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AI IN THE PREDICTION OF ONSET AND PROGRESSION OF NEURODEGENERATIVE DISORDERS USING MACHINE LEARNING MODELS

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Abstract
Medical research receives fundamental transformation through Artificial Intelligence (AI) which particularly optimizes the analysis of neurodegenerative disorders consisting of Alzheimer's disease (AD), Parkinson's disease (PD) and Multiple Sclerosis (MS). The processing and analysis of extensive and intricate dataset groups that contain medical images together with genetic data in conjunction with speech patterns and clinical files become achievable to AI systems through machine learning (ML) and deep learning (DL) algorithms. The technological tools provide healthcare professionals with opportunities to discover diseases at their onset and achieve precise diagnostic outcomes as well as estimate disease development and craft individualized therapeutic solutions .Artificial intelligence enables analysis of nervous system scans along with genetic information and cognitive screening tests which helps identify early symptoms of cognitive decline and predict how MCI leads to dementia. PD AI models recognize preclinical markers that consist of early nocturnal breathing problems together with motor control issues before symptoms emerge clinically. Fast diagnosis and long-term monitoring in MS is possible because AI joins MRI evaluation with fluid biomarker evaluation.AI models facilitate biomarker research while enabling medical staff to create decision support systems which allow them to evaluate therapeutic results and forecast results and adapt individual patient treatments. The evaluation of diseases and creation of patient groups becomes more effective through machine learning approaches which utilize supervised, unsupervised, and reinforcement learning strategies. Neurodegenerative disorder patients benefit from AI through improved diagnosis accuracy and

enhanced treatment systems which lead to elevated patient care quality and better life quality endpoints.

INTRODUCTION

Among numerous transformations AI has brought into the world medical research represents one important advancement. Since its integration into medical sciences Artificial Intelligence brings significant advantages that benefit patients and healthcare providers and the entire sector within this period of information technology (Dwivedi et al., 2022). Artificial Intelligence systems work efficiently with substantial medical data and they have the capability to identify structural patterns that are beyond human detection. Medical research and personalized medicine can experience a revolution because artificial intelligence effectively learns from enormous medical data collections. Recent advancements in artificial intelligence have enabled computational approaches to assist in diagnosis and monitoring through detection of disease onset together with disease characterization and improved differential diagnosis and disease progression quantification as well as medicine effect tracking (Ayaz et al., 2022). These types of work functions become automated through machine learning algorithms or reach elevated performance levels by using them. Through AI methods and algorithms medical personnel gain insights into large datasets that cannot be obtained through conventional means (Bohr & Memarzadeh, 2020). Different disorders in the category of neurodegenerative diseases result in the degeneration of brain and spinal cord neurons. This medical condition leads to cognitive and mobility problems together with mental symptoms according to research (HekİMoğlu & Yücel, 2024). Millions of people throughout the world develop neurodegenerative disorders creating significant negative consequences to their daily life quality. Medical experts remain uncertain about neurodegenerative disease origins although they accept such conditions develop from genetic and environmental and behavioral triggers (Essa et al., 2016). Different types of neurodegenerative conditions exist as distinct entities with unique cluster of symptoms. The generally widespread neurodegenerative diseases include Amyotrophic lateral sclerosis (ALS), Huntington's disease, Parkinson's disease and Alzheimer's disease (AD). The progressive brain illness AD creates a permanent condition which destroys memory and thinking abilities. Age serves as a key risk element in AD development because the disease typically strikes adults in their later years and generates most dementia instances (Hardiman & Doherty, 2011). Three distinct phases describe the development of AD according to 10 and 11. During pre-clinical AD patients exhibit cerebral amyloidosis as a brain dysfunction whereas the symptoms remain undetectable to medical assessment. The only people who detect mild brain changes in victims are their caring family members (Council et al., 2014). The transit through MCI marks the second developmental phase before the progression to AD. The severe symptoms of AD-induced dementia emerge during the third stage making it impossible for patients to conduct their daily responsibilities (Budson & Kowall, 2013). The recent developments in artificial intelligence brought substantial advancements to the diagnosis and prognosis as well as treatment strategies and disease tracking of neurodegenerative diseases. Neurodegenerative disease management is helped by artificial intelligence through which algorithms examine extensive data sets from distinct sources which include genetic profiles and clinical files and medical images (Bui & Taira, 2009)

