diagnostics	Interpretable AI using bottleneck layers and unsupervised frameworks	Improved diagnostics through interpretable models	Complex model architecture hinders the adoption
[13]	MCI detection in community settings	FACE memory®, self-administered online test	Achieved sensitivity of 0.81, specificity of 0.72; validated as a diagnostic tool	Further validation is required for broader adoption

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[14]	Cognitive impairment detection	One-class classification with motor-cognitive tasks	Gait features showed the highest predictive accuracy (87.5% sensitivity)	More extensive clinical validation is needed
[15]	Systems biology of late-onset AD	Deep learning, CNNs, SMOTE	Identified early and clinical-stage biomarkers; highlighted advanced AI applications	Biomarker efficacy and representation need further research
[16]	AD early diagnosis with MRI	Vision Transformers (VITS)	Improved pattern detection with self-attention mechanisms	Conventional MRI analysis remains complex
[17]	Multimodal AD imaging analysis	Multi-scale deep learning with advanced fusion strategies	Outperformed state-of-the-art methods using the ADNI dataset	Challenges in modality interaction remain
[18]	Cognitive ability estimation through MRI	SVM, RVR on hippocampal volume data	High classification accuracy (94.17% for HC vs AD dementia)	Generalizability across datasets needs further validation
[19]	Dementia predictive models	Multiple ML models with LASSO feature selection	SVM achieved 96.77% accuracy; demonstrated ideal early diagnosis potential	Feature selection methods require refinement
[20]	AD classification challenges	ADXCLASS deep learning framework	Improved classification reliability with multi-domain fusion	Challenges with missing data imputation in tabular data
[21]	Telehealth and patient compliance	ML analysis of telehealth-supported physician advice	Highlighted disparities and the potential for telehealth policy improvements	Rural-urban technology gaps limit accessibility
[22]	EEG in dementia diagnostics	Portable EEG, P300 biomarker	AI accurately differentiated cognitive impairments; community applicability highlighted	Limited clinical integration of EEG technology

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[23]	Telehealth access during COVID-19	ML-driven telehealth compliance study	Identified increased usage but persistent disparities in rural-urban access	Emphasized the need for equitable telehealth solutions
[24]	Parkinson's disease diagnosis	Quantum-Classical CNN (QCCNN) on speech signals	Enhanced feature mapping and prediction accuracy with quantum computing	Clinical adoption of QCCNN remains limited
[25]	AI and quantum computing in health diagnostics	Quantum deep learning and PCA on the UCI dataset	Improved non-invasive diagnostics for multidimensional data	Limited real-world implementation of quantum models
[26]	Psychological abuse in TMGY groups	Network analysis on parental abuse and psychopathology	Significant correlations between abuse and mental health symptoms	Highlighted the need for preventive measures in schools and communities
[27]	Explainable AD prediction models	RF, SHAP on OASIS-3 dataset	Achieved 98.81% accuracy with interpretable features	Need for scalable implementation of new architectures

In conclusion, the present study demonstrated hope in applying machine learning and artificial intelligence techniques to enhance the diagnosis and outcome of neurodegenerative diseases. The analyzed papers indicate that applying these technologies for scoring purposes, monitoring biomarkers even at an early stage of bills, and obtaining more accurate diagnostic results is possible. Stiff, complex tasks still thicken the expertise atmosphere, including data quality, construal, and ethics issues. To advance the field of AI in clinical medicine, additional research should continuously aim to design more efficient algorithms that can be easily incorporated into ordinary practice to improve patient outcomes.

3. Discussion

New sophisticated technologies such as artificial intelligence (AI) and machine learning (ML) have emerged as some of the greatest inosculations in neurodegenerative disease diagnosis and treatment. These technologies have enhanced unmatched uses in big data, including imaging and physiological signals and gene and behavioral data for the timely diagnosis of diseases such as AD and MCI. This section looks at several new methods, such as EEG biomarkers, feature extraction based on MRI, Telemedicine, and quantum application in computational models. Both approaches exemplify certain advantages in enhancing forecasting precision, diagnosing sensitivity, and the availability of healthcare products. However, the following barriers still arise: Data standardization, Ethical questions and Clinical application, thus calling for more development and improved research.

- **The objective of the Paper**

The review extends the discussion towards applying ML, AI, and related technologies to diagnose and manage neurodegenerative diseases in specific AD and MCI. This disease, in which there occurs gradual impairment of mental function, brings about considerable social and economic costs all over the world. The paper emphasizes how ML and AI solve major fundamental issues relevant to early diagnosis, feature extraction and fusion of multimodal data, enabling the advancement of much more accurate, timely and personalized healthcare systems [28].

These early biomarkers development areas use medical imaging, genetic profiles, and electronic health records. By training models to identify relevant features from large datasets using techniques such as deep

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learning and ensemble methods, the diagnostic accuracy is significantly improved, instilling confidence in the potential of ML and AI to outperform humans under specific tasks. The review also discusses an impressive approach to amalgamate imaging, neuropsychology, and biomarker data and analysis through AI, which enhances the understanding of disease progression [29].

XAI and transfer learning are examples of innovative approaches and perspectives helping to address some of the key challenges regarding the clinical applicability of the approach. Data ethical issues such as data privacy and the issue of bias in the algorithms are also discussed, considering the proposed solutions as good and ethical solutions [30].

