Role of artificial intelligence in multiple sclerosis management

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ABSTRACT. – From a clinical viewpoint, there are enormous obstacles to early detection and diagnosis as well as treatment interventions for multiple sclerosis (MS). With the growing application of methods based on artificial intelligence (AI) to medical problems, there might be an opportunity for MS specialists and their patients. However, to develop accurate AI models, researchers must first examine large quantities of patient data (demographics, genetics-based information, clinical and radiological presentation) to identify the characteristics that distinguish illness from health. These are seen as promising approaches toward improved disease diagnosis, treatment individualization, and prognosis prediction. When applied to imaging data, the application of AI subdomains, such as machine learning (ML), deep learning (DL), and neural networks, have proven their value in healthcare. The application of AI in MS management marks a milestone within the healthcare sector. Now, as research and applications of AI continue to advance steadily, breakthroughs are coming at an ever-accelerating pace. As MS continues to develop, the integration of AI is more and more necessary for continuing progress in diagnosis and treatment as well as patient outcomes. In the field of multiple sclerosis, these algorithms have been used for many purposes, such as disease monitoring and therapy.

Key Words:

Antibacterial activity, Diabetes mellitus, Diabetic foot ulcers, Multidrug-resistant bacteria, Proteus mirabilis, Sansevieria zeylanica.

Introduction

MS is a demyelinating and neurodegenerative disease in which the insulating layer of myelin surrounding the brain's nerve cells deteriorates. Inflammation, neurodegeneration, and damage to myelin sheaths that protect neurons are the hallmark symptoms of this autoimmune disease[1]. MS often has a cycle of remission and recurrence, which progressively worsens[2]. In the early or recurrent phases, from a clinician's perspective, the condition is defined by sensory deficits and cerebellar signs, as well as optic neuritis. But the manifestations of progression are descending tract dysfunctions, muscle weakness and ataxia spasticity[3]. MS has a global impact, reaching and affecting over 2.8 million people (approximately one in every 3,000 individuals) worldwide. The MS prevalence rates have risen more than twofold over the past 15 years. Moreover, the proportion of female to male individuals affected by MS has risen threefold over the past 50 years[4]. The exact cause of MS is still unknown, but genes like *CD24* are implicated, the IL-7 receptor, and protein tyrosine phosphatase (CD 45) have been closely linked to higher odds of developing MS[1]. Also, other environmental factors, such as low vitamin D intake and Epstein-Barr virus, are thought to increase the risk of being afflicted with MS, while higher latitudes also play a role in the matter[5-7].

Because of its heterogeneity, MS has many different preclinical phases that manifest themselves in one way or another. Sometimes, the prodrome phase seems quite generic one[8]. Moreover, MS presents a range of phenotypes, including relapsing-remitting type (RRMS), clinically isolated syndrome (CIS), and progressive form (PrMS)[9]. The earlier and more accurate diagnosis of MS is crucial for slowing down its progression as well as dealing with subsequent disability[10]. The diagnosis of MS centers on assessment by clinical presentation. This involves magnetic resonance imaging (MRI) and examination for the presence or absence of immunoglobulin G in cerebrospinal fluid[11]. MRI has revolutionized proper care and handling of MS with its great contributions to the diagnosis, differential diagnosis, prognosis assessment, therapy planning, and monitoring of

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the condition[12]. In the past, medical professionals and radiologists could only rely on their professional experience and visual pattern recognition abilities for image evaluation. Computer-assisted investigation programs are currently being increasingly used in medicine for this purpose, and they include making use of artificial intelligence (AI) to improve efficiency in dealing with medical and epidemiological imaging data. Artificial intelligence is often defined as the capability of digital computers to perform tasks typically associated with human intelligence. The capacity to automate repetitive tasks and analyze large volumes of data more quickly and accurately than humans has made AI algorithms particularly appealing for use in the medical field[13-14].

Standing amidst the treatment of MS, AI has become one of the most popular tools today, particularly in the field of neuroradiology. The ability of AI to predict clinical deterioration or assess the safety of disease-modifying treatments (DMT) in people diagnosed with MS is high[15]. When used to distinguish between MS patients and healthy people or for differential diagnosis, studies[15] examining the efficacy of AI-based diagnosis have produced interesting results, particularly in MS patients, where many AI-based methods have been suggested for detecting MRI images. In addition, AI has been experimentally applied to forecast cognitive decline and physical degeneration in MS patients[16]. The overarching illustration of how AI is being used to treat MS can be seen in Figure 1. This review article explores the role of AI in the detection, monitoring, and management of MS, along with the future advancements of AI.

