

Artificial Intelligence in Neurodegenerative Diseases

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Abstract

AI allows for automated data interpretation and decision-making. The peculiarity of AI is to be able to learn from data to acquire knowledge, represent and process information related to the task it has to perform, thereby overcoming the difficulty to assimilate and extract valuable information from large datasets. Thus, AI can be used as a powerful tool in the elaboration of biomedical data for the development of predictive models. One of the most relevant data sources for AI comes from the biomedical field, and the ability of DL- one of AI's most important branches, alongside ML- to automatically learn complex representations from data is showing to be particularly promising to help ND research and clinical management. Neurodegenerative diseases have shown an increasing incidence in the older population in recent years. A significant amount of research has been conducted to characterize these diseases. Computational methods, and particularly machine learning techniques, are now very useful tools in helping and improving the diagnosis as well as the disease monitoring process. In this paper, we provide an in-depth review on existing computational approaches used in the whole neurodegenerative spectrum, namely for Alzheimer's, Parkinson's.

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Introduction

Neuronal degeneration is a common cause of morbidity and cognitive impairment in the elderly. Neurodegenerative Diseases (ND) are a large group of neurological disorders with heterogeneous clinical and pathological expressions, affecting specific subsets of neurons in specific functional anatomic systems, placing a considerable burden on an increasingly aging society. ND are broadly identified as proteinopathies due to conformational changes affecting protein functionality, thereby causing toxicity or losing their physiological function: misfolded proteins start to aggregate resulting in neurotoxicity. ND are characterized by a high level of heterogeneity and complexity in terms of clinical presentation and etiology because of the interaction of genetic, lifestyle, and environmental factors. Notably, the heterogeneity of ND is a key confounding factor that complicates the understanding of disease mechanisms and the identification of treatments. Case-control cohorts often include multiple phenotypes on distinct disease trajectories or rely on models that only account for a few features of the central nervous system at a time, which has been reductive for complex diseases. Alzheimer's (AD) and Parkinson's (PD) diseases are two of the most frequent and heterogeneous pathologies among all the complex neurodegenerative proteinopathies, affecting 24 and 6.1 million people worldwide, respectively. Both disorders include hereditary Mendelian forms, caused by mutations in single genes and complex sporadic forms characterized by polymorphisms in multiple genes that interact with environmental, epigenetic, and transcriptomic signatures in determining the heterogeneity and the differential susceptibility to disease. To date, the identification of AD and PD therapeutic targets and in vivo biomarkers for early diagnosis is still challenging, because of the existence of different disease subtypes (phenotypic heterogeneity) and stages of disease (temporal heterogeneity). Driven first by genomic studies and more recently by transcriptomic and epigenomic studies, a large volume of data has been rapidly produced to tackle this heterogeneity. In the perspective of ND as a big data issue, such diverse observations could be pulled together to provide a personalized, multi-layer representation of patients, which considers the complex heterogeneity of the disease and the availability of effective diagnostic criteria and drug development deliverables. In this context, computational modeling and simulation represented key components of the scientific method in which both reductionist and holistic approaches are not treated as separate fields but as convergent and

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cross-supportive paths. Therefore, this review aims to analyze the rapidly evolving techniques for data integration of multi-omics, clinical, and neuroimaging data discussing their role in a precision medicine framework.

Artificial Intelligence in Neurology

In the subsequent section, we discuss the usefulness of merging multiple data types, including

multi-omics, clinical, and neuroimaging data to obtain a holistic representation of subjects Artificial Intelligence Applications on ND Multi-Omics and Clinical Data Integration Researchers exploiting biomedical big data for ND aim to empower clinical efficiency by combining various sources of information such as multi-omics, EHRs, and medical imaging (e.g., MRI) data, building a holistic representation of patients. DL models can be used as a cutting-edge data analysis technique to find patterns in a patient's broadscope view. This kind of approach can be hypothesis-free, exploring data in search of explanations for differences between groups instead of being hypothesis-driven as classical experiments. By building the most accurate representation of patients possible through the integration of all sources of biomedical data, DL allows researchers to find multi-modal biomarkers to develop more effective and personalized treatments, early diagnosis tools, as well as useful information for drug discovering and repurposing.

