Journal of Neurology (2021) 268:1623–1642
https://doi.org/10.1007/s00415-019-09518-3

REVIEW

Artificial intelligence as an emerging technology in the current care of neurological disorders

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Received: 23 July 2019 / Revised: 14 August 2019 / Accepted: 17 August 2019 / Published online: 26 August 2019

Abstract

Background Artificial intelligence (AI) has influenced all aspects of human life and neurology is no exception to this growing trend. The aim of this paper is to guide medical practitioners on the relevant aspects of artificial intelligence, i.e., machine learning, and deep learning, to review the development of technological advancement equipped with AI, and to elucidate how machine learning can revolutionize the management of neurological diseases. This review focuses on unsupervised aspects of machine learning, and how these aspects could be applied to precision neurology to improve patient outcomes. We have mentioned various forms of available AI, prior research, outcomes, benefits and limitations of AI, effective accessibility and future of AI, keeping the current burden of neurological disorders in mind.

Discussion The smart device system to monitor tremors and to recognize its phenotypes for better outcomes of deep brain stimulation, applications evaluating fine motor functions, AI integrated electroencephalogram learning to diagnose epilepsy and psychological non-epileptic seizure, predict outcome of seizure surgeries, recognize patterns of autonomic instability to prevent sudden unexpected death in epilepsy (SUDEP), identify the pattern of complex algorithm in neuroimaging classifying cognitive impairment, differentiating and classifying concussion phenotypes, smartwatches monitoring atrial fibrillation to prevent strokes, and prediction of prognosis in dementia are unique examples of experimental utilizations of AI in the field of neurology. Though there are obvious limitations of AI, the general consensus among several nationwide studies is that this new technology has the ability to improve the prognosis of neurological disorders and as a result should become a staple in the medical community.

Conclusion AI not only helps to analyze medical data in disease prevention, diagnosis, patient monitoring, and development of new protocols, but can also assist clinicians in dealing with voluminous data in a more accurate and efficient manner.

Keywords Artificial intelligence · Machine learning · Deep learning · Neurological disorders · Stroke · Epilepsy · SUDEP · Movement disorders · Concussion · Alzheimer's disease · Technology

Introduction

In 1956, an American computer scientist John McCarthy first introduced the term and principles of 'artificial intelligence (AI)' [1, 2]. The term AI is used to describe 'machines' capable of demonstrating cognitive functions that humans associate with other human minds such as 'learning' and 'problem solving' [3]. The foundation of AI is 'machine learning', a form of intelligence based on the compilation of a complex algorithm and software that mimics the human mind to decipher critical problems that include visual perception, speech recognition, and decision-making [4]. Similarly, 'deep learning' is described as a class of artificial neural networks that learn in a supervised and unsupervised manner [5] (Fig. 1).

In health care, AI uses this ability to analyze medical data in disease prevention, diagnosis, patient monitoring, and development of new protocols [6]. Clinicians today are drowning in voluminous data, but AI gives the hope of easing the burden [7]. After the digitization of health-care data beginning in the mid-1960s until the incorporation of the electronic health record (EHR) in the American Recovery and Reinvestment Act 2009 [8], the increasing availability and progress of analytical techniques are opening new doors

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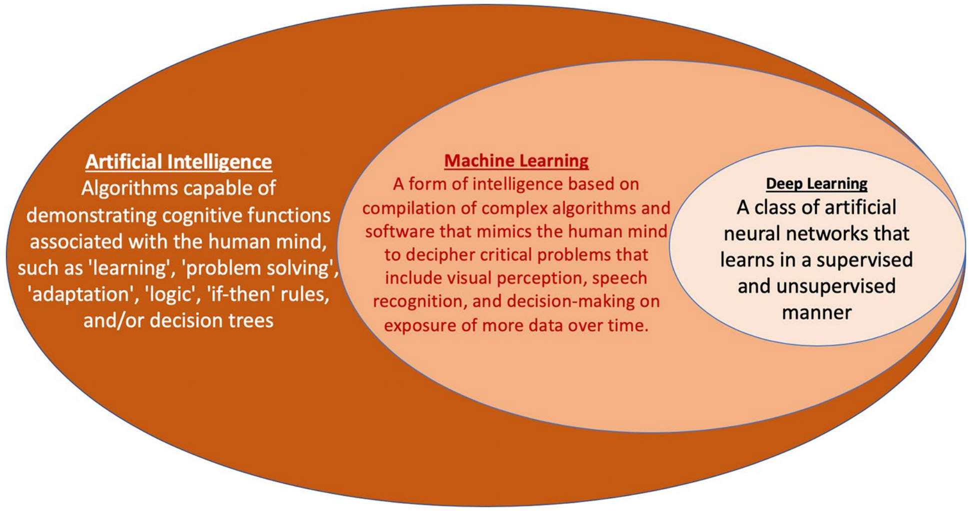

Fig. 1 Artificial intelligence and subtypes

in health care [9]. AI is helping clinicians assess only clinically relevant information buried under massive amounts of data.