AI Techniques

The predominant technique seen in MS research is the use of bottom-up AI algorithms, mostly centered on machine learning (ML) and deep learning (DL) methods[16]. The bottom-up method focuses on the development of fundamental elements, which then undergo modification *via* interactions with data. Specifically, the bottom-up technique in AI aims to establish associations within datasets and is often known as the "connectionist" technique, which resembles the functioning of the human brain. Symbolic or the top-down AI, on the other hand, looks at cognition without considering the biological makeup of the brain in order to mimic intelligence. Instead, it focuses on symbol processing[17].

Machine Learning (ML)

In machine learning, algorithms are utilized to learn and perform complex tasks and develop predictive models from datasets. These algorithms rely on feature engineering, the process of selecting or creating a collection of useful characteristics for constructing predictive models. ML is used to make decisions based on patterns in data[18].

There are two main categories of ML algorithms based on the desired output: supervised

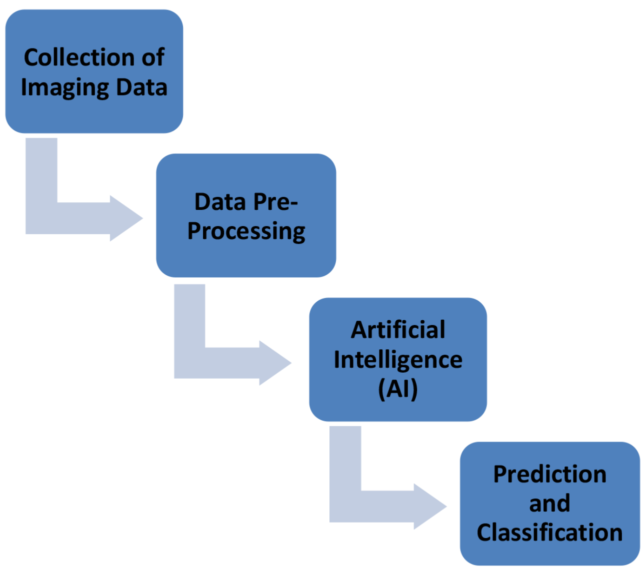

Figure 1. AI in MS analysis.

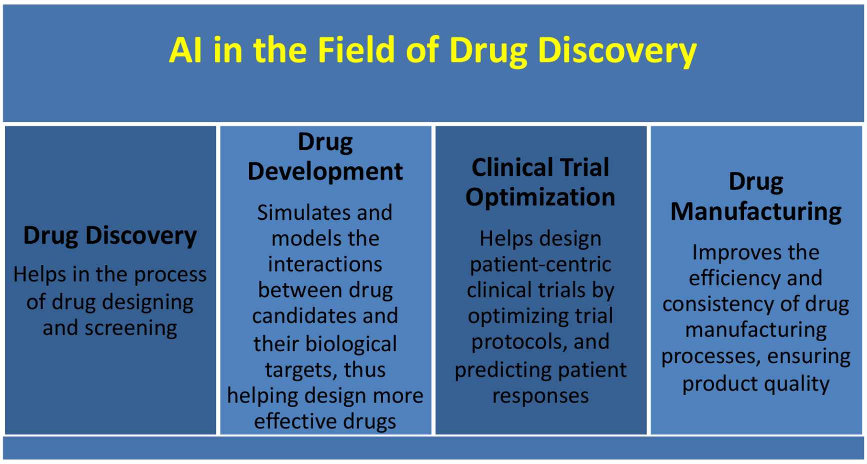

Figure 2. AI in drug development.

or unsupervised. With supervised ML, the output labels are already known, utilizing prior knowledge, and the machine is tasked with mapping or assigning the input to the output values. K-nearest neighbor (KNN), random forest, logistic regression, and support vector machine (SVM) are among the supervised learning algorithms that are successfully used in MS data analysis[17].

The observation's ground-truth label is absent in unsupervised ML. For the most part, unsupervised ML algorithms are trained on unlabeled data, from which they discover the underlying structure and extract relevant features and patterns. Three common applications for unsupervised ML models are dimensionality reduction, association, and clustering. Unsupervised ML techniques include association techniques like a priori algorithms, dimensionality reduction techniques like principal component analysis and singular value decomposition, and clustering techniques like K-means and hierarchical clustering[19-20].

Deep Learning (DL)

DL is a specialized area within the umbrella field of ML that focuses on using artificial neural network topologies to learn from data and make decisions in a manner analogous to how the human brain works[21]. By attempting to learn the ideal collection of features from data, DL approaches obviate the requirement for feature engineering (although feature selection may still be employed to improve efficiency in certain situations). The use of convolutional neural networks (CNNs) for medical image processing is widespread[22-23].

Clinical Applications of AI in the Context of MS

In the following paragraphs, we will examine the use of AI algorithms for MS diagnosis, prognosis, and treatment monitoring in further detail.

Diagnosis

AI has shown significant promise in facilitating the diagnosis of MS *via* the analysis of medical imaging data, namely MRI scans[15-16]. AI has been found to automate the segmentation and quantification of lesions in multiple studies[24]. This automation enables more precise diagnosis of MS. This feature offers significant advantages as it reduces the human effort and time required for neurologists and radiologists to interpret digital images[24].