Along with neuroimaging data, EHRs can provide useful information when AI takes the field. De-identified data from the PPMI database was used for the identification of PD subtypes. The authors used a Long-Short Term Memory (LSTM) network to analyze patient data referred to six years of measurements on potential PD progression markers, including clinical features, imaging, bio-specimen measures, and demographics. LSTM can analyze time series data, allowing the authors to represent patients by considering value progression for the available features. The analysis brought to identify three PD subtypes with distinct patterns of progression, demonstrating heterogeneous characteristics within PD patients' features. The integration of biomarkers and clinical data for DL application showed that the disease progression rates, and the baseline severities are not necessarily associated and that motor and non-motor symptoms are not necessarily correlated. This experiment is a good example of how DL techniques enable the management of integrated multi-domain data. Another application of a multi-modal DL approach was used to predict MCI to AD progression. ADNI longitudinal data from cerebrospinal fluid biomarkers, neuroimaging, cognitive performance, and demographics were integrated and analyzed through a multimodal Recurrent Neural Network (RNN). This method allows integrating multiple domain data for multiple time points. Their results show that DL models perform better on integrated data than on separated single modality data, achieving a higher prediction accuracy. This approach could potentially identify people who might benefit the most from a clinical trial and assess risk stratification within clinical trials. Integration of multi-omics heterogeneous data was used to predict AD diagnosis.

The authors implemented a DNN to predict AD using large-scale gene expression and DNA methylation data from prefrontal region tissue of different individuals diagnosed with late-onset AD. Results showed higher accuracy in predicting AD with multi-omics integrated data rather than with single-omics data. The authors also compare accuracy results from conventional ML methods with their proposed DL method, observing an improved predictive performance. Currently, the use of DL methods on multi-omics integrated data is far more common in cancer research than in ND research, as fewer studies report the use of these methods in this area. Overall, data integration yields better classification and prediction results in almost every field where it is applied and is standing as the next level in biomedical research (Termine, 2021).

Definitions of Neurodegenerative diseases

Alzheimer's Disease: is a progressive age-related neurodegenerative disease characterized by the accumulation of amyloid plaques (beta-amyloid protein mixture), neurobrillary tangles (clumps of tau proteins) and a severe loss of connections between neurons responsible for memory and learning. Symptoms appear initially as mild memory impairments which can also be confounded with age related memory

losses. These progress into severe memory impairments leading up to personality changes, language difficulties, motor difficulties, delu-

sions and hallucinations. Diagnostic criteria include the presence of AD biomarkers assessed through MRI or PET images along with an assessment of dementia symptoms and the degree of cognitive impairment (Tăuțan, 2021).

Alzheimer disease (AD) and related dementias represent intricate, multifaceted neurodegenerative conditions, with AD prevailing as the most common form. The escalating incidence and prevalence observed across global populations could be attributed to a deficiency in primary and/or secondary prevention strategies. Despite affecting both sexes, AD exhibits a higher prevalence among females. While the extended life expectancy of women might contribute to this discrepancy, studies have revealed sex disparities in incidence, progression, pathology, and risk profiles for AD; the underlying mechanisms of which largely remain unclear (Toopchiani, S. et al. 2025).

Increasing evidence points to a pivotal role of immune processes in the pathogenesis of Alzheimer disease, which is the most prevalent neurodegenerative and dementia-causing disease of our time. Multiple lines of information provided by experimental, epidemiological, neuropathological and genetic studies suggest a pathological role for innate and adaptive immune activation in this disease (Heneka, et al.2025).

Dementia with Lewy Bodies: is caused by the accumulation of Lewy bodies (clusters of alpha-synuclein protein) inside the nuclei of neurons from the cerebral cortex and basal ganglia. Since both neurons involved with memory function and motor control are affected, the clinical symptoms of DLB are very similar to the dementia symptoms of AD and the abnormal movements encountered in PD (Tăuțan, 2021).

Dementia with Lewy Bodies (DLB) is one of the most common forms of dementia in the aged population after Alzheimer's disease (AD)¹ and is clinically characterized by cognitive fluctuations, visual hallucinations, parkinsonism and rapid eye movement sleep behavior disorder. DLB is pathologically characterized by the intraneuronal accumulation of α -synuclein (α -syn) in Lewy bodies in the neocortex². The clinical and pathological presentation strongly overlap with AD, challenging differential diagnosis and leading to a large proportion of miss- or undiagnosed DLB patients (del Campo et al, 2023).