Neurological disorders comprise structural, biochemical or electrical abnormalities of the brain, spinal cord and nerves. With increasing population and aging, the burden of chronic neurological disorders has increased substantially despite a decrease in mortality due to stroke and other communicable neurological diseases [10]. In 2014, nine of the most common neurological disorders—dementia, stroke, epilepsy, Parkinson's disease, multiple sclerosis, migraine, and tension-type headache—cost the US economy nearly $789 billion [11]. In 2015, neurological disorders caused 250.7 million disability-adjusted life years (DALYs), which comprised 10.2% of global DALYs and 9.4 million deaths, and16.8% of global deaths [12]. Today, neurology faces multiple challenges in the field of diagnostic and management modalities. This ranges from simple issues like identification of healthy sleep patterns to more complicated issues like early detection and reduction in the duration of rehabilitation of acute ischemic stroke diagnosis of rare subtypes of epilepsy and prevention of sudden unexpected death in epilepsy (SUDEP), or considering multiple attributes of epilepsy and inter-observer variability of reading EEG. The vast amount of data compiled in neurology every year requires deep learning to structuralize the data to help neurologists in making an early diagnosis and improving care [13]. Artificial Intelligence has gained a lot of attention in the realms of detecting, diagnosing, and even preventing irreversible outcomes due to neurological disorders [13].

The founding principle of precision medicine is AI, which will eventually be part of neurological management. It is an emerging approach for disease treatment and prevention that takes multiple variables such as gene, environment, and lifestyle into account. It has the potential to work at an unprecedented rate by using massive computer power without any human programming [14]. The future of AI in every field is reassuring, especially in neurology from the prediction of outcomes of seizure disorder, grading of brain tumors, upskilling neurosurgical procedures, rehabilitation of stroke patients to smartphone apps monitoring patient symptoms and progress, the future seems promising [15]. During the last two decades, multiple gadgets equipped with artificial intelligence have been invented and researched to improve the functionality, diagnostic efficiency, and prognosis in patients suffering from neurological disorders. Few examples of such include the Apple Watch monitoring tremors and asymptomatic arrhythmia; iPad devices monitoring patient drawing capability with suspected movement disorders; CT scans and MRI equipped with AI to help radiologists diagnose complicated images; AI health applications to improve patient medication adherence; EpiFinder application to identify seizure types and epilepsy syndromes for triage [16]. A new horizon is emerging in neurology in the form of artificial intelligence, helping patients to improve their prognosis.

The primary objective of this narrative review is to highlight the emerging AI technologies that are creating new ways of neurological disorder management and improvement of patients' overall functional outcomes. We have described various forms of AI used and available for use, as well as prior research, outcomes, benefits, and limitations of AI, effective accessibility and future of AI, keeping the current burden of neurological disorders in mind.

Discussion

Types of AI and prior research

In spite of the voluminous research helping to diagnose a complex spectrum of diseases, the translation into clinical practice has been challenging. Machine learning (ML) may be able to bridge the gap between translation of relevant clinical data and accurate clinical diagnosis [7]. Smart devices with AI technology, including smartwatches, smartphones, and tablets are being used by researchers not only to identify and stratify complex movement disorders [17] or arrhythmias including atrial fibrillation [18], but also to predict aspiration pneumonia in patients with swallowing difficulties secondary to stroke and dementia [19] and to improve medication compliance in patients on anticoagulation therapy [20]. Epileptologists are using smart devices with wrist annotated sensors to detect seizure activity [12, 21] and AI-enabled iPads to come up with a differential diagnosis and therapeutic approaches for rare epilepsy syndromes [22]. These studies could further pave a way to a better understanding of the pathophysiology involved in SUDEP [21]. Table 1 lists various types of AI technology and their clinical applications in neurological disorders.

