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Review Article

Artificial Intelligence in the Field of Neurological Studies: Challenges and Future Directions

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ABSTRACT

The currently growing field of health care and diagnostics is artificial intelligence. AI is becoming the primary tool for diagnosing a variety of illnesses, including neurological problems, thanks to its advanced algorithms. AI is transforming the early diagnosis of neurological disorders by making it possible to analyze complicated data in a precise, quick, and scalable manner. With the help of AI-powered algorithms, medical imaging, including MRI and CT scans, may be analyzed with surprising precision to find early indicators of diseases including multiple sclerosis, Parkinson's disease, and Alzheimer's disease often before symptoms appear. To find minute patterns connected to the start of disease, machine learning algorithms also analyze enormous datasets from genetic data, wearable technology, and electronic health records (EHRs). For instance, NLP techniques can examine a patient's handwriting or speech to find early indicators of motor deficits or cognitive decline. Because AI-driven systems can identify trends in symptoms and biomarkers, they also improve diagnostic accuracy in less frequent illnesses like autoimmune encephalitis. For individuals with neurological disorders, artificial intelligence (AI) has the potential to greatly enhance outcomes by facilitating earlier intervention and individualized treatment. AI has been used, for instance, to find particular genetic abnormalities or protein misfolding patterns that act as early diagnostic markers in rare neurodegenerative or autoimmune illnesses. AI speeds up the identification of these biomarkers, which improves treatment results for patients with uncommon and poorly understood diseases by increasing diagnosis accuracy and facilitating the creation of focused medicines.

KEYWORDS

• Artificial Intelligence (AI) • Neurological disorders • Early biomarkers detection • High throughput data • Machine learning

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INTRODUCTION

The presence and degree of biomarkers, which are biological indicators that function as a patient's unique medical signature, can serve as both a basis for diagnosis and an indicator of the patient's health. The U.S. Food and Drug Administration (FDA) defines a biomarker as "a defined feature, which is measured as an indicator of natural biological processes, pathogenic or biological processes being a response to exposure or intervention, including therapeutic interventions" in the document Biomarkers, Endpoints and Other Tools (BEST)[1].

If we talk about neurological diseases Alzheimer's is the one of the neurodegenerative disease. A bleak picture of the future is painted by the worrisome statistics on Alzheimer's disease (AD). The most common cause of dementia in people 65 and older is AD, a disease that is common throughout the world. The number of people 65 and older worldwide is expected to rise from 420 million in 2000 to about 1 billion by 2030, according to studies from the US Centers for Disease Control and Prevention and the UN Aging Program[2]. The percentage of older people will rise significantly as a result of this demographic shift, from 7% to 12% of the global population. An estimated 6.7 million adults 65 and older in the United States have AD, and by 2060, that figure might rise to 13.8 million, according to the Special Report study[3].

According to the World Alzheimer Report, dementia is one of the leading chronic illnesses with the largest worldwide economic impact. Since there is presently no therapy for AD, research has concentrated on finding trustworthy indicators of the illness, particularly when it is still in the preclinical stages. The pathophysiological process of AD is likely to start years before a person shows any clinical symptoms, according to a wealth of research. By identifying this asymptomatic stage, doctors can start treating patients with early stage AD (early AD), potentially halting the illness or delaying its course, maintaining function, and eventually lowering the disease burden[4].

In case of neurodevelopment disorder the most cronic illness is ADHD (Attention Deficit Hyperactivity Disorder). ADHD is found to be increasing day by day in children among the age of 12-24. Inattention, hyperactivity, impulsivity, and emotional dysregulation are among the primary symptoms that hinder day-to-day functioning. ADHD assessment is still difficult because of subjective biases and a lack of reliable biomarkers, even though systematic clinical examinations are the gold standard for diagnosis. Previous studies have attempted to enhance behavioral evaluations by utilizing neurophysiological characteristics from genetics, functional magnetic resonance imaging (fMRI), and electroencephalograms (EEG)[5]. Patients frequently suffer grave consequences when they lose the communication routes that allow them to communicate with their surroundings. Some negative effects can be lessened with continued advancements and growing use of brain-computer interfaces (BCI) and robotics in neurorehabilitation.[6,7]

CD is a behavioral illness characterized by a person's disrespect for fundamental social norms and regulations, which leads to rule breaking activities like stealing, breaching the law, damaging property, and acting aggressively against people and animals. Consequently, CD is closely associated with subsequent criminal conduct and delinquency, especially when paired with ADHD[8-11].