Parkinson's Disease: is a motor disorder characterized by the loss of dopamine producing neurons through the accumulation of alpha-synuclein proteins. The main clinical characteristics include resting tremor, bradykinesia (a slowing of movements), muscle rigidity, gait and postural disturbances, sleep disorders, tiny handwriting and difficulties when speaking or swallowing. A cure for the disease has not been discovered and current treatments focus on alleviating the symptoms, either through medication, physical therapy or deep brain stimulation. Two severity rating scales are used predominantly in medical practice: Movement Disorder Society - Unified Parkinson's Disease Rating Scale (MDS-UPDRS) - rating based on behavior and mood, activities of daily living, motor tasks and therapy effect; Hoehn and Yahr Scale - rating based exclusively on gait and posture impairments (Tăuțan, 2021).

Objective, quantifiable, and easy to operate evaluation methods are crucial for assisting in the diagnosis of Parkinson's disease. In the widely used Unified Parkinson's Disease Rating Scale (UPDRS) III, item 3.12 (postural stability) is used to evaluate the patient's body balance. But in actual clinical scenarios, doctors' judgments are subjective and have high internal variability. We propose a method based on monocular vision to objectively evaluate patients' body balance. Firstly, we use a combination of deep algorithms to obtain joint point sequences of patients and doctors in the video. Then, we use these sequences to further extract three features to evaluate the patient's balance, which are the patient's backward steps, the patient's body tilt, and the patient doctor's body distance (Ding et al, 2024).

Multiple System Atrophy: is a progressive neurodegenerative disease that affects multiple areas of the brain and spinal cord responsible with the coordination of the autonomic nervous system. As DLB and PD, it is also linked to the accumulation of alpha-synuclein but in this case in the glia cells. Symptoms

include bradykinesia, impaired speech, orthostatic hypotension, bladder control problems, abnormal sweating and sleep disorders (Tăuțan, 2021).

Multiple system atrophy (MSA) is an adult-onset, sporadic, and rapidly progressive neurodegenerative disorder, that currently lacks a cure. It manifests with a combination of symptoms such as parkinsonism, dysfunction of the autonomic system, impairment of the cerebellum, involvement of the pyramidal tract, and a poor response to medications targeting dopamine. The pathological features of MSA include the loss of cells, gliosis, and the presence of abnormal α -synuclein protein aggregates in oligodendroglia in various structures of the central nervous system. Clinically, MSA can be classified into two phenotypes based on the primary motor system affected: the parkinsonian variant (MSA-P) and the cerebellar variant (MSA-C). The diagnosis of MSA primarily relies on a thorough medical history and a meticulous neurological examination. Symptomatic treatment targeting various clinical manifestations and providing palliative care during the advanced stages of MSA form the cornerstone of current treatment strategies (Rukmani et al, 2024).

Amyotrophic Lateral Sclerosis: is a progressive neurodegenerative disease that affects motor neurons. Muscles begin to atrophy as their control is no longer possible. The incipient phases of ALS usually affect the limbs and symptoms rapidly progress to other parts of the body. In the final phase of the disease, the muscles controlling the respiratory system begin to weaken. Death usually occurs within 3 to 5 years from disease onset due to respiratory failure. The most relevant clinical features include: severe motor impairments, muscle twitches, speech impairments, difficulties swallowing.

Huntington's Disease is an inherited progressive neurodegenerative disease characterized by a mutation in the huntingtin gene that causes motor neurons controlling voluntary movements to die. The symptoms include chorea (uncontrolled movements), abnormal body postures, speech impairments, changes in behavior, emotion, judgment and cognition. Death occurs 10 to 30 years after disease onset. The diagnosis is based on genetic testing and neuroimaging techniques (Tăuțan, 2021).

Motor neuron diseases (MNDs) are motor syndromes (sensory sparing) that begin insidiously, are chronically progressive, can be distal, proximal, or mixed, and can have different combinations of upper and lower motor neuron findings. These are usually sporadic while some forms can be familial. Amyotrophic lateral sclerosis (ALS), perhaps the most common of MNDs, is a progressive disorder of motor neurons in the brain and spinal cord. ALS is fundamentally a clinical diagnosis, supported by neurophysiological testing. There are no cures for ALS, but there are evidence-based guidelines for standards of care (Khadilkar et al, 2024).