Different algorithms play an integral part in ML. ML algorithms such as random forest that use neuroimaging data in small sample data with high-dimensional parameter spaces are more stable than other algorithms and have been successful not only in classification of dementia, including mild cognitive impairment (MCI) [23] and Alzheimer's [24], but also in other disorders including psychogenic non-epileptic seizures (PNES) [23, 25], Parkinson's disease [26, 27], and schizophrenia. In the same note, different algorithms have been used in the classification of similar disorders such as dementia [23, 25, 28]. Algorithms of the self-organizing map have been used by a group of researchers to identify distinctive phenotypes among concussive patients [29]. Deep learning algorithms are being used to predict the time since stroke onset (TSS) to help clinicians come up with better tools to guide stroke treatment [19]. EpiFinder algorithms help in diagnosing seizure in adult patients with spells [22]. These tools can help diagnose elusive disorders and prevent delay in diagnosis and treatment. Prior studies, utilizing the role of AI in neurological care, are mentioned in Table 2.

Stroke

Stroke is the leading cause of disability and the fifth leading cause of death in the USA (102). Each year 795,000 Americans experience a new or recurrent stroke [30], and an estimated 24 billion dollars is spent annually on direct medical expenses [30]. Only 5% or fewer receive intravenous thrombolytic therapy in spite of the urgent need to administer it to preserve tissue in acute ischemic stroke [31, 32]. This can be due to lack of physician experience in administering thrombolytics, risk of 6% hemorrhage with thrombolytics, patients living in rural areas with limited resources, and strokes are unwitnessed or wake-up strokes [31–34]. Thus, there is an urgent need to streamline care and improve technology to solve this complex issue and bring down the rising costs [35]. ML has shown that it not only predicts the risk of recurrent stroke within 1 year after a TIA or minor stroke [36], but also predicts time since stroke onset (TSS) and is a better alternative than current DWI–FLAIR mismatch [37–42] in patients with unknown TSS (wake-up strokes or unwitnessed strokes); thus, it guides physicians to make better therapeutic approaches [19]. Smart devices with apps, using techniques like photoplethysmography, and handheld electrocardiograph recorders with greater accuracy are being used to check the heart rate and heart rate variability and to screen for asymptomatic atrial fibrillation which helps to prevent embolic stroke [18].

Epilepsy

Given its varied clinical manifestations, the rates of misdiagnosis are 26% in epilepsy centers and 20–40% in community settings. This often leads to unwarranted investigations and treatments [43]. Machine learning applications in epilepsy ranges from diagnosis of epilepsy [22, 44], PNES [45], and rare subtypes of epilepsy to the prevention of SUDEP and minimizing inter-observer variability of EEG interpretation.

Rajagopalan et al. showed that ML can diagnose temporal epilepsy by detecting microstate alterations than depending on ictal or interictal charges on repeated scalp EEG [44]. These, in turn, are affected by a multitude of factors such as medications, sleep deprivation, and inter-observer variability [46]. ML-detected alterations in microstate C shows a possible reflection of the inappropriate activation of alpha activity [47–49] with 76.1% accuracy, even in the absence of a visible interictal epileptiform (IED) discharges on EEG [44]. The EpiFinder algorithm used in a tertiary center was able to generate a differential of seizure types and epilepsy syndromes from other spells [22].

A pilot study using wristband sensors detected increased EDA, i.e., epidermal activity in epileptic seizures. The increase in EDA was proportionally higher in generalized tonic–clonic seizures (GTCS) versus complex partial seizures (CPS) [21]. Similar observations have been noted by Van Buren in 1958 [50], and elevated plasma catecholamines following GTCS support this assumption [51, 52]. They propose that this autonomic instability of sympathetic surge during seizures could play a role in SUDEP [21].

Psychogenic non-epileptic seizures (PNES) resemble epileptic seizures and consist of episodes of paroxysmal behavioral manifestations including a range of motor, sensory, and behavioral manifestations [53, 54]. 20% of the epilepsy patients referred to a tertiary center are eventually diagnosed with PNES using the gold standard video electroencephalography (vEEG); hence, there is a need to identify better, quicker, and affordable tests to reduce the significant chronic