This research discusses the prospective utilization of AI and its components for AD diagnosis, prognosis, treatment, follow-up, biomarker creation, drug development, along with AD predictions for this prevalent neurodegenerative disease (Ozkan et al., 2021). The current patient numbers for Alzheimer's disease at nearly 55 million worldwide will increase to approximately 150 million population by 2050. The incidence of Parkinson's disease has doubled during the last quarter century to become the fasting expanding neurological condition. Dementia costs the economy more than $1 trillion annually because of care expenses (Organization, 2003).

Medical challenges emerge due to the difficulties in detecting Parkinson's disease at early stages and monitoring its disease progression. The diagnostic tools such as clinical evaluations and neuroimaging and biomarker evaluation lead current diagnostic methods but these approaches identify diseases too late in their progression which reduces treatment effectiveness (Litvan, 2005). The resolution of these problems needs creative artificial intelligence approaches for both early identification and disease management improvement. The artificial intelligence techniques using machine learning together with natural language processing enable the analysis of multiple datasets to detect new possible patterns in the data. Research labors in neurodegenerative disorders through machine learning operations to create potential early diagnosing instruments and predictive models in addition to generating innovative therapeutic strategies (Bohr & Memarzadeh, 2020b).Executing machine learning results requires selecting the appropriate algorithm from numerous choices which suits the specific data type for achieving accurate outcomes. The initial benefit of machine learning techniques occurred in neuroimaging diagnostics but recent applications of these techniques for language and motor features analysis reduced evaluation durations(Machine Learning, 2017).Prediction of disease outcome alongside patient group analysis becomes more effective through machine learning applications in continuous healthcare data collection and health information systems. Current implementation of machine learning in diagnostic and prognostic neurology requires extensive collections of selected data combined with proper evaluation of machine learning techniques to achieve complete integration. (Bohr & Memarzadeh, 2020c)

Neurodegenerative disorders:

Neurodegenerative diseases represent a collection of medical issues which lead to central nervous system (CNS) cell death or deterioration until cells become non-operational. The cells in central nervous system (CNS) degenerate to such a degree that their ability to perform functions properly ends properly (Excerpta Medica, 1991). Moreover these disorders have both a genetic link and tumor-caused origins vascular dysfunction, viral infection, or exposure to toxins. This essay provides details on three major uses of artificial intelligence (AI) to study the prevalent neurodegenerative diseases Alzheimer's disease (AD), multiple sclerosis (MS), and Parkinson's disease (PD). (Hanin et al., 2013)