A number of reviews have examined the reciprocal relationship between AI and neurology in recent years. The authors of conducted a review that emphasized both the uses of AI for the advancement of neuroscience and the role of neuroscience in furthering AI research. The authors talked about how neuroscience may be used to validate AI techniques and how it might inspire the creation of new kinds of algorithms[12]. The authors of examined the connection between AI and neuroscience as well as the latest developments in four fields: computational psychiatry, AI visual processing[13], AI working memory models, and AI analysis of large neuroscience datasets. The authors reviewed how neuroscience provided guidelines for building artificial neural networks (ANNs) to deep networks and their subsequent modifications in[14]. The authors of[15] examined the connections between psychology and neurobiology and reinforcement learning. The authors of[16] highlighted the connections between biological vision and AI vision networks in order to discuss the sharing relationship between AI and neuroscience. The

study[17] also explores the ways in which AI and neuroscience complement one another when working with large amounts of data.

To sum up it briefly, AI and neurology are interwoven. The ability to make machines intelligent like humans is a common feature of artificial intelligence (AI), which has a wide range of applications in different fields. This enables the efficient completion of complex tasks like speech recognition, game applications, self-driving car applications, intelligent traffic management, robotics-based surgery, image and video analytics, natural language processing, etc. Neuroscience aids in the efficient identification and diagnosis of a range of neurological conditions by examining the composition and operation of the brain[18].

Types of potential biomarkers involved in neurological studies:

1. Molecular Biomarkers

- **Proteins and Peptides**:
  - Tau protein (total tau, phosphorylated tau): Alzheimer's disease.
  - Amyloid-beta: Alzheimer's disease and other dementias.
  - Alpha-synuclein: Parkinson's disease and related disorders.
  - Neurofilament light chain (NfL): Neurodegeneration in multiple conditions (e.g., ALS, MS).[19]
- Metabolites:

  Homocysteine: Stroke risk and cognitive deterioration.
  Lactate: malfunctioning mitochondria.
- Biomarkers of genetics:

  Alzheimer's disease risk is associated with the APOE ε4 allele. Huntington's disease is caused by a mutation in the huntingtin gene.

2. Structural Imaging for Imaging Biomarkers:

1. Magnetic resonance imaging, or MRI, can be used to detect atrophy patterns in Alzheimer's and multiple sclerosis lesions.
2. CT (Computerized Tomography): Ischemic strokes and hemorrhages. Imaging Functions:
3. Fluorodeoxyglucose Positron Emission Tomography, or FDG-PET: Dementia-related brain metabolism.
4. Single Photon Emission Computed Tomography (SPECT): Brain blood flow in epilepsy and Parkinson's disease.
5. Molecular Imaging

   Amyloid PET: Alzheimer's disease amyloid plaque detection. Parkinson's disease using dopamine transporter imaging, or DaTSCAN.[20]

3. Cerebrospinal fluid (CSF) biomarkers:

1. Alzheimer's disease is associated with tau and amyloid-beta ratios. Bands of oligoclonal Multiple sclerosis.
2. Biomarkers of blood: Neurodegeneration in all diseases (NfL). Astrocytic damage is caused by glial fibrillary acidic protein (GFAP).[21]

4. Electroencephalography, or EEG, is an electrophysiological biomarker:

1. Unusual electrical activity is a sign of epilepsy. Sleep disorders: Changes in the stages of sleep.[22]
2. Potentials Awakened: Multiple sclerosis is one example of a visual evoked potential. Spinal cord injury and neuropathy are examples of somatosensory evoked potentials.

5. Oxidative Stress Markers and Metabolic and Cellular Biomarkers:

1. 8-Hydroxy-2′-deoxyguanosine:Neurodegenerative DNA damage. Malondialdehyde: Stroke lipid peroxidation. The biomarkers of inflammation:
2. Cytokines (such as TNF-α and IL-6): Neuroinflammation in ALS and MS. Systemic inflammation is indicated by C-reactive protein (CRP).[23]

6. Wearable and Digital Data, Digital and Physiological Biomarkers:

1. Analysis of gait: progression of Parkinson's disease. Quantification of tremor: Differences between Parkinson's disease and essential tremor. Health related Measures:[24]
2. Heart rate variability: Neurodegenerative diseases involving autonomic dysfunction.

