Artificial intelligence and Machine learning-based approaches for Neurodegenerative Diseases Diagnosis

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Surya Pratap Singh[1*], Dr. Sushil Kumar Shukla [2], Dr. Ramakant Yadav[3]

[1]Research Scientist-1, Multi-Disciplinary Research Unit (MRU), Uttar Pradesh University of Medical Sciences, Saifai, Etawah (U.P.).
[2] Co-coordinator-MRU In-charge, Department of Community Medicine, Uttar Pradesh University of Medical Sciences, Saifai, Etawah (U.P.).
[3] Pro-Vice-Chancellor and Professor & Head Department of Neurology, Uttar Pradesh University of Medical Sciences, Saifai, Etawah (U.P.).

Abstract

This review paper delves into the transformative impact of machine learning on the diagnosis of neurodegenerative diseases, such as Alzheimer's, Parkinson's, and ALS. The importance of high-quality medical data, diverse data sources, and specific machine learning algorithms, including Support Vector Machines, Convolutional Neural Networks, and Long Short-Term Memory networks, is emphasized. Case studies showcase the practical applications of machine learning, highlighting the methodologies, findings, and limitations of various projects. Machine learning's significance in advancing neurodegenerative disease diagnosis lies in its ability to enable early detection, enhance diagnostic accuracy, and facilitate personalized treatment strategies. The future of machine learning in this field is marked by the integration of diverse data modalities, interpretable models, ethical considerations, the recognition of disease heterogeneity, and the pursuit of early detection and intervention. Collaboration among researchers, clinicians, and technologists is pivotal for realizing the potential of machine learning in improving patient care and quality of life for individuals affected by these challenging diseases. As we venture into the future, machine learning promises to continue pushing the boundaries of what is achievable in neurodegenerative disease diagnosis.

Keyword: Neurodegenerative diseases, Machine learning, Diagnosis, Alzheimer's disease, Parkinson's disease, Amyotrophic lateral sclerosis (ALS)

I. Introduction

Neurodegenerative diseases, characterized by the gradual and irreversible degeneration of neurons, present a profound and growing challenge to global healthcare systems and the quality of life for affected individuals. Conditions such as Alzheimer's disease, Parkinson's disease, and Amyotrophic Lateral Sclerosis (ALS) exact a heavy toll, affecting millions of individuals worldwide and posing a substantial burden on both patients and caregivers. Amidst this pressing healthcare crisis, technology, particularly machine learning, has emerged as a beacon of hope, promising transformative advancements in the diagnosis and management of neurodegenerative diseases.

Neurodegenerative diseases encompass a group of disorders, each characterized by distinct clinical features and pathological mechanisms. Alzheimer's disease, the most prevalent neurodegenerative disorder, leads to memory loss, cognitive decline, and behavioral changes, ultimately diminishing a patient's capacity to perform daily activities [Alzheimer's Association 2020]. Parkinson's disease manifests with motor symptoms such as tremors, rigidity, and bradykinesia, severely impacting the quality of life. ALS, on the other hand, is a rapidly progressive disorder marked by motor neuron degeneration, resulting in muscle weakness, spasticity, and eventual paralysis [Brown and Al-Chalabi 2017]. The increasing prevalence of these disorders, alongside the high healthcare costs and significant emotional toll they exact, underscores the critical importance of early and accurate diagnosis for effective management and potential interventions [Prince et al. 2015].

Machine learning, a branch of artificial intelligence, has demonstrated a remarkable ability to analyze complex medical data, identify patterns, and make predictions that can aid in the diagnosis and prognosis of neurodegenerative diseases. The ability of machine learning algorithms to process vast amounts of data and extract valuable insights, often imperceptible to human experts, has transformed the landscape of medical diagnosis. By leveraging diverse data sources, including medical images, clinical records, and genetic information, machine learning models can contribute to early detection, disease subtyping, and personalized treatment strategies, potentially improving patient outcomes [Shailaja 2018].

This review paper aims to provide a comprehensive overview of the state-of-the-art machine learning-based approaches for neurodegenerative diseases diagnosis. We will explore the methods, datasets, and performance metrics commonly used in this domain, and discuss the challenges and limitations that researchers face. Furthermore, we will outline the potential future directions in this field, underscoring the significance of ongoing research efforts to enhance our understanding and management of neurodegenerative diseases. By examining the intersection of machine learning and neurodegenerative disease diagnosis, we aim to shed light on the exciting possibilities and critical considerations for the advancement of healthcare in the face of these debilitating conditions.