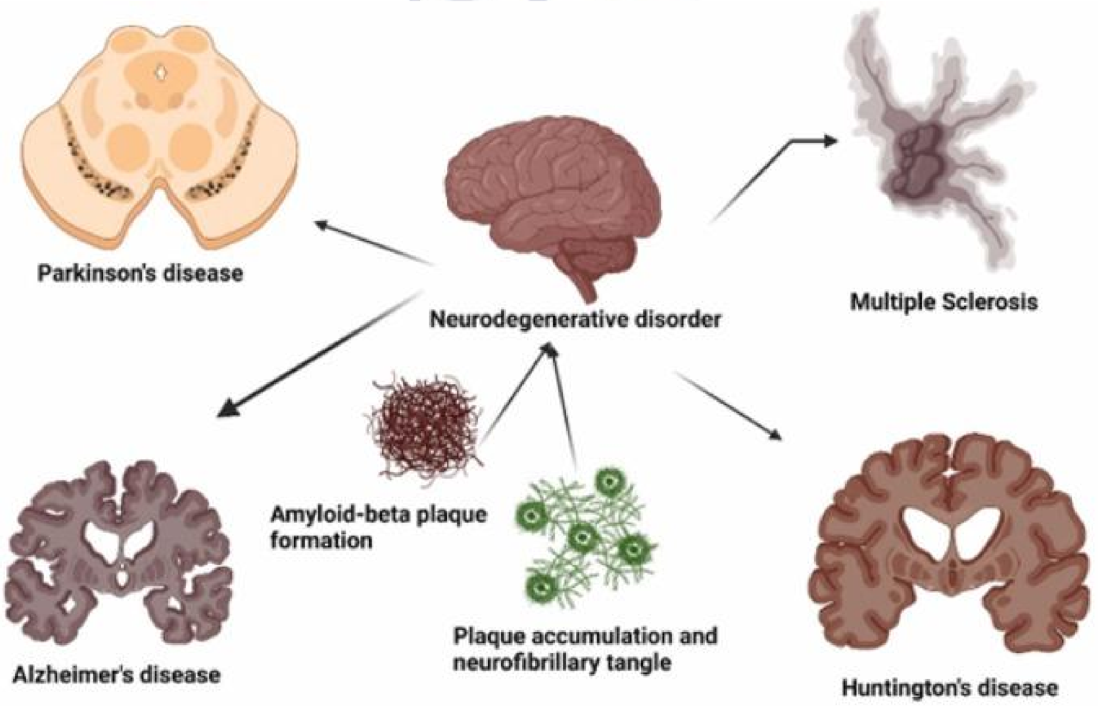

Fig. 1. Illustration of various neurodegenerative disorders such as Parkinson's disease, Multiple sclerosis, Alzheimer's disease, and Huntington's disease.

Alzheimer's disease (AD) represents the primary form of dementia because it progresses as a neurodegenerative illness which displays an unknown cause yet begins modestly with memory problems until blocking all mental functioning (Essa et al., 2016b). The statistical data from the US Centres for Disease Control and Prevention indicates that Alzheimer's diagnoses in Americans over 65 years old reached 5.8 million in 2020 and projections show this number will grow to 13.9 million by 2060 (Medicine et al., 2016). Patients with AD can utilize multiple medications currently which include lecanemab as the newest monoclonal antibody that targets specified beta-amyloid proteins. All these medications offer limited benefit because they cannot cure the illness yet they demonstrate effectiveness in managing symptoms and preserving disease progression. (Association, 2016)

The paper by Fabrizio et al. highlights AI as a valuable instrument for understanding this disease condition. The authors incorporate AD-related metagenomic and proteomic data obtained from diagnosed patients to demonstrate AI capabilities for trend analysis of large-scale datasets encompassing co-morbidities and psychological test data and neuroimaging findings plus lifestyle information (Cassidy & Taylor, 2020). The primary goal revolves around discovering patterns which enable the identification of subjects moving from moderate cognitive impairment (MCI) toward AD development. The research by Frizzell et al. presented a systematic evaluation of AI systems that diagnose brain MR imaging scans in AD and MCI patients (Keller & Chung, 2012). The authors evaluated 97 published studies before finding deep learning-based convolution neural network algorithms to have the best performance among all AI methods analyzed. An AI/deep-learning system employed by McKenzie et al. demonstrated how early AD-related changes appear through its applications (Bui & Taira, 2009b). Researchers performed an unbiased study of cognitive-associated histological changes using entire-slide brain tissue photographs from deceased elderly participants. The researchers examined 600 test subjects through their analysis and established a direct correlation between white matter myelin pallor and cognitive impairment (De La Monte, 2011). The findings from this study support previous studies which investigated AD-related white matter damage effects. The ensemble of initiatives at present does not show direct diagnostic or treatment achievements but their combined research suggests potential initial neurological signs that could lead to targeted intervention (Bagchi, 2010).

The autoimmune disease **multiple sclerosis** produces CNS demyelination and neurodegeneration as its main symptoms. The global estimate of multiple sclerosis patients will increase to 2.8 million by 2020 according to Walton et al (Brusa et al., 2022).

All clinical cases of multiple sclerosis patients experience acute attacks that lead to worsening disease impairment. Existing medical treatments and disease-modifying drugs against this illness still fail to produce suitable solutions for reversing its course (Mitoma & Manto, 2019). Addressing multiple sclerosis through AI-based diagnostic evaluation and outcome prediction and treatment monitoring by using MRI data in combination with blood and cerebral spinal fluid analysis results was introduced by Bonnachi et al. (Nistal et al., 2018). Multiple sclerosis poses challenges because its diverse condition exhibits the same symptoms as many non-inflammatory and inflammatory diseases. Proof of disease spread temporally and spatially stands as a requirement for rendering an MS diagnosis. The current need requires healthcare specialists to oversee and assess all AI results in spite of potential diagnostic advancements it may offer. (Cron & Behrens, 2024)