AI and its relation and with neurology:

AI is now becoming backbone of health care By greatly enhancing human clinical capabilities

in diagnosis, drug discovery epidemiology, personalized medicine, and operational efficiency, such AI-clinician cooperation where AI is used to provide the clinician with comprehensive evidence-based clinical decision support (AI-Health) could present excellent opportunities for the improvement of healthcare services and, eventually[25], patients' health. However, as Ngiam and Khor (2019) emphasize, a clear governance framework is required to safeguard individuals from harm, including harm resulting from unethical activity, if these AI solutions are to be integrated into clinical practice. We refer to this as "cooperation" and propose that clinical decision assistance will be the primary use of AI. This is distinct from claims that AI will "replace" clinicians, which are frequently made by the media[26].

AI systems are capable of simulating human intellect in a number of ways. Deep learning (DL) and machine learning (ML) are both subcategories of artificial intelligence. At the most fundamental level, machine learning enables systems to learn from data. DL is a subset of ML that builds models using more intricate structures. Obemeyer and Emanuel[27] claim that traditional AI techniques (such expert systems) may "take general principles about medicine and apply them to new patients" in a way that is comparable to that of first-year medical residents. Similar to what a doctor could encounter during his residency, machine learning (ML) extracts rules from the data[28].

ERRORS IN AI ALGORTHEMS:

It is essential that we set up mechanisms for routine monitoring and maintenance in order to guarantee the long-term dependability and efficacy of clinical algorithms based on AI/ML. A paradigm that works well in one hospital or one historical period may not function well in another when the clinical environment is very dynamic and the patient demographics are diverse. In a recent example, the emergence of COVID-19[24] revealed a decline in the performance of an ML algorithm that used input variables like respiratory rate and arrival mode, which were greatly impacted by the spread of COVID-19, to identify patients who were at high risk of hospitalization based on their ED presentation[29].

Due to some "common causes" and "special causes" these types of errors takes place. Variability in the system that is predictable and inevitable is referred to as common cause variation. Special-cause variation, on the other hand, denotes an unforeseen shift in the system. for the purpose of fixing frequent cause mistakes[30]. Developers can use independent data to characterize common-cause variation and calibrate the model before deploying it. To increase the model's generalizability, model makers might also include recognized sources of common-cause variation[31].

Another way to describe special cause variation is as isolated or maintained (i.e., affecting only one observation). The focus in this manuscript is on the former, which can degrade performance for significant periods of time[32]. Analyzing a stream of observations is usually necessary to discover such system level adjustments, as it is not possible to do so by examining each observation separately. On the other hand, isolated errors might be considered outliers and can be targeted with general outlier identification techniques and Shewhart control charts, a common tool in SPC.[33-35]

Data of patients facing ADHD (2023):

Symptoms of attention deficit/hyperactivity disorder (ADHD) are very common among college students. These symptoms, especially the inattentive cluster, put adolescents at risk for inferior academic adjustment and performance. Additionally, symptoms of ADHD frequently co-occur with those of other prevalent mental illnesses, which also has a negative impact on outcomes. Students from South Africa may lack the resources necessary to make a smooth transition to college. Therefore, our longitudinal study examined the following:

a. The relationship between ADHD symptoms and academic performance/ adjustment
b. The independent effects of the inattentive and hyperactivity impulsivity clusters on academic performance/adjustment
c. The combined effects of ADHD and psychiatric comorbidities on academic performance/adjustment. We did this using data from a sample of first-year undergraduate students in South Africa.

Challenges in the field of biomarkers study by using AI:

There are many obstacles to overcome before integrating AI into neurology, but there are also

many interesting potential. It can be difficult to find sufficiently large and high-quality datasets for AI training and validation, particularly for uncommon neurological conditions. It can be difficult to integrate AI systems into healthcare IT infrastructure and make sure they work with different data sources and formats. It is essential to address ethical conundrums pertaining to patient permission, openness, bias in AI algorithms, and responsible AI use[36]. It can be difficult to navigate the shifting regulatory environment for AI in healthcare, including getting approvals and making sure that regulations are followed. conducting thorough clinical validation studies to show the practical efficacy and safety of AI-driven diagnostic and treatment tools, as well as identifying and reducing biases in AI algorithms to guarantee fair and equitable diagnosis and treatment recommendations for a variety of patient populations. promoting patient interaction with AI-powered products, making sure patients comprehend and believe AI advice, assessing the financial viability of AI neurology solutions, and calculating the ROI for healthcare institutions. ensuring that individual preferences, quality of life, and patient outcomes are given top priority in AI-driven solutions[37]. Notwithstanding these obstacles, the application of AI in neurology has enormous potential to enhance patient care, diagnosis, and therapy.