II. NEURODEGENERATIVE DISEASES: A COMPREHENSIVE LOOK

Neurodegenerative diseases are a group of debilitating disorders characterized by the progressive degeneration of neurons, leading to a myriad of physical, cognitive, and psychological impairments. The burden of these diseases extends far beyond individual patients, impacting families, caregivers, and healthcare systems [Alzheimer's Association 2020]. This section provides an overview of three major neurodegenerative diseases: Alzheimer's disease, Parkinson's disease, and Amyotrophic Lateral Sclerosis (ALS).

A. Alzheimer's Disease

Alzheimer's disease is the most common neurodegenerative disease, accounting for a substantial proportion of dementia cases. It primarily affects older adults and is characterized by the accumulation of amyloid plaques and tau tangles in the brain, leading to cognitive decline, memory loss, and changes in behavior [Alzheimer's Association 2020]. The global prevalence of Alzheimer's disease is staggering, affecting millions of people and their families, and its impact is profound, robbing individuals of their independence and cognitive abilities [Prince et al. 2015].

B. Parkinson's Disease

Parkinson's disease is a neurodegenerative disorder primarily characterized by motor symptoms such as tremors, rigidity, bradykinesia, and postural instability. It results from the degeneration of dopaminergic neurons in the substantia nigra of the brain. The prevalence of Parkinson's disease is steadily increasing, with significant consequences for patients who experience not only motor impairments but also non-motor symptoms, such as depression and cognitive dysfunction [Kalia, Lorraine V and Anthony E. Lang, 2015].

C. Amyotrophic Lateral Sclerosis (ALS)

ALS is a rapidly progressive neurodegenerative disease that affects motor neurons in the brain and spinal cord. Patients with ALS experience muscle weakness, spasticity, and eventual paralysis, leading to severe disability and a shortened life expectancy. The prevalence of ALS is relatively low compared to other neurodegenerative diseases, but its impact is devastating, as it robs individuals of their ability to move, speak, and, ultimately, breathe [Brown and Al-Chalabi 2017].

The impact of these neurodegenerative diseases is profound, not only affecting the patients themselves but also placing significant emotional, financial, and healthcare burdens on their families and society at large. The quest to diagnose these diseases accurately and at an early stage is of paramount importance to enable interventions and treatments that may slow down their progression and improve the quality of life for those affected.

III. INNOVATIONS IN MEDICAL DIAGNOSIS: MACHINE LEARNING APPROACHES

The application of machine learning (ML) in healthcare has ushered in a transformative era in the field of medical diagnosis. ML leverages advanced computational algorithms to analyze vast datasets and make predictions or classifications, holding the potential to significantly enhance healthcare processes and outcomes [Obermeyer and Emanuel 2016]. This section elucidates the pivotal role of machine learning in healthcare and highlights its numerous advantages in medical diagnosis.

Machine learning is widely applied in healthcare for a multitude of purposes, such as disease detection, risk assessment, treatment planning, and patient management.

ML algorithms are adept at processing diverse data types, including medical images, electronic health records, genomics data, and sensor data, allowing for more precise, data-driven decision-making [Esteva et al. 2017]. In the context of medical diagnosis, machine learning models analyze patient data to identify patterns, anomalies, and potential disease indicators.

The advantages of utilizing machine learning for medical diagnosis are manifold. One of the most significant benefits is early detection. ML algorithms can detect subtle signs of diseases at an earlier stage than traditional methods, potentially leading to timely interventions and improved patient outcomes [Esteva et al. 2017]. The accuracy of ML models in diagnostic tasks is another notable advantage. These algorithms can analyze vast datasets, extracting intricate patterns and relationships that may not be discernible to human experts, resulting in more precise diagnoses . Furthermore, machine learning offers speed and efficiency, allowing for rapid analysis of medical data, which is crucial in time-sensitive situations and resource-constrained healthcare settings [Litjens et al. 2017].

Machine learning in healthcare also promotes the personalization of treatment strategies, as it can consider individual patient characteristics, genetic profiles, and treatment responses. This personalized approach leads to more effective and less invasive treatments, reducing healthcare costs and minimizing patient discomfort.

As medical data availability and computational power continue to grow, machine learning's role in healthcare is poised to expand further, revolutionizing the diagnostic process and improving patient care.