Integrating DL and a computer-aided diagnostic system (CADS) aids in the differentiation of MS-related anomalies from those of other illnesses, leading to a more precise diagnosis[25-26]. Automated or semi-automatic approaches for accurate detection of MS involve lesional imaging indicators like the central vein sign (CVS), paramagnetic rim lesions (PRL), and cortical lesions (CL). For automated categorization of MS lesions in MRI, other approaches use a supervised classification method utilizing an adaptive dictionary learning technique[27]. In addition, functional and diffusion MRI and 3D MRI fingerprinting can distinguish between individuals with MS and those without the condition, often referred to as healthy controls, with a considerable level of precision, specifically an accuracy of 89% ± 2%[28].

Prognosis Prediction

In the past 50 years, it has become common practice to include clinical data in AI-based evaluations of MS. Using basic demographic data and the Expanded Disability Status Scale (EDSS) score, the ProMiSi project can accurately forecast the disease's prognosis[29-30]. Furthermore, medical professionals may benefit from a patient-centered approach made possible by the integration of Masked Language Models (MLMs) and gait data to monitor MS[31].

People originally diagnosed with RR-MS have used ML techniques to predict SP progression. A study found that when a support vector machine (SVM) was used to process clinical data, it could predict whether the patient would ultimately change from primary progressive multiple sclerosis (PPMS) to secondary progressive multiple sclerosis within two years. The accuracy rate reached 86%[32]. In this study, strong prognostic markers of a poor outlook were relapses aggravating the spinal cord, cerebellum, or sensory systems and higher scores on the Expanded Disability Status Scale (EDSS)[32].

Treatment Monitoring

A three-step plan has been presented to achieve personalized care for MS. The key components of this study[33] include: (A) a comprehensive and accurate diagnosis; (B) the effective integration of relevant data into electronic health record systems, along with the use of efficient machine learning techniques to analyze large datasets; and (C) the development, validation, and implementation of multimodal therapies[33]. The development of digital twins, or DTs, has gained a lot of interest in the last several years. The use of a virtual replication (twin) technique for phenotyping individuals with MS is a noteworthy approach since it involves the examination of substantial amounts of data. The DTs provide personalized treatment simulation in advance, allowing for the visualization of potential therapeutic outcomes and the progression of the disease[34]. However, DTs are still in the experimental stages of their usage in healthcare. Only time will tell whether digital twins truly to revolutionize the management of MS[34].

New treatment targets for MS are an ongoing research area. Next-generation nanorobotics is being designed with the use of AI, in addition to new DMTs and MLMs. These nano-robots can cross the blood-brain barrier to deliver medicine directly to inflamed areas of the central nervous system[35]. Artificial intelligence also has implications for rehabilitation technologies in MS treatment[36]. Recent years have seen a rise in the popularity of robot-assisted gait training (RAGT) as a potential remedy for balance and gait dysfunctions in people with MS. It has been demonstrated to help reduce MS-related deficits by increasing gait speed and resistance[37-38].

With the help of AI, doctors may determine the most effective treatment plan for each patient, down to the specific medicines they should prescribe, monitor the gathering of clinical data, utilize that information to guide future drug development and speed up bringing new treatments to market[39-41]. Figure 2 depicts some examples of how AI is being used in the field of drug discovery and development.

Conclusions

Over the past few decades, AI has profoundly revolutionized personalized treatment plans for MS. By integrating vast amounts of patient data, such as real-world evidence, genetic information, imaging results, and biomarkers, AI models have the potential to provide more accurate and personalized therapy suggestions by leveraging the distinct characteristics of each patient. By analyzing longitudinal patient data and continuous monitoring of patients in real-time, AI algorithms can provide predictions about the course of diseases, the likelihood of relapse, and the response to treatment. Despite AI's benefits in MS management, developed and developing nations employ and develop AI differently. This gap is caused by data, resources, skills, and infrastructural shortages. Developing nations should prioritize integrating AI education across all educational groups, enhance their technical infrastructure, facilitate data sharing, and foster international partnerships to address the disparity in AI capabilities.

The future of AI in MS lies in the collaborative efforts of researchers, clinicians, and patients from across the world to learn from and share their experiences. AI models may achieve enhanced security and generalizability by sharing data, methodologies, and insights across many organizations and countries. This collaborative approach facilitates the training of AI models on comprehensive and diverse datasets, ultimately benefiting the whole community of MS patients.

Conflict of Interest
The authors declare that they have no conflict of interest.

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Data Availability

Not applicable.

Informed Consent

The datasets generated during the current study are available from the corresponding author on reasonable request.

Ethics Approval

This study was conducted according to the relevant guidelines and regulations; however, institutional ethical approval was not required as the research did not encompass any human participants or biological specimens of human origin.

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