Artificial Intelligence for Alzheimer's Disease: Promise or Challenge?

Alzheimer's disease (AD) is an irreversible neurodegenerative disease that progressively destroys cognitive skills, up to the development of dementia. The clinical diagnosis of AD is based on the presence of objective cognitive deficits (which are, typically, prominent memory impairments). In some cases, AD may show atypical presentations, with impairments in non-amnesic domains (i.e., attention, executive functions, visuo-constructive practice and language). However, AD shares many common clinical features with other neurodegenerative dementia, including Lewy body dementia, frontotemporal disorders, and vascular dementia, making early and differential diagnosis difficult, especially in the first stage of the disease.

In atypical AD, clinical signs of fluent and non-fluent progressive aphasia, or dysexecutive/behavioral changes, may overlap with frontotemporal dementia syndromes; posterior cortical atrophy (PCA) with underlying AD etiology may clinically overlap with dementia with Lewy bodies or corticobasal syndrome. Finally, the occurrence of co-existing pathologies is a common feature in those cases of neurodegenerative diseases that share a common pathogenic mechanism, consisting of extracellular and/or intracellular insoluble fibril aggregates of abnormal misfolded proteins (e.g., the formation of amyloid plaques, tau tangles, or α -synuclein inclusions). In this context, the system biology approach, which aims at the integration of clinical and multi-omics data, can help to detect and recognize the pathophysiological and

molecular changes characteristic of AD or other pathologies, as well as the associated clinical manifestations occurring, in particular, in the pre-clinical stages.

Amyloid plaques and neurofibrillary tangles are the neuropathological hallmarks of the disease, which can be evaluated *in vivo* by neuroimaging investigation and cerebrospinal fluid (CSF) biomarker assessment; namely, considering amyloid₁₋₄₂ (A₄₂), its ratio with amyloid₁₋₄₀ (A₄₂/A₄₀), total tau protein (t-tau), and hyperphosphorylated tau (p-tau181).

As AD is multi-factorial, many conditions can influence the individual risk and age of onset, particularly metabolic impairments (diabetes mellitus, hypertension, obesity, and low HDL cholesterol), depression, hearing loss, traumatic brain injury, and alcohol abuse. Lifestyle factors such as smoking, low physical activity, and social isolation are potentially modifiable, while several of these may have bi-directional relationships and may be early manifestations, other than risk factors, in the prodromal phase of dementia. All of these clinical, biological, socio-demographic, and lifestyle factors contribute to defining the development of the disease and, therefore, are useful in trying to understand the still-misunderstood etiology of AD.

Decades of experimental and clinical research have contributed to unraveling many mechanisms in the pathogenesis of the disease, such as the amyloid hypothesis, but the puzzle remains incomplete. Clinical and biological data from electronic health records and multi-omics sciences represent a potentially unlimited amount of information about biological processes, such as genomes, transcriptomes, and proteomes, which can be explored through Big Data exploitation. The rapid collection of data from tens of thousands of AD patients far exceeds the human ability to make sense of the disease.

Complex AI-based models can be successful in extracting meaningful information from Big Data; however, as their complexity increases, it becomes more and more difficult to interpret how they produce their output. Thus, they have been called black-box models.

Making AI explainable is a key problem of AI technological development in recent years, and is of pivotal importance in healthcare applications, where both patients and clinicians need to trust research methods to make decisions about people's health. The AD pathology is characterized by high complexity and heterogeneity, and many authors have demonstrated the absence of etiological uniformity and diverse treatment suitability for each patient, supporting the need for an accurate individual diagnosis. In order to make the most of biological experiments and refine their findings, they have to be supported and followed by complex biological modeling, based on mathematical and statistical tools such as Artificial Neural Networks. Formalized domain expertise from psychology, neuroscience, neurology, psychiatry, geriatric medicine, biology, and genetics can be integrated with novel analytic approaches from bioinformatics and statistics to be applied on Big Data in AD research projects, with the aim of answering detailed questions through the use of predictive models. These can succeed in answering key questions about promising biomarker combinations, patient sub-groups, and disease progression, finally leading to the development of effective treatment strategies, helping patients with tailored medical approaches.