Patients affected by **Parkinson's disease** commonly experience the degenerative illness which triggers the disappearance of dopaminergic neurons in the nigrostriatal pathway (Ellenberg et al., 1995). Patients who have Parkinson's disease (PD) often display different manifestations including tremors alongside bradykinesia, hypokinesia, rigidity and postural instability symptoms. Current diagnosis of Parkinson's disease (PD) depends on identifying motor symptoms but these symptoms often emerge only after dopaminergic cell loss reaches a significant level (Ellenberg et al., 1995b). Scientists have not discovered any cure for the condition yet they can manage its symptoms through medication. The identification of nocturnal breathing problems through AI algorithms serves as an objective early marker to detect Parkinson's disease in a recent groundbreaking work by Yang et al. (Shahid et al., 2012). People develop respiratory indicators which medical personnel can detect several years before symptoms of clinical motor onset (Waller & Hitchings, 2021).

The study's AI techniques showed that PD both prediction and monitoring become possible through analysis of sleep study data and home-deployed radio frequency sensing devices for breath monitoring during nighttime (Syed-Abdul et al., 2020). The established tool will help detection of PD at an early stage while enabling scientists to develop new targets to improve existing PD management techniques.

AI in ND diagnosis:

Two essential aspects appear when using artificial intelligence (AI) in neurodegenerative disease (ND) applications. The use of AI analysis assesses various biomarkers covering metabolites alongside genes and proteins as well as images and extra biomarkers for improving diagnostic accuracy (Schulte & Perera, 2012). The clinical application of AI consists of two critical functions which help physicians forecast disease trajectories while evaluating treatment options and generating personal treatment recommendations (Mahler, 2021).

Imaging techniques provide one of the main biomarkers used for ND diagnosis through functional and structural modalities that include PET and SPECT in addition to MRI and CT. Two key structural brain changes in experimental subjects revealed by imaging tests consist of atrophy along with ventriculomegaly (Transcranial Sonography in Movement Disorders, 2010). Of all functional imaging methods changes in brain activity measurement appears through metabolic and perfusion changes and receptor density modifications. Reliable automatic processing of image data with ML or DL algorithms happens through AI which performs feature extraction and classification in addition to segmentation and registration procedures (Bui & Taira, 2009c). This process operates accurately and effectively. The implementation of this system will lead physicians toward objective and precise medical diagnoses. ML data analysis between PD patients and healthy controls revealed important volume loss in substantia nigra together with globus pallidum and striatum regions (Baltuch & Stern, 2007). An MRI-based model for Parkinson's disease diagnosis was created using ML with an 86.7% accuracy rating. The author documented in [4] how DL algorithms processed PET data from AD patients and healthy controls which demonstrated decreased frontal, parietal, and temporal lobes metabolic rates (Reilly & Atkinson, 2009). Research scientists in [4] produced a PET-based diagnostic model for AD that achieved remarkable performance with its 94.4% accuracy rate. A diagnosis model for AD based on brain tissue slices achieved 98.6% accuracy by applying the DL algorithm for analyzing AD patient and control group data (Gentilini et al., 2020). The findings demonstrated that AD patients presented distinct amyloid plaques together with cerebrovascular amyloidosis throughout the hippocampus and cingulate gyrus and various other regions. The diagnosis of ND greatly depends on gene biomarker examinations which primarily consist of single nucleotide polymorphisms (SNPs) and gene expression and epigenetics analysis (Ibáñez et al., 2018). Genetic materials enable doctors to understand both ND patients' risk factors and pathophysiological processes and therapeutic opportunities. The combination of feature selection followed by grouping along with classification and regression through AI powered by ML or DL algorithms enables analysis of complex large-scale genetic data techniques for physicians to perform complete distinctive medical diagnoses (Bohr & Memarzadeh, 2020d). The testing of a PD diagnostic model using gene expression features reached 93.8% accuracy after an ML algorithm processed gene expression data between PD patients and healthy controls. The research published in demonstrated major variations between various biological pathways (Brünner et al., 2012). The authors utilized the ML algorithm to evaluate SNP data obtained from both normal controls and AD patients. AD patients exhibited substantial mitochondrial gene variations and misplaced chemicals causing mitophagy which led to a potential new therapeutic approach for AD (Maestroni et al., 1997). The authors of [8] analyzed genetic information from over three types of ND patients and healthy participants by utilizing the DL method. Scientists identified major genetic differences throughout the immunological response and cell cycle and neuron function domains in ND patients (Kendler & Eaves, 2007). The diagnostic model developed to identify different forms of AND reached a 95.2% accurate diagnosis rate. Artificial intelligence system influences biomarkers through fundamental analysis of genetic data and imaging studies as well as complementary analysis of proteins and metabolites and cognitive assessments and speech patterns and behaviors (O'Brien et al., 2005). By implementing ML or DL techniques such as feature fusion and dimensionality reduction and augmentation AI fully connects and maximizes the valuable data to enhance physician diagnosis quality. A study in showed machine learning algorithms performed identical assessments on biomarker information including images and genes and proteins along with cognitive testing belonging to both AD patients and healthy volunteers (Mahler, 2021b). These aspects allowed the algorithm to develop an AD diagnostic model which produced 97.8% accurate results. The data analysis of PD patient speech and healthy control speech using DL produced a PD diagnosis through speech features having a 91.4% accuracy (Tappero & Honeyfield, 2014). The research developed a diagnostic model through machine learning analysis to distinguish between 68 ND types along with their severity levels using behavioral data from patients and healthy controls with an 88.6% accuracy (Vohland et al., 2021). AI offers clinical decision support for ND patients through three functionalities that include disease progression predictions and therapy assessments and customized treatment recommendations as well as ND differential diagnostics based on biomarkers (Giavina-Bianchi & KO, 2024). These applications enable medical staff to construct logical treatment plans which lead to improved patient results as well as better quality of life.