Challenges for Brain Tumor Diagnosis: There are still issues even if AI models have been successfully incorporated into various stages of brain tumor treatment. Concerns about the interpretability and explainability of DL models, limited access to high-quality data, and the requirement for generalizability across various tumor types and populations are some of these difficulties. Differences in image capture characteristics, such as equipment, models, and contrast amounts, make it difficult for radiomic based features to be reproduced across different institutions. In particular, attaining repeatability in MR radiomics is more difficult than in CT radiomics. The creation of the radiomic quality score (RQS) has proven essential to standardizing radiomics. However, only 29.4% of the original research incorporated external validation, despite the significance of doing so in neuro-oncology using external datasets.[38]

The reinforcement of biases seen in the training data is one possible consequence of depending too much on AI models. An AI model for forecasting medication toxicity, for instance, might not be able to anticipate hazards for different populations, such as women, children, or the elderly, if it is primarily trained on data from young, healthy males. When creating and using AI models, researchers need to be careful to spot and address these biases.[39]

Future directions:

New neuroimaging methods have emerged in recent years, including pharmacologically induced functional ultrasound (pharmaco-fUS) and pharmacological functional magnetic resonance imaging (pharmacoMRI), which offer in vivo functional data of particular drug effects on the brain. PharmacoMRI is still a valuable method in neuropharmacology research, although its preclinical application is restricted by a number of issues (such as limited sensitivity, anesthetic requirement, and blood oxygenation-level dependent imaging).[41,42]

Major drug manufacturers are starting to include AI-based techniques into their drug discovery pipelines for neurological illnesses, such as computational modeling and machine learning[43]. New businesses are starting to market AI products designed especially for neuroscience uses, like brain-computer interfaces and customized neuromodulation treatments.[44]

Additionally, governments and foundations are funding in the study and advancement of these alternative approaches as they see the potential of AI in neurology. For instance, a number of initiatives focused at creating AI-based instruments for researching the brain and neurological illnesses have received funding from the US Brain Research through Advancing Innovative Neurotechnologies (BRAIN) Initiative[45]. Another significant project that is using AI and computational modeling to improve our knowledge of the brain and create novel treatments for neurological disorders is the European Human Brain Project[46].

Digital brain twins and neuromorphic computing are examples of emerging technologies with enormous promise. Personalized brain simulations could transform treatment approaches, and brain inspired computing architectures could produce AI models that are more effective and medically appropriate. AI-driven

disease modifying treatment discovery may result in ground breaking therapeutics for neurodegenerative disorders like Parkinson's and Alzheimer's, where conventional research approaches have failed to provide meaningful results. Lastly, it is impossible to exaggerate the ethical ramifications of AI in neurology research. Strong ethical frameworks must be established as these technologies get more potent and widespread in order to guarantee their responsible and advantageous use. In summary, artificial intelligence (AI) in neurology research has the potential to revolutionize how we perceive and treat neurological conditions[47].

Table 1: Experimental dataset for the patients suffering from neurological disorders[48]