IV. DATA SOURCES AND DATASETS

In the realm of neurodegenerative disease diagnosis, the quality and availability of medical data play a pivotal role in the development and evaluation of machine learning models. Access to high-quality, well-curated medical datasets is essential to train and test these models effectively [De Bruijne 2016].

A. Importance of High-Quality Medical Data

High-quality medical data are crucial for several reasons. First, they serve as the foundation for the development and validation of machine learning algorithms. Accurate, reliable, and well-annotated datasets ensure that models can learn meaningful patterns and relationships in the data [Litjens et al. 2017]. Second, high-quality data are essential for ensuring patient safety and the efficacy of diagnostic tools. Erroneous or incomplete data can lead to incorrect diagnoses and treatment decisions, potentially harming patients [Obermeyer and Emanuel 2016]. Lastly, the consistency and quality of medical data impact the generalizability of machine learning models. Models trained on high-quality data are more likely to perform well across diverse patient populations and healthcare settings.

B. Commonly Used Datasets for Neurodegenerative Disease Diagnosis

Several well-established datasets are frequently employed in research related to neurodegenerative disease diagnosis. These datasets are valuable resources for training and evaluating machine learning models. Below is a list of some commonly used datasets in this field.

Table1Commonly Used Datasets for Neurodegenerative Disease Diagnosis

Dataset Name	Description	References
ADNI (Alzheimer's Disease Neuroimaging Initiative)	Longitudinal imaging and clinical data for Alzheimer's research	Jack et al. 2008
Parkinson's Progression Markers Initiative (PPMI)	Data for the study of Parkinson's disease progression	Marek et al. 2011
OASIS (Open Access Series of Imaging Studies)	MRI and clinical data for Alzheimer's disease research	Marcus et al. 2007
ABIDE (Autism Brain Imaging Data Exchange)	Data on brain imaging and clinical assessments for autism research	Di Martino et al. 2014
CAM CAN (Cambridge Centre for Ageing and Neuroscience)	Multimodal neuroimaging data for dementia research	Shafto, Michael, et al 2010

These datasets encompass a variety of neuroimaging and clinical data, allowing researchers to investigate different aspects of neurodegenerative diseases and test the efficacy of machine learning models for diagnosis and prognosis.

V. MACHINE LEARNING IN THE DETECTION OF NEURODEGENERATIVE DISEASES

Machine learning algorithms have been instrumental in enhancing the accuracy and efficiency of neurodegenerative disease diagnosis. These algorithms leverage various techniques to process complex medical data and extract valuable insights. This section provides an overview of some commonly used machine learning algorithms in this context and the specific features and data types to which they are applied.

Support Vector Machines (SVM): Support Vector Machines are widely utilized for classification tasks in neurodegenerative disease diagnosis. SVMs are effective in distinguishing between disease and non-disease states by finding the optimal hyperplane that maximizes the margin between classes. They are often applied to structural neuroimaging data, such as MRI scans, to identify patterns of brain atrophy associated with diseases like Alzheimer's [Klöppel et al. 2008].

Convolutional Neural Networks (CNN): Convolutional Neural Networks have shown exceptional promise in processing medical images, making them suitable for tasks like MRI-based diagnosis. CNNs are proficient in automatically learning relevant features from images and are particularly useful in detecting subtle structural changes in the brain associated with neurodegenerative diseases. They have been used in the identification of abnormalities in neuroimaging data, aiding in early diagnosis [Sarraf and Tofighi 2016].

Long Short-Term Memory (LSTM): Long Short-Term Memory networks are recurrent neural networks commonly employed for analyzing sequential data. In the context of neurodegenerative diseases, they are applied to time-series data, such as patient monitoring and sensor data. LSTMs can capture temporal dependencies and detect subtle changes in patients' conditions, assisting in the diagnosis and monitoring of diseases like ALS [Ravì et al. 2016].

Random Forests: Random Forests are an ensemble learning method often used for classification tasks in neurodegenerative disease diagnosis. They are applied to a wide range of data types, including neuroimaging, clinical, and genetic data. Random Forests excel in feature selection and handling missing data, contributing to the development of robust diagnostic models.

Deep Learning Architectures: Deep learning architectures, such as deep neural networks, have gained prominence in neurodegenerative disease diagnosis. They can process multimodal data, combining information from various sources, such as imaging, genetics, and clinical records. These models learn intricate patterns and relationships, improving diagnostic accuracy and enabling early detection [Eskildsen et al. 2012].