In this context, AI technology represents a promising approach to investigate the pathological mechanisms of AD by analyzing such complex data. In this review, we focus on recent findings using AI for AD research and future challenges awaiting its application: Will it be possible to make an early diagnosis of AD with AI? Will AI be able to predict conversion from Mild Cognitive Impairment (MCI) to AD dementia, stratify patients, and identify “malignant” forms with worse disease progression? Finally, will AI be able to predict the course and progression of the disease and help in finding a cure for AD? (Fabrizio, 2021).

5. Artificial intelligence and neuropsychological measures: The case of Alzheimer's disease

In the last few years, artificial intelligence has proven to be a new effective way in designing prognostic/diagnostic tools for improving the clinical practice of AD. In particular, machine learning (ML) methods, which are intelligent systems capable of learning complex relationships or patterns from empirical data and extracting predictive data models, have found fertile ground in the study of AD with promising

results for biomarkers also at an early-stage (Bishop, 2006; Orru et al., 2012; Salvatore et al., 2016). ML methods have been applied on several features with ability in the prediction of which subjects with MCI will progress to AD. These include biological, neuroimaging data and neuropsychological testing. Neuroimaging is the most important realm where ML methods have widely been applied (Weiner et al., 2017). By combining, in a multivariate way, information hidden in the brain images of patients and invisible to a naked eye, ML methods can automatically classify an individual subject on the basis of image differences or similarities with images of known classes of subjects (Noirhomme et al., 2014; Bryan, 2016). From the first seminal paper by Klöppel et al. (2008), in the last 10 years, a plethora of ML studies on neuroimaging have been published with the aim to reach the best accuracy level in the automated clinical diagnosis of AD. Whilst classification accuracy in discriminating AD from healthy controls (HC) range between 80–95% (Mateos-Pérez et al., 2018) the real challenge is to automatically classify between prodromal forms of disease. A recent review of more than 30 papers showed that the ML automatic classification of MCIc vs MCIc, based on neuroimaging data, can achieve a median accuracy, specificity and sensitivity of 70 %, 66 % and 75 %, respectively.

ML has also been applied to biological data of AD and MCI patients. By combining different biological markers in a multivariate way, this approach has been used to identify a biological signature of AD. For example, it was shown that the cerebrospinal fluid calbindin combined ML has also been applied to biological data of AD and MCI patients. By combining different biological markers in a multivariate way, this approach has been used to identify a biological signature of AD. For example, it was shown that the cerebrospinal fluid calbindin combined with cerebrospinal fluid A β 42 can automatically discriminate between mildly and very mildly demented subjects from HC with a sensitivity and specificity >80 % (Craig-Schapiro et al., 2011). However, in the classification of MCIc vs MCIc, this combination of measures led to a good sensitivity (80 %) but a very low specificity (44 %), with a balanced accuracy of 62 % . At a cognitive and behavioural level, international Working Group guidelines have proposed a list of neuropsychological tests for the diagnosis of AD. However, there is still no clear consensus on the specific composite measures to be used for the early diagnosis of AD, since the discussion is still open as to what the most sensitive/specific tests are for early-stage AD. Some authors have argued that stringent cut-off should be fixed in order to identify whether performance is impaired for MCI subjects. To date, studies on the application of ML to neuropsychological tests are increasingly emerging, since some evidence show that ML systems can support the clinical classification of AD patients when trained on neuropsychological measures (Battista, 2020).

Artificial intelligence techniques in Alzheimer's disease detection

AI is a concept that enables the optimization of the performance criteria using a set of data or some experience. The process of learning is actually the execution of the model parameter optimization with training dataset or past experience. Models can be either predictive, for making future predictions; descriptive, for extracting knowledge from input data; and both. In machine learning, two important tasks are performed: processing the huge amount of data and optimizing the model and testing the model and representing the solution in an efficient way. In some applications, the efficiency of learning is as important as classification accuracy. Additionally, AI techniques enable the system to learn the changes in different environments and adapt to those changes. For example, AI helps us in vision, speech, face or any other types of recognitions.

Why artificial intelligence is important for Alzheimer's disease

AI techniques have been taking significant consideration in the neuroimaging research community because of its advantages over conventional diagnostic techniques which utilize mass-univariate statistical methods. Particularly, AI techniques use the correlation among the areas, while mass-univariate statistical techniques assume diverse areas work individually. Moreover, AI techniques might be employed to find implications at the subject level whereas mass-univariate statistical techniques utilize differences at the group level. DNN is gradually employed in neuroimaging subsequently causing to scientific improvements in the computer vision by expressively beating other state-of-the-art recognition techniques. The main difference between

DNN and conventional AI techniques is DNN can learn features from the raw data without employing feature extraction and selection.