Age	Sex	Symptoms	Medications
20	Female	I was diagnosed with major depressive disorder and general anxiety disorder between 2020 and 2021 and autism spectrum disorder in 2022	yes
19	Female	Anxiety	no
19	Female	N/A	no
19	Female	Anxiety	yes
20	Female	I struggled with anxiety from a very young age, and have early childhood trauma. as a result, i was put into therapy at the age of 4 and have been going ever since. i also had a particularly traumatic experience in high school which was very overwhelming.	yes
20	Male	Not applicable	not applicable
19	Female	None	no
19	Female	I've gone into depression and i 3 have anxiety attacks when i am overwhelmed	yes
19	Female	None	no
21	Male	Depression, anxiety, bipolar disorder	yes
18	Female	Not applicable	not applicable
19	Female	Prolonged sadness	no
19	Male	I had undiagnosed suicidal ideation, going as far as to put a noose around my neck at the edge of a chair.	not applicable
19	Female	N/A	no
19	Female	Anxiety and depression	yes
19	Female	Low motivation and feelings of lonliness	no
19	Male	Not applicable	no
19	Male	I had a bit of anxiety and sort of a panic attack or two in matric when times got a bit to stressful	no
20	Other	Being anxious	not applicable
19	Male	None	no
19	Female	Struggle to keep afloat with work load. stressing out about things that need to be done, then not doing it only to cause more stress and anxiety.	not applicable
18	Female	Anxiety	yes
20	Female	Anxiety	no
19	Female	Panic attacks, general anxiety, depressive episodes, suicidal thoughts	yes
20	Female	Anger, anxiety ,panic attacks, depression	no
18	Female	-	not applicable
19	Male	Mild depression, anxiety/panick attacks. trauma related to gangsterism	no
19	Female	I have suffered from anxiety and acute depression in the past	no
19	Female	I was just feeling really down and not happy during my matric finals.	no
22	Female	No appetite, lack of motivation to complete simple everyday tasks. not wanting to socialise, and lack of sleep.	no

Age	Sex	Symptoms	Medications
19	Female	In primary school at the age of 13, i dealt with grief for the first time. i was experiencing one of the phases of grief which was slowly accepting the loss of my grandfather after a couple months.	not applicable
19	Female	Anxiety and stress	yes
19	Female	Depression and anxiety	yes
20	Male	I have been depressed over low marks.	not applicable
19	Female	Anxiety and depression	no
20	Male	Anxiety, lonliness and depression	no
19	Female	Non-applicable	no
19	Female	N/A	not applicable
19	Male	*Minor depression	no
19	Female	Depression	not applicable
18	Female	N/A	no
19	Female	Anxiety attacks depression breathing issues	no
19	Male	Depression and anxiety	yes
19	Female	Anxiety	not applicable
19	Female	Anxiety	no
19	Female	-	yes
19	Female	I was 0 diagnosed with anything, but when i was 15 i experienced symptoms of depression, feeling heavy and low and numb for a period of a few months.	no
20	Female	I have battled with anxiety for two years coming on three.	no
19	Female	Mainly anxiety (particularly social)	no
19	Female	Symptoms of anxiety	no
20	Female	I've struggled with anxiety for a few years and went through a depression some time ago.	no
19	Female	Anxiety, self harm, unhealthy mentality around food, self isolation	yes
18	Female	Self harm, depression, anxiety, severe mood swings, suspected adhd or other neurodivergence	no
18	Female	Feelings of anxiety and stress.	no
18	Female	Anxiety & depression	yes
18	Female	Insomnia caused by anxiety and depression	no
18	Female	Anxiety, depression	yes

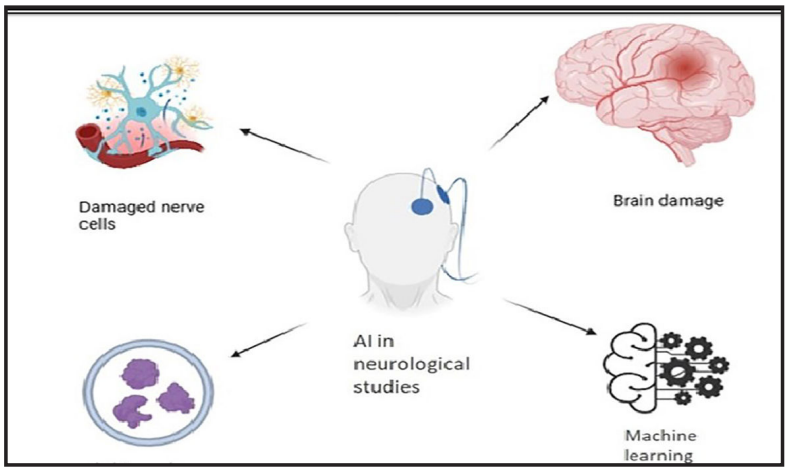


Figure 1: Artificial intelligence implementation in the field of neurological studies and advanced studies[40]