Table 1 Types of artificial intelligence technology and their applications

Type of models integrated with AI and ML	Description	Usefulness
Smartwatches [17]	The smart device system (SDS) based on apple device application helps to identify and monitor movements using two smartwatches worn on both wrists of the patient during neurological examination that provoke different types of tremors. The accelerated data collected from the smartwatches are used to analyze and infer the tremor amplitude and frequency in each examination and aid in identification and diagnosis of different movement disorders	AI captures high-resolution tremors, diagnoses different movement disorders, the results of which are transferred to the examiner's smartphone
Smartphone [17]	The Apple-based smartphone device application is incorporated with 8-min assessment of electronic questionnaires for the patients regarding their demographics, medical and family history, medication/drug consumption and non-motor symptoms	Helps to classify and stratify tremor in patients
Tablet-based device [17]	A 2-min assessment on iPad enables assessment of Archimedean spiral drawing and the pressure during drawing by the patient during neurological examination. This SDS uses the data captured during spiral drawings and the data will be processed for angular feature detection, direction inversion, and pattern deviation, and the pressure during drawing from the ideal spiral pattern according Zham et al.	The sum of all the data will be used to predict the diagnosis of different movement disorders
Algorithm of self-organizing map (SOM) [29]	The study explored the use of machine learning (ML) as a bottom-up approach to study the difference in phenotypes between concussion patients based on their epidemiology, balance and vestibular diagnostic outcomes Patients were assigned to two groups using SOM, as it gives reliable clustering. One group included patients with prominent vestibular disorders, while the second group did not have any vestibular or balance dysfunction	Observing how ML algorithm formed two cluster groups, helps to identify distinctive aspects of phenotypes of concussion
Neuroimaging (adaptive boosting method) [19]	Bouts et al. analyzed the ability of five algorithms to depict potentially salvageable tissue using MRI imaging from rats subjected to a right-sided middle cerebral artery (MCA) occlusion without subsequent reperfusion, and with spontaneous or thrombolysis-induced reperfusion The implementations of ML are numerous, from early identification of diagnostic findings, estimating time of onset, lesion segmentation, and fate of salvageable tissue, to the analysis of cerebral edema, and predicting complications and patient outcomes after treatment	ML algorithms have been used to assist in the diagnosis and individualized treatment decisions in acute ischemic stroke

Table 1 (continued)

Type of models integrated with AI and ML	Description	Usefulness
Imaging-based time since stroke onset (TSS) (deep learning algorithm) [19]	It is an ML approach for TSS classification using routinely acquired imaging sequences. Imaging features from the MRI and train machine learning models to classify TSS. It also proposes a deep learning model to extract hidden representations for the MR perfusion-weighted images and demonstrate classification improvement by incorporating these additional deep features	This work advances MRI analysis one step closer to an operational decision support tool for stroke treatment guidance
Health applications (MEDITECH MHealth, VizAI) [19]	These applications perform an analysis of the available CT scans and analyzes the signs of stroke and then communicate with the neurologist. The US Food and Drug Administration has limited these applications to only imaging data analysis and discouraged its use to full patient evaluation	These applications are important in patients with stroke by shortening the time-to-treatment duration that helps in better outcomes
Smart devices [19]	These wearable devices continuously monitor swallowing activities and assess the swallowing ability without causing discomfort. They use the sound process algorithm for automatic screening	Swallow scopes are AI-facilitated smart devices that uses ML power to screen, evaluate, and visualize swallowing abilities in patients suffering from stroke and severe Alzheimer's disease and help reduce the rate of aspiration pneumonia
Augmented EEGs learning [44]	The machines use multiple models such as support vector machine (SVM), independent component analysis (ICA), principal component analysis (PCA), linear discriminant analysis (LDA), and power spectrum to predict seizures	Using AI to predict outcome of epilepsy surgery by considering multiple factors such as clinical, pathological, and neuropsychological
Improvement of medication non-adherence [20]	AI uses HIPAA-compliant application to identify patients, their medication, and dosing instruction. It gives reminders and medication non-adherence by clinic staff are notified	AI uses this to increase medication adherence in patients with stroke, Alzheimer's, and epilepsy, hence improving the clinical outcome
EpiFinder—AI integrated application [22]	It is a form of AI based on pattern recognition-iPad application. It was developed to help triage in decision making and better therapeutic approaches for rare epilepsy identification and classification EpiFinder helps to record the data while the neurologist takes history and saves all that information. It uses standardized terminology and empirical algorithm that make a list of differential diagnosis based on the cluster of semiology against International League against Epilepsy (ILAE)—defined epilepsy criteria	The application compares symptoms aggregate bundle with knowledge representation of ILAE recommendation and makes a list of differential diagnosis of epilepsy syndromes
Mobile phone-based photoplethysmography (PPG) [18]	It is an optical technique that detects heart beat by analyzing changes in skin color and light absorption. With the help of the mobile app, the PPG sensor detects changes in light intensity via reflection from the tissue. Changes in intensity are related to changes in blood perfusion of tissue and based on these changes heart-related information can be retrieved	Mobile phone-based PPG helps to detect heart rate, heart rate variability, and atrial fibrillation and is helpful for paramedics, especially the stroke team
Machine learning integrated with handheld electrocardiography (ECG) [18]	The handheld ECG sensor unit basically involves mobile phone app involving external ECG component. It helps to record one lead ECG recordings	Handheld ECG helps to detect different types of arrhythmias like atrial fibrillation, atrial flutter, atrial and ventricular premature beats, bundle branch blocks, and ST segment abnormalities