Table 2 Machine Learning Algorithms and Their Applications in Neurodegenerative Disease Diagnosis

Algorithm	Application	References
Support Vector Machines	Classification based on structural neuroimaging	Klöppel et al. 2008
Convolutional Neural Networks	Image-based diagnosis	Sarraf and Tofighi 2016
Long Short-Term Memory	Time-series data analysis	Ravì et al. 2016
Random Forests	Multimodal data analysis	Khajeh and Heidari 2016
Deep Learning	Multimodal data integration and analysis	Eskildsen et al. 2015

These machine learning algorithms and techniques offer diverse capabilities for diagnosing neurodegenerative diseases, enabling the integration of multiple data modalities and the extraction of meaningful insights for accurate and early disease detection.

VI. CASE STUDIES AND APPLICATIONS

Machine learning has become an invaluable tool in the diagnosis of neurodegenerative diseases, with numerous case studies and projects showcasing its potential. These studies have employed various methodologies, resulting in valuable findings and insights. However, it is crucial to consider the limitations inherent to these applications.

1. **Case Study 1: Alzheimer's Disease Diagnosis**

Methodology: A study by Klöppel et al. (2008) used Support Vector Machines (SVM) to analyze structural neuroimaging data, specifically MRI scans, for the diagnosis of Alzheimer's disease. The study involved a large dataset of patients with Alzheimer's and healthy controls. SVM was used to differentiate between the two groups based on brain structure and atrophy patterns.

Findings: The study achieved high accuracy in Alzheimer's disease classification, with specific brain regions identified as significant contributors to the diagnostic process. SVM demonstrated its effectiveness in identifying subtle structural changes associated with the disease [Klöppel et al. 2008].

Limitations: While SVM was successful in classification, the study had limitations related to the interpretation of the identified brain regions and the need for larger and more diverse datasets for broader applicability.

2. **Case Study 2: Parkinson's Disease Progression**

Methodology: The Parkinson's Progression Markers Initiative (PPMI), led by Marek et al. (2011), utilized various machine learning techniques, including Random Forests, for the analysis of multimodal data. This initiative aimed to identify biomarkers and predict the progression of Parkinson's disease. The dataset included clinical, genetic, imaging, and other types of data.

Findings: The PPMI project identified potential biomarkers for Parkinson's disease progression and developed predictive models using machine learning techniques. The initiative contributed valuable insights into the dynamics of the disease, assisting in patient management and therapeutic interventions [Marek et al. 2011].

Limitations: While the PPMI project made significant strides, it encountered challenges related to data integration and standardization, highlighting the importance of harmonizing diverse data sources for accurate modeling.

3. Case Study 3: Multimodal Diagnosis of Alzheimer's

Methodology: Eskildsen et al. (2015) presented a case study focused on the diagnosis of Alzheimer's disease using deep learning techniques. The study integrated multiple data modalities, including neuroimaging, clinical, and genetic data, into a deep neural network model.

Findings: The study demonstrated the potential of deep learning for multimodal diagnosis of Alzheimer's disease. By combining information from diverse sources, the model improved diagnostic accuracy and early detection, aiding in the development of more personalized treatment strategies [Eskildsen et al. 2012].

Limitations: Challenges included the need for large and diverse datasets to train complex deep learning models effectively and the interpretability of deep neural networks in clinical practice.

These case studies exemplify the power of machine learning in neurodegenerative disease diagnosis. They have advanced our understanding of disease mechanisms, provided accurate diagnostic tools, and shown the potential for early detection and personalized treatment. Nevertheless, it is essential to address limitations, such as dataset size, interpretability, and data integration, to ensure the continued progress of these applications.

VII. CHALLENGES AND LIMITATIONS

While machine learning holds immense promise in neurodegenerative disease diagnosis, several challenges and limitations must be considered to ensure its effective and ethical application in healthcare.

Data Availability and Quality: Access to large and high-quality datasets is a fundamental requirement for training accurate machine learning models. Data collection, curation, and annotation processes can be time-consuming and resource-intensive, especially for rare diseases like ALS. Limited data availability, especially for specific disease subtypes, can hinder the development of robust diagnostic models. Furthermore, noisy or incomplete data can lead to inaccurate predictions and hinder model generalization [Eskildsen et al. 2012].

Interpretability: Deep learning models, while highly effective, often lack interpretability. Understanding how and why a model arrives at a specific diagnosis can be challenging, making it difficult for clinicians to trust and apply these models in real-world healthcare settings. The 'black box' nature of deep learning algorithms raises concerns about model transparency and accountability, which are critical in the context of patient care and medical decision-making [Ravì et al. 2016].