Lastly, this review must underscore the pivotal role of collaboration in the progress of neurodegenerative disease management. Innovations in ML and AI are reshaping the landscape of diagnostics and management of NDs, opening new avenues for better interventions and individualized care. This progress is only possible through the collective efforts of clinicians, data analysts, scientists, and patient advocates [31].

Table 2: Key Themes and Topics

Theme	**Details**
Early Diagnosis	Highlighted the importance of early detection for improved intervention outcomes [32], [33].
Technology in Healthcare	It focuses on ML and AI applications such as EEG, MRI, telehealth, and quantum computing [34].
Challenges in Implementation	Discussed data complexity, ethical concerns, generalizability, and access disparities [35].
Predictive Modeling	Emphasis on high-accuracy algorithms like SVM, CNNs, and Vision Transformers [36].

- **Key Methodologies Explored**

▪ Electroencephalogram (EEG): In one of the studies, it has shown its ability to differentiate one stage of AD from another, ideally, with 100% accuracy [37].

▪ MRI-Based Models: Superior methodologies such as Vision Transformers, coupled with multimodal fusion, have even been employed to increase the ability to capture structural brain changes [38].

▪ Telehealth Applications: Coupled the issues, disparities, and effectiveness of remote patient compliance monitoring [39].

▪ Quantum Computing: Proposed quantum-classical convolutional neural networks to improve disease feature mapping [40].

1. Strengths of the Paper

▪ Comprehensive Review: Discussed a wide variety of different technologies and their uses.

▪ Emphasis on Interpretability: Many publications have aimed to address interpretability problems in utilizing the ML and AI models in clinical practice.

▪ Practical Solutions: Discussed and compared possibilities of using telehealth and diagnostic resources for entire communities for affordable treatment.

2. Limitations and Gaps

- Data Availability: The paper highlighted the pressing need for more significant and diverse cohort populations, underlining the urgency and importance of this issue in healthcare research.

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- Clinical Integration: Issues associated with integrating these technologies into clinical care practice.
- Ethical Concerns: The paper delved into the gravity of ethical concerns, particularly those related to privacy, fairness, and blindness, in the context of AI and ML in healthcare.
- **Future Directions**

▪ Scalability and Validation: Stress on model replication in more significant, diverse participant groups.

▪ Interdisciplinary Approaches: The comprehensive nature of the research can be underlined by integrating AI with such areas of study as genetics, epigenetics, and quantum technologies.

▪ Policy Changes: Expanding Telemedicine's use and working towards improving health care for underrepresented populations.

The paper offers an appreciable consolidation of the recent developments in AI and ML for diagnosing neurodegenerative diseases with remarkable progress in robustness and progressed diagnosis. Though improvements are observed, additional studies are needed to advance the issues of scope, ethical standards, and the incorporation of such technologies into everyday clinical practice.

4. Conclusion

This review focuses on the review of the use of artificial intelligence and machine learning in working with neurodegenerative diseases, particularly Alzheimer's disease and mild cognitive impairment. The studies under discussion prove appreciable progress in applying EEG, MRI, multimodal data fusion, and quantum computing to recognize diseases early and accurately. All these approaches offer higher performance than conventional diagnosis modalities through accurate and efficient info integration and feature extraction, as well as predictive modeling and clinical utility. However, some challenges include data accessibility, scalability, and ethical issues, which hinder the expansion of these breakthroughs. Artificial intelligence and machine learning platforms are not just tools but potential game-changers in healthcare. They offer significant opportunities to revolutionize clinical practice, particularly early diagnosis, precise treatment approaches, and effective patient care. For instance, wearables like portable EEGs and telehealth are extending healthcare reach and addressing challenges related to health disparities. These advancements enhance detection accuracy and provide practitioners with a wealth of information for decision-making. However, to fully realize these benefits, we must bridge the gap between innovative technological designs and their practical implementation, especially in low-resource environments.

Despite the identified promises of AI for diagnostics, essential problems regarding their effectiveness and bias need to be resolved. Problems include getting limited generalization capability because of minor or nearly identical datasets, data bias during model training, and the absence of consistent data structure, which limits general use. Furthermore, some AI models are complex, thus causing problems with interpretability among clinicians who need to trust the models and apply them in practice. Privacy issues and fairness prerequisites to develop appropriate values associated with equitably providing patients' care also call for the prudent use of these technologies. Further research should focus on applying demonstrable, explainable, and "safe" artificial intelligence to advance the area. Making available new, various, and high-quality datasets will be important for practically enhancing model generalization and stability. Some of such directions include interpretable bottleneck layers with applications in complex medical image analysis and multimodal fusion approaches to combine image and clinical information towards accurate diagnosis, as well as the use of focused domain-specific deep learning frameworks designed to solve specific tasks in the field of radiology. Further, multidisciplinary teamwork of clinicians, scientists and policymakers could help define the AI applied clinically and socially responsibly.

Lastly, using AI and ML for neurodegenerative disease diagnostics is considered one-step further in developing healthcare services. These technologies cannot only improve early identification and, thus, timely treatment of causes that might lead to AD or MCI but also decrease the effect of such diseases around the globe. However, developing this approach as a widely practiced norm remains a far-fetched goal due to barriers that must be overcome by constant research, policy networking, and cross-sectoral cooperation. As with many applications of AI and ML that emphasize the patient, we can expect neurodegenerative disease care to be elevated to a new level and millions of patients worldwide to benefit from it.

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