Table 1 (continued)

Type of models integrated with AI and ML	Description	Usefulness
Frideswide AI algorithm (FwA) [28]	FwA is an intelligent agent for analytic tool. It studies the available environment data (clinical information, reports letters, requests, etc.) in different time frames. It then tries to maximize the diagnostic efficiency	It is used for quick diagnosis of frontotemporal dementia
Wrist annotated wearable sensors using video EEG monitor [12, 21, 45]	Electrodermal activity (EDA) and accelerometer (ACM) signals were used. There are three different components of each epoch, one made of 19 features (classifier I), 46 features (classifier II), and 25 features (classifier III). Each noted epoch was classified as seizure or non-seizure by applying posterior probability estimates	To detect seizure activity with precision
Imaging services [36]	This model collects magnetic resonance imaging (MRI) and computed tomography scan (CT) scan and classify them according to severity and clinical clues	Helps in quick and easy evaluation of imaging

disability, lost wage hours, multiple hospitalizations, and associated risk of morbidity and mortality [53–57].

A group from Italy was able to identify PNES using ML with multivariate neuroimaging analysis and also secondarily locate brain regions within the limbic and the right inferior frontal cortex (IFC) [45]. IFC has also been implicated in other disorders such as compulsive–impulsive disorders, Tourette syndrome, and Parkinson's disease with levodopa-induced dyskinesia [58]. The EpiFinder algorithm used in a tertiary center was able to differentiate epileptic seizures from PNES [22].

Concussion

Concussion is another multidimensional problem with no validated criteria for diagnosis, leading to inter-examiner variability [59–62]. Its clinical presentation varies from cognitive to non-cognitive domains including sleep and balance [62–66]. Prior studies have focused on scans, symptoms, and cognitive testing [62, 65, 66] despite its varied symptomatology.

ML has not only been able to differentiate concussed and control subjects, and improve diagnosis based on individual data including conventional imaging, cognitive domains, eye movement, and clinical presentation [66–74], but has also made it possible to look into less understood and complex pathologies such as vestibular impairments [75–79], to better understand and identify varied phenotypes like cognitive problems, oculomotor dysfunction, affective disturbances, cervical spine disorders, headaches, and cardiovascular and vestibular anomalies [29, 80].

Dementia

Frontotemporal dementia (FTD) is a neurodegenerative disorder that accounts for 20% of young-onset dementia and has a high rate of misdiagnosis [81, 82]. This often leads to poor patient satisfaction and well-being, unnecessary laboratory tests, clinic visits, and imaging, and addition to the health-care costs [28, 83]. It has the worst prognosis and reduced life expectancy when compared to other dementias [12]. A study in the UK has shown that deep learning algorithms can reduce unnecessary investigations and improve costs and patient satisfaction through better clinical practice guidelines [28].

Movement disorders

The diagnosis of the two most common movement disorders, Parkinson's disease (PD) and essential tremor (ET), is challenging and based primarily on clinical criteria [84]. Researchers are using novel methods to synchronize data into deep learning from tremor characteristics in varied

Table 2 Use of artificial intelligence and machine learning for management of neurological disorders

Study, country	Clinical conditions	Sample size and timeline of study	Methods	Outcomes/objectives	Results
Varghese et al. (2019), Italy [17]	Parkinson's disease and essential tremor	120 patients with essential tremor (ET) and 954 patients with Parkinson disorder (PD), followed over 21 months period	The smart device system (SDS) will be applied and tested within a 20-min assessment including: 1. Smartphone-based questionnaires (8 min), will cover data on medication, family history and non-motor symptoms 2. Two smartwatches including calibration and putting them at both wrists (10 min), capturing high-resolution tremor 3. Tablet-based Archimedean spirals drawing (1–2 min) for deeper tremor analyses The sum of all captured and processed data will train a neural network model to predict the diagnosis label (PD, ET, none of them) and identify data patterns that could represent new biomarkers	To find out the most accurate device and application to diagnose Essential tremor and Parkinson disease	1. Synchronization of these multimodal data and integrative pattern recognition analyses are expected to provide deeper insights into tremor characteristics 2. Demonstrated the use of Smart wearables not only for fitness but also for valid medical use 3. An advantage of the SDS system is that all of its devices can be programmed and adapted by any Apple-based App developer, therefore preventing vendor lock-in

Table 2 (continued)