AI-based "predicting disease progression" determines the health modifications and risk elements of ND patients to help medical personnel provide accurate timely patient care (Latifi, 2019). The combination of data from ND patient cognitive tests with imaging results along with genetics and other information leads scholars to develop a machine learning-based clinical support system which predicts dementia probabilities for up to one year (Rekik et al., 2019). This system displays both analyzed results and their agreed confidence ratings. A deep learning-based clinical decision support system emerges from PD patient test data relating to motor responses together with speech and eye movements alongside other data points as noted in. The system obtains a six-month prognosis regarding motor issues in PD patients along with their probabilities while providing explanations. The evaluation of treatment impact uses artificial intelligence to offer unsolicited recommendations and feedback to doctors about how ND patients improve alongside their treatment side effects from various options (OECD, 2017). For AD patient evaluation of medication-based treatment effects on cognitive performance and brain anatomy researchers developed an AI-powered clinical support tool that combines neurological tests with brain scans and fluid analyses. According to the output the system establishes different ratings combined with rankings. The deep learning-based clinical decision support system observes PD patients through eye movement monitoring and speech evaluations together with motor tests after procedures as it measures surgical outcomes on patient motor capabilities while generating relevant data indicators(Bohr & Memarzadeh, 2020e).

Personalised advise represents AI technology analyzing specific patient requirements and characteristics of ND individuals for delivering customized treatment selections and care approaches to medical professionals (Popular Mechanics, 2000). The clinical decision support system utilizes machine learning to process age, gender, education level and family heritage data of AD patients along with other patient-related information. A support system employs matching justification and predicted outcomes to design personalized recommendations about cognition training and social interaction and psychiatric counseling as well as relevant services based on disease stages (Aota, 2014). A deep learning-based clinical decision support system offered by researchers assesses PD patient weight data combined with eating patterns and exercise routine activities to deliver medication guidance along with dosage recommendations based on different stages of the disease (Bohr & Memarzadeh, 2020f).

Machine learning models;

Machine learning approaches break into three fundamental groups which include supervised methods alongside unsupervised techniques together with reinforcement learning approaches. The present data analysis of neurodegenerative diseases relies mainly on supervised machine learning algorithms that learn through datasets with provided labels (Bisong, 2019). Human experts are often needed for labeling medical information such as neuropathalogist evaluations of post-mortem photos and radiologist interpretation of MRI scans. After being provided a "benchmark" dataset that underwent labeling the algorithm develops a model that links diagnostic categories with the input dimensions shown in MRI brain scans (Cohen et al., 2019). Using the detected pattern the computer system forecasts the label value of fresh observation sets containing unlabeled input attributes. Supervised machine learning requires an exact amount of labeled data which may prove hard to obtain (Chapelle et al., 2010).