Besides, DNN employs a hierarchy of nonlinear transformations that achieve ideally suitable for distinguishing scattered, subtle, and complex patterns.

The results available so far propose that DNN can be useful for AD detection and the classification accuracies were high (above 95%) for binary recognition among the CS and patients. As discussed before, these modest results might be described by the lack of proper approaches to circumvent overfitting of the DNN classifier. DNN is a flexible method which merges diverse structures and employs a variety of hyper-parameters inside the same model. Furthermore, since most of the existing studies published in the last 5 years, the area of DNN used in neuroimaging of AD must be considered still at the early phase. CNNs are a special type of ANN stimulated from the human visual cortex. CNNs were breaching histories in computer vision across numerous competitions, creating this method a very hopeful one. CNNs have achieved the most inspiring outcomes in the context of AD detection. Two fundamental properties of CNNs are local connectivity and weight sharing, yield an expressively decreased number of weights, producing a computationally conceivable to run the network. Although in AD detection CNNs are not only employed to discriminate the AD and MCI patients, the performance of the researches done so far is reliably high. High performances were achieved with diverse modalities including structural MRI, CT imaging, and resting-state fMRI, as well as large and with small sample sizes. employed an exciting and alternative method that included pretrained CNN in CAD Dementia Alzheimer's dataset and then adjusting and testing it with another dataset from the same investigative group. The outcomes were very optimistic for AD vs MCI; HC vs MCI; HC vs AD; and HC vs AD vs MCI. Hence, these studies with the effective performances of CNN-based models described in other research fields and presents CNNs as a talented method in AD detection. Moreover, these are encouraging findings reveals that how AI can be a bridge between the real-world clinical practice and neuroimaging findings.

Use of artificial intelligence in Alzheimer's disease detection Alzheimer's Disease (AD), characterized by a decline in cognitive function, is one of the most common degenerative brain disorders. Because this disease characteristically presents in people over 65 years old, the incidence of AD has increased sharply in concert with the increase of the elderly population. Given the difficulties in managing the advanced stages of AD, accurate diagnosis of the disorder is important for effective treatment. F-18 fluorodeoxyglucose (FDG) positron emission tomography/ computed tomography (PET/CT) has been widely used to diagnose AD by comparing the rate of glucose metabolism throughout the brain. A convolutional neural network (CNN) is a highly effective method of deep learning used to analyze and classify visual images of all kinds that cannot be resolved by conventional machine learning algorithms. An error rate of 3.5% has been demonstrated with the use of CNN, a value less than the error rate of manual classification by humans in classification of the CIFAR10 dataset. Krizhevsky et al. Reported an error rate of 15.3% at the Image-net Large-Scale Visual Recognition Competition (ILSVRC), significantly lower than the 26.2% error rate reported using the conventional machine learning method. Because the CNN-based method extracts appropriate features learned from images, unlike conventional machine learning algorithms, it does not require domain knowledge to extract Regions of Interest (ROI) or handcrafted features. Deep learning methods have recently been applied to AD classification. An autoencoder was applied to extract high-level features from MRI and PET images (Subasi, 2020).

Conclusion

Decades of experimental and clinical research have contributed to unraveling many mechanisms in the pathogenesis of Alzheimer's disease (AD), but the puzzle is still incomplete.

Although we can suppose that there is no complete set of puzzle pieces, the recent growth of open data-sharing initiatives collecting lifestyle, clinical, and biological data from AD patients has provided a potentially unlimited amount of information about the disease, far exceeding the human ability to make sense of it. Moreover, integrating Big Data from multi-omics studies provides the potential to explore the

pathophysiological mechanisms of the entire biological continuum of AD. In this context, Artificial Intelligence (AI) offers a wide variety of methods to analyze large and complex data in order to improve knowledge in the AD field. In this review, we focus on recent findings and future challenges for AI in AD research. In particular, we discuss the use of Computer-Aided Diagnosis tools for AD diagnosis and the use of AI to potentially support clinical practices for the prediction of individual risk of AD conversion as well as patient stratification in order to finally develop effective and personalized therapies.

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