Study, country	Clinical conditions	Sample size and timeline of study	Methods	Outcomes/objectives	Results
Visscher et al. (2019), Switzerland [29]	Sports-related concussion (SRC) or post-concussion syndrome (PCS)	212 patients suffering from sports-related concussion (SRC) or post-concussion syndrome (PCS). Only 96 who underwent balance and vestibular diagnostic testing from January 2015 to November 2017 were included	Cluster analysis was conducted on balance and vestibular diagnostic database of Swiss Concussion Center (SCC) *Balance diagnostic testing* sensory organization test (SOT, from which 5 variables were extracted) *Vestibular diagnostic testing* Dynamic visual acuity (DVA, 8 variables), video head impulse test (V-HIT, 9 variables), cervical and ocular vestibular-evoked myogenic potential (cVEMP, oVEMP, together 3 variables referred to as VEMPs), subjective visual vertical (SVV, 11 variables), caloric (11 variables), and fundus photography (3 variables) tests *Two different clustering tools* K-means and Kohonen's self-organizing map (SOM)	To explore the use of machine learning (ML) for novel insights into the phenotypic differences between patients with concussions based on objective vestibular and balance performance	The data divided into two groups, group-1 ($n=38$) and group-2 ($n=58$) 1. A large significant difference was found for the caloric summary score for the maximal speed of the slow phase, where group-1 scored 30.7% lower than group-2 2. Group-1 also scored significantly lower on the sensory organization test composite score and higher on the visual acuity and dynamic visual acuity tests 3. The importance of caloric, SOT and DVA, was supported by the PCA outcomes. Group-1 tended to report headaches, blurred vision and balance problems more frequently than group-2 (> 10% difference)

Table 2 (continued)

Study, country	Clinical conditions	Sample size and timeline of study	Methods	Outcomes/objectives	Results
Ho et al. (2019), USA [19]	Ischemic stroke	181 patients' MRI were examined from University of California Los Angeles' picture archiving and communication system (PACS) between December 2011 and December 2017	The performance of constructed five machine learning methods was compared for binary time-since-stroke (TSS) classification (TSS < 4.5 h or TSS ≥ 4.5 h): logistic regression (LR), random forest (RF), gradient boosted regression tree (GBRT), support vector machine (SVM) and stepwise multilinear regression (SMR) In addition to the five machine learning models, trained four popular end-to-end convolutional neural networks (CNNs) to classify TSS	1. To develop a set of imaging features from the MR images and compared five machine learning models on TSS classification using these imaging features 2. To propose a deep learning models with training patch coupling strategies to learn latent deep features from four-dimension (4-D) PWIs that can be used in TSS classification	1. The cross-validation results showed, best classifier achieved an AUC of 0.765, sensitivity 0.788 and a negative predictive value of 0.609, outperforming existing methods 2. The features generated by our deep learning algorithm correlated with MR imaging features and validate the robustness of the model on imaging parameter variations (e.g., year of imaging) 3. These results advances MRI analysis one step closer to an operational decision support tool for stroke treatment guidance
Rajagopalan et al. (2018), India [44]	Temporal lobe epilepsy (TLE)	Total of 42 patients were selected: 21 patients with TLE and 21 were control	Electroencephalography (EEG) data were recorded using a 32-channel and 10–20 acquisition system Also four classes of microstates were computed from 2 min artifacti-free EEG epochs. Their frequency, time coverage, duration was computed to analyze the microstate alterations via feature selection methods Subsequently, Fisher's linear discriminant analysis (FLDA) and logistic regression were used for classification	Machine learning technique was used to explore, if abnormalities in microstates can identify patients with TLE in the absence of an interictal discharge	1. FLDA resulted in an overall accuracy of 73.8% with 81.0% sensitivity and 66.7% specificity, 3/42 patients classified correctly 2. Logistic regression had an overall accuracy of 66.7% with 71.4% sensitivity and 61.9% specificity, 28/42 patients classified correctly

Table 2 (continued)