The methods comprising regression and classification functions use supervised machine learning18. The shown classification algorithm functions on data samples (patients) to predict categorical outputs (diagnostic categories) (Bishop, 2023). Each data sample within the framework of regression methods receives a precise numerical forecast for variables such as functional impairment extent. Both regression and classification algorithms enable healthcare organizations to discover patterns in their data which allows effective endotype establishment for patients (Raudys, 2012). A practical application of regression methods involves using algorithms which subtype patients through genotypic progressions by modeling motor function decline patterns and disease lengths and progression slope rates to create advanced patterns of time series data. Endotyping through category-based identification stands different from this regression methodology. The extensive set of machine learning algorithms contains modifications that enable users to execute regression or classification tasks (Wiersinga & Seymour, 2018). The absence of label requirements enables unsupervised machine learning algorithms to process data samples while generating simplified data representations of complex datasets. They also perform unguided data clustering's. Consisting of gene expression data can be processed by unsupervised clustering algorithms to discover groups of patients who share identical molecular characteristics (Feldman & Sanger, 2006). Latent variable models help discover gene co-expression modules which consist of genes that probably interact together or correspond to equal biological mechanisms and pathways (Hancock & Zvelebil, 2006).

Through unsupervised clustering algorithms models predict future outcomes even though they start by analyzing existing data such that historical clinical information can create models which use cluster assignments to estimate patient survival rates (Gonçalves & De Castro, 2024).

Researchers create semi-supervised learning techniques through the combination of supervised and unsupervised learning methods23. When using semi-supervised techniques the team can boost small amounts of labeled data through larger collections of unlabeled data to enhance prediction models and improve supervised classification through unsupervised clustering methods (Deng, 2018). Transductive learning methods utilize test samples as unlabeled data to boost standard supervised classifications so they achieve better outcomes when working with limited data without label exposure issues (Yang et al., 2020).The reinforcement learning approaches use rewards or punishments to achieve the intended results according to approach. Basing evaluation on patient medical records allows algorithms to experiment with new treatment plans (Oecd, 2008). While in training, in case of an unfavorable drug-drug interaction or a bad reaction to a new medication. The outcomes of interest would lead to rewards for the algorithm while an enhanced treatment trajectory of the disease remained as the desired final effect. Extreme technical development is underway regarding these methods yet they remain less popular than supervised and unsupervised learning methods within the field of neurodegenerative disorders (Education, 2021).