Ethical Concerns: The use of machine learning in healthcare raises ethical concerns, such as patient privacy, data security, and the potential for algorithmic bias.

Safeguarding patient information and ensuring equitable access to diagnostic tools are essential considerations. Ethical challenges may result in legal and regulatory barriers, as well as concerns about the fairness and transparency of machine learning models in the diagnosis and treatment of neurodegenerative diseases [Obermeyer and Emanuel 2016].

Generalization and Heterogeneity: Machine learning models developed on one dataset may not generalize well to other populations or healthcare settings. Neurodegenerative diseases exhibit substantial heterogeneity, both in terms of symptoms and underlying biology. Models that do not account for this heterogeneity may yield inaccurate diagnoses or treatment recommendations. Thus, ensuring model generalizability across diverse populations is a persistent challenge [Khajeh and Heidari 2016].

Data Integration: Combining data from multiple sources, such as neuroimaging, clinical records, and genetic information, can be technically complex. Data harmonization and standardization are critical for meaningful integration, but achieving this can be challenging. Data integration challenges may lead to inconsistencies and errors, affecting the overall accuracy and reliability of machine learning models, especially in large-scale initiatives like the Parkinson's Progression Markers Initiative (PPMI) [Marek et al. 2011].

Addressing these challenges and limitations is vital to harness the full potential of machine learning in neurodegenerative disease diagnosis. Researchers and clinicians must work together to ensure data availability, develop interpretable models, navigate ethical issues, account for disease heterogeneity, and effectively integrate multimodal data to advance the field while maintaining high standards of patient care and ethical practice.

VIII. CONCLUSION

In this review paper, we have explored the vital intersection of machine learning and neurodegenerative disease diagnosis. Neurodegenerative diseases, such as Alzheimer's, Parkinson's, and ALS, present significant medical challenges due to their complex nature, heterogeneity, and the need for early and accurate diagnosis. Machine learning has emerged as a transformative tool in addressing these challenges, offering the potential to revolutionize the diagnostic process.

Our discussion has highlighted the importance of high-quality medical data, the specific machine learning algorithms applied, and the diverse data sources employed in neurodegenerative disease diagnosis. We have examined case studies and applications that demonstrate the real-world impact of machine learning in this field, from Alzheimer's disease classification to predicting the progression of Parkinson's disease.

The Importance of Machine Learning in Advancing Neurodegenerative Disease Diagnosis

Machine learning plays a pivotal role in advancing neurodegenerative disease diagnosis. It enables early detection, enhances diagnostic accuracy, and contributes to the development of personalized treatment strategies. With the ability to analyze diverse data modalities, including neuroimaging, clinical records, and genetic information, machine learning models offer a holistic view of disease processes. By addressing the challenges associated with data availability, interpretability, and ethical concerns, machine learning holds the promise of transforming the landscape of neurodegenerative disease diagnosis.

Future Directions

As we look to the future, several exciting avenues emerge for the application of machine learning in neurodegenerative disease diagnosis:

Multimodal Integration: Integrating data from multiple sources, including imaging, genetics, and clinical records, will continue to be a focus. Developing models that effectively leverage this diverse information will lead to more accurate and comprehensive diagnoses.

Interpretable Models: The need for interpretable machine learning models remains a priority. Research into model interpretability and explain ability will enhance trust among clinicians and facilitate the integration of machine learning into clinical practice.

Ethical Considerations: Ethical concerns, particularly related to patient privacy and data security, require ongoing attention. Innovations in privacy-preserving machine learning and robust data sharing frameworks are crucial.

Heterogeneity and Personalized Medicine: Recognizing disease heterogeneity and tailoring diagnostic and treatment approaches to individual patients will gain prominence. Machine learning will be at the forefront of enabling personalized medicine for neurodegenerative diseases.

Early Detection and Intervention: The focus on early detection will intensify, driven by the potential for more effective interventions at the earliest stages of disease. Machine learning will continue to play a crucial role in identifying subtle biomarkers and predictive factors.

In summary, the future of machine learning in neurodegenerative disease diagnosis is bright and promising. With advancements in technology, the availability of larger and more diverse datasets, and a growing emphasis on ethical considerations, machine learning will remain a driving force in the quest to improve the lives of individuals affected by these devastating diseases. As research and innovation progress, we anticipate that machine learning will continue to push the boundaries of what is achievable in the field of neurodegenerative disease diagnosis.

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