Study, country	Clinical conditions	Sample size and timeline of study	Methods	Outcomes/objectives	Results
Labovitz et al. (2017), USA [20]	Ischemic stroke	A single center, 12-week study of 28 patients with recently diagnosed ischemic stroke and receiving any anticoagulation	1. 28 patients randomized into two groups: daily monitoring by the AI Platform (intervention:15) and no-daily monitoring (control:13) 2. Patients attended four clinic visits (baseline and weeks 4, 8, and 12); PT/INR and APTT were regularly measured 3. Software installed in the mobile device (intervention group) identified the patient, the medication and confirmed ingestion along with medication reminders and dosing instructions 4. Medication adherence was measured by pill counts, plasma sampling, and the AI Platform	This study evaluated the use of artificial intelligence (AI) platform on mobile devices in measuring and increasing medication adherence in stroke patients on anticoagulation therapy	1. Mean (SD) age was 57 (13.2) years and 53.6% were female 2. Mean (SD) cumulative adherence based on the AI Platform was 90.5% (7.5%) 3. Mean (SD) cumulative adherence based on pill count was 97.2 (4.4%) for the AI Platform group and 90.6% (5.8%) for the control group 4. Plasma drug concentration levels indicated that adherence was 100% and 50% in the intervention and 50% in the control groups
Okazaki et al. (2018), USA [22]	Epilepsy	Total 57, patients admitted in epilepsy monitoring unit (EMU), from January 2017 to June 2017	The "EpiFinder" application generates a list of epilepsy syndromes, based on some input. For each patient, EpiFinder-generated diagnosis was compared to the final diagnosis obtained via continuous video electroencephalogram (cVEEG) monitoring	To test the use and diagnostic accuracy of the clinical decision support application EpiFinder in an adult population	Findings from EpiFinder as compared to video EEG has 86.8% accuracy, 86.4% sensitivity and 85.1% specificity

Table 2 (continued)

Study, country	Clinical conditions	Sample size and timeline of study	Methods	Outcomes/objectives	Results
Li et al. (2019), China [18]	Atrial fibrillation	124 papers out of 1006 papers were included from 2014 to 2019	PubMed and EMBASE search, the use of mobile phone apps for monitoring heart rate (HR), heart rate volume (HRV), and atrial fibrillation (AF) was conducted Four core principles of this narrative review: (1) mobile phone apps, (2) HR, (3) HRV, and (4) AF	A review to explore the current state of mobile phone apps in cardiac rhythmology while highlighting shortcoming for future research	1. Mobile phone apps play a significant role in the diagnosis, monitoring, and screening of arrhythmias and HR 2. Mobile phone based photoplethysmography and hand held ECG are important devices in this respect
Brzezicki et al. (2019), UK [28]	Frontotemporal dementia (FTD)	Total of 47 patients diagnosed with FTD were selected from Memory Clinic in the Brain Centre retrospectively for 939 days	AI algorithm was used to retrospectively analyze 47 patients by combining all diagnostic and imaging information. Algorithm use reward signal of − 1 to + 1 to make diagnosis Frideswide AI algorithm (FwA) is generated from clinical letters, request sheets, and investigation present in computer system of health	To make the firm diagnosis of frontotemporal dementia (FTD) at an early stage	FwA efficiently guide clinical diagnosis of FTD, altered 7.37 times compared to normal
Vasta et al. (2018), Italy [45]	Psychogenic nonepileptic seizures (PNES)	23 patients with PNES and 21-age adjusted control group	All participants completed 50 min long comprehensive neuropsychiatric tests. MRI data were obtained from 3 T MRI scanners, then 34 gyral-based regions of interest (ROIs) per hemisphere were formed, and random forest (RF) algorithm was used to analyze the result	To diagnose PNES with the help of ML	PNES compared to controls with a mean accuracy of 74.5%, has main localization at limbic and motor inhibition systems This heterogeneity can be detected by using ML based MRI data

Table 2 (continued)

Study, country	Clinical conditions	Sample size and timeline of study	Methods	Outcomes/objectives	Results
Onorati et al. (2017), Italy [12]	Epilepsy	69 patients from six clinical sites were followed for 247 days	Hand-annotated video-electroencephalographic seizure events were collected from patients. Three kinds of wristbands were used to record electrodermal activity (EDA) and accelerometer (ACM) signals. 55 epileptic seizure episodes were included. Recordings were then analyzed Seizure-motion duration and autonomic responses were also noted	To quantify wrist-worn convulsive seizure detectors in detecting seizures episodes	Results showed that wrist worn detector has a sensitivity of 94.55% in detecting seizures episodes and are more accurate than previous automated detectors. False alarm rate was 0.2 events/day and No nocturnal seizures were missed
Poh et al. (2010), USA [21]	Epilepsy	Seven patients from Massachusetts Institute of Technology and Children's Hospital Boston were enrolled and monitored for 24 h	In all selected patients, scalp EEG with 256 Hz were recorded. Electrodermal applicators (EDAs) were placed with electrodes on the ventral side of the forearm. EDA recordings were synchronized with EEG at the beginning and end of the session. Each session lasted for 24 h	To investigate the relation between autonomic activity and seizures control	Study showed that EDA activity is significantly increased after seizures activity, and also help to differentiate between generalized tonic clonic and partial convulsive

Table 2 (continued)