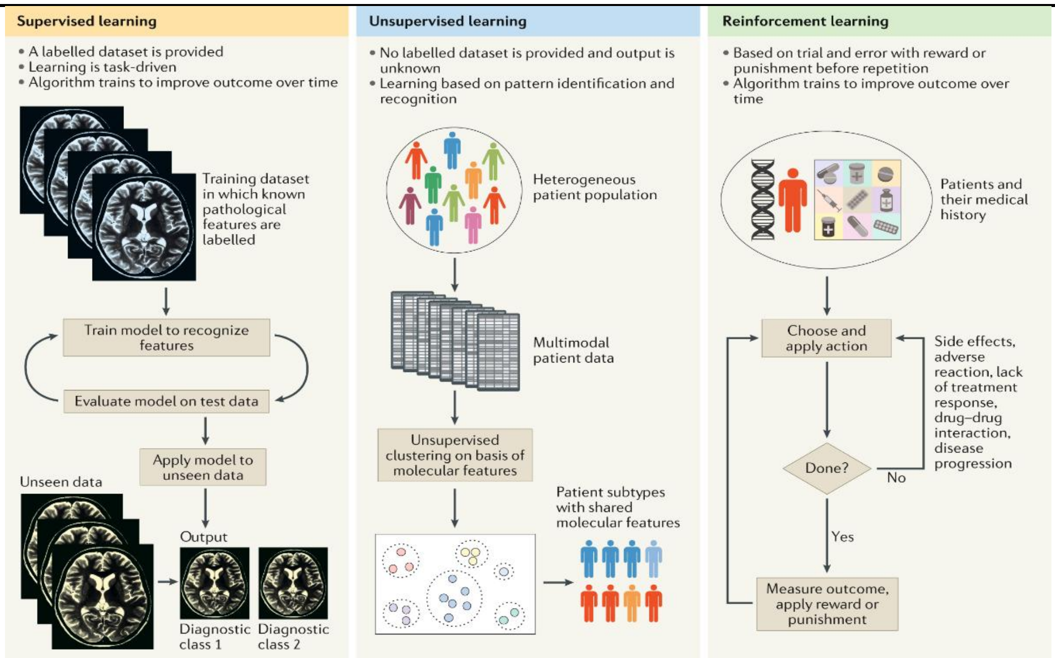

Fig. 2. Categories of machine learning

The Application of AI to Monitor and Forecast the Decline of Cognitive Function

The current diagnostic techniques fall short to provide reliable long-term forecasts because mild cognitive declines are hard to detect at the early stages (Popular Science, 2005). AI models analyze continuous patient information to identify forecasted mind deterioration indications before medical signs become detectable. Therapeutic planning becomes possible when clinicians utilize supervised learning to teach machine learning algorithms how to predict personal disease tracks (Gundlapalli et al., 2018).

Modern approaches to cognitive decline detection utilize random forest classification by studying data sets of neuropsychological outcomes and memory tests together with attention measurement results. (Medicine et al., 2022) Support vector machines (SVMs) succeed in distinguishing clinical decline from normal aging which leads to more precise diagnosis results.

ML Models Trained on Brain Imaging Data, Behavioral Patterns, and Cognitive Test Results

Scientists have investigated brain imaging biomarkers with digital evaluation behavioral data for enhancing cognitive decline prediction. Speech fluency changes alongside modifications in sentence structure provide input to NLP systems that look for early Alzheimer's disease markers (Albert & Knoefel, 1994).

- The AI technology employs fMRI to measure brain activity patterns until it locates regions that show connections with executive dysfunction and memory reduction.
- AI-based cognitive assessment programs now operate in both healthcare institutions and personal health tracking systems to monitor patients' cognitive health from home or clinical settings.
- Analyzing behavioral tracking data through machine learning algorithms monitors irregular cognitive pattern changes that often appear in people who face dementia risk

Diagnosis:

Several neurodegenerative conditions like AD, PD and MND become hard to diagnose early since symptoms emerge late after substantial neuron loss occurs. Research into machine learning detection models keeps expanding as shown through the data (Leigh & Swash, 2012). This study aims to use machine learning techniques for the identification of easy-to-acquire MRI and Electronic Health Record data containing prognostic signals for prospective screening of aging populations. (Bohr & Memarzadeh, 2020g)

After machine learning-based diagnostic screening a patient becomes eligible for medical examination through clinical investigations. Such an approach requires machine learning models with integrity levels high enough to spot early illness symptoms while low enough to prevent unnecessary medical testing of patients (Bulletin of the Atomic Scientists, 1996). Current medical practice depends on qualified personnel to evaluate testing results before medical diagnosis becomes available.
Machine learning systems deployed at the time of sampling clinical data would help reduce diagnosis delays. Such data comparison between present disease development patterns and previous records of patients with identical endotypes or phenotypes allows for patient outcome forecasting. Medical records from history cover entire disease periods which makes them valuable for training predictive algorithms (Raudys, 2012b).

Conclusion:
Research and treatment of multiple sclerosis as well as Parkinson's disease and Alzheimer's have experienced substantial development through artificial intelligence technologies. AI conducts early disease detection by processing massive data sets that include monitoring brain images as well as voice patterns and behavioral indicators in addition to genetic sequencing data. Machine learning and deep learning models enable doctors to obtain fast and correct clinical assistance through their ability to detect early cognitive decline markers. AI enables scientists to evaluate treatment outcomes alongside reactions to improve the quality of clinical decisions.AI demonstrates major potential within disease detection and treatment methods of neurodegenerative illnesses by potentially delivering improved medical solutions that enhance patient quality of life despite challenges relating to data quality and clinical integration.

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