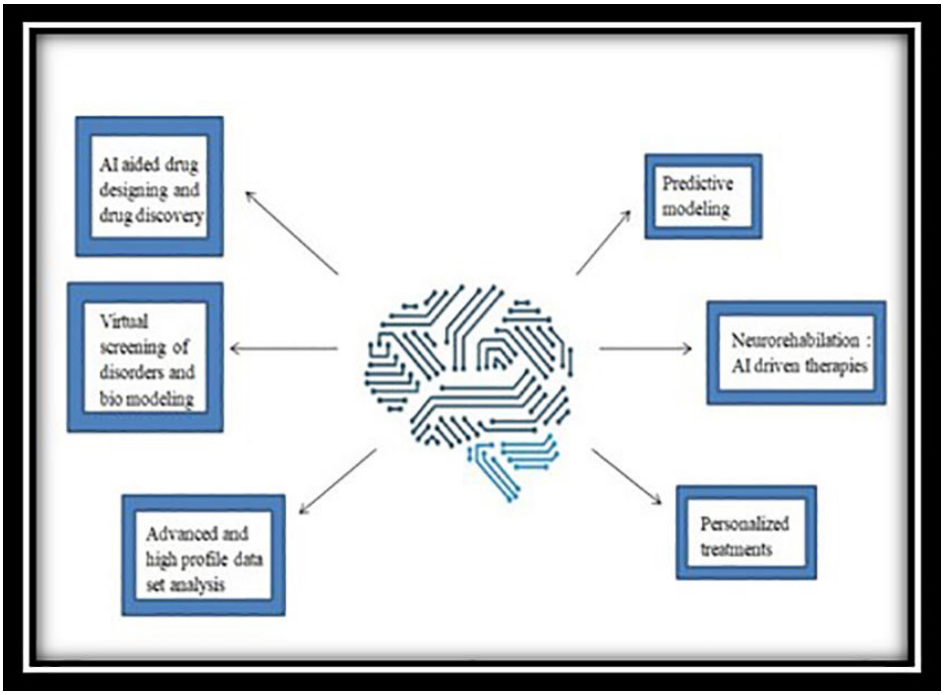


Figure 2: AI and its application and future prospects in others field of health care[40]

CONCLUSION

The understanding, diagnosis, and treatment of neurological illnesses could be completely transformed by the use of artificial intelligence (AI) into neurological research and the identification of biomarkers. Researchers and medical professionals can find previously invisible tiny patterns and relationships in the brain by utilizing AI's capacity to evaluate enormous volumes of complex data. This feature makes it possible to find new biomarkers from a variety of sources, such as wearable device outputs, genetic information, neuroimaging, and proteomics. In addition to offering insights into disease mechanisms that may direct the development of tailored therapeutics, these biomarkers have the potential to improve early detection, enabling interventions at times when treatments are most effective.

Beyond the identification of biomarkers, AI helps develop patient-specific customized treatment strategies. While real-time monitoring solutions, such wearables with AI enhancements, offer continuous data streams to diagnose and manage diseases dynamically, predictive algorithms can evaluate the course of a disease and the effectiveness of treatment. AI models are already showing great promise in the field of neurodegenerative disorders, such as Parkinson's and Alzheimer's, in terms of forecasting the beginning and course of the disease. In a similar vein, AI-powered diagnostic tools enhance accuracy and shorten treatment times for illnesses like epilepsy and stroke, which directly affects patient outcomes.

AI's incorporation into neurological research also speeds up the development of new medications and treatments. AI lowers the time and expense involved in launching novel medications by locating possible targets and more effectively evaluating clinical trial data. Additionally, its use in neurorehabilitation through robotic assistance and adaptive learning systems offers creative approaches to enhance the quality of life and speed of recovery for individuals with neurological disabilities.

Although these developments, there are still issues that need to be resolved before AI is widely used in neurology. Strong validation against real-world data is essential, as are ethical concerns about data privacy and possible biases in AI algorithms. For AI tools to be successfully incorporated into healthcare systems, it is equally important that professionals can access and understand them. These challenges will probably be addressed, though, as interdisciplinary cooperation improves and technology advances.

In conclusion, both neurology and AI are entering a transformational era as a result of their merger. AI is not only increasing neurological research but also changing the possibilities for patient care by facilitating deeper insights into brain function, improving the detection and comprehension of biomarkers, and tailoring treatments. Its ongoing research holds up the prospect of a time when neurological conditions will be better understood, identified sooner, and treated more skillfully, ultimately leading to better results and a higher standard of living for millions of people globally.

Conflict of Interest: Nil

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