Study, country	Clinical conditions	Sample size and timeline of study	Methods	Outcomes/objectives	Results
Chan et al. (2019), China [36]	Minor stroke and transient Ischemic stroke	450 patients with acute TIA or minor stroke with 40 patients randomly selected for no recurrent stroke and followed for 1 year	All patients who presented with TIA or minor stroke in 1-year time period were included, their demographics, vitals, NHSS, pre-morbid score, symptoms duration, and medication details were noted. Neuroimaging features and digital subtraction angiography (DSI) were collected. Three-layer approach of artificial neural network (ANN) was used and 5 rounds of training were used and compared with support vector machine and naive Bayes classifier for risk stratification	To find the use of ANN for risk stratification of TIA or minor stroke patients	The median sensitivity, specificity, accuracy and c statistic of the ANN models to predict recurrent stroke at 1 year was 75%, 75%, 75%, and 0.77, respectively. ANN can be used as an effective model for risk stratification in minor stroke or TIA patients

environments, questionnaires addressing non-motor issues, and Archimedean spirals drawn to identify newer phenotypes [17]. Prior studies have used each of these characteristics individually to diagnose movement disorders [85].

Outcomes and limitations

As discussed above, AI has played an important role in identifying neurological disorders [13]. It has been transformational in converting the voluminous data collected into those of clinical relevance [13]. For all the benefits, however, there are huge limitations and unknown legal ramifications.

First, there is a lack of data standards and open data repositories in machine learning [7, 86]. For example, limitations in the integration of already available commercial medical devices such as Parkinson's Kinetigraph TM into routine health care have been secondary to non-integration of motor and nonmotor characteristics, lacking open data storages and open programs [87]. Varghese et al. have overcome the limitations mentioned by not only integrating motor and non-motor phenomena, but also by using large data models with massive infrastructure like Medical-Data Models Portal (MDM), and combining affordable devices with customizable apps and SDS (smart device systems) that can be programmed by any Apple-based App developer [17]. This can help reach the level of data required to quicken the regulatory steps and rollout devices sooner with improved diagnostic accuracy [17, 84, 88] (Table 3).

Moreover, deep learning will never be 100% complete, especially with inter-examiner differences and varied environments [17]. Studies reveal that data entered by specialists improve performance in deep learning methods especially with pattern recognition [17].

In ML, there is some literature that the size of the samples should be a multiple of the number of input and output variables [19] nonetheless studies were affected by small sample size [17, 44, 45].

ML's clinical application in confounding groups with similar neurological, psychological, or pathological presentation is limited [45]: for instance, ML's application in distinguishing PNES not only from patients with epilepsy, but also with similar psychopathological presentation such as major depression [45], or ML's ability to distinguish epilepsy from healthy controls [44] versus application in patients with panic disorder [89], schizophrenia [90], drug-induced, and memory deficit with similar alterations in microstate C [44].

AI or deep learning uses different reasoning methods to diagnose a disease. A systematic review by Arani et al. in multiple sclerosis showed different reasoning methods or a combination of methods, e.g., case based, rule based, model based, fuzzy logic, genetic algorithms, natural language processing, and neural networks were used by different computers and each method had its own capabilities and limitations [91]. The efficiency of each method varied, and, hence, affected its applicability in the diagnosis of rare and complicated disease such as multiple sclerosis [91]. Nonetheless, they can play a major role in helping patients and physicians with timely clinical diagnosis [91].

It is impossible to account for all potential positive or negative side effects even with the best algorithms [28]. Deep learning algorithms tend to avoid negative side effects and confounding factors like test results to achieve its goal, and thus in turn can affect patient safety and outcomes [28, 92].

Mobile apps are currently being used to monitor paroxysmal AF and long-term anticoagulation (39) and have shown to be effective tools in monitoring and screening of arrhythmias [18], but this has often led to a large number of false positives and in turn to expensive and unnecessary testing [18, 93]. This inadvertently raises the medico-legal aspect and logistics for governments and public health bodies with regard to systematic and opportunistic screening, cost-effectiveness, and management of newly identified patients with AF [18]; hence, a better understanding of local screening guidelines is required, e.g., European Heart Rhythm Association Consensus guidelines on screening AF.

Lastly, the ethical and legal ramifications are beyond the scope of this paper, but sustaining patient trust would be the key in promoting collaboration and implementation of AI [94].The black box scenario is that decisions made by AI-enabled computer-aided diagnosis (CAD) systems [95] cannot be explained. The legal ramifications of a misdiagnosis are unclear, especially with regard to whether the fault lies

Table 3 Benefits and barriers of artificial intelligence and machine learning

Benefits:
Increased practice efficiency
Quick in making diagnosis without bias
Help in prevention of undesirable events like seizures
Help in risk stratification of recurrent attack
Recordings can be checked again and again
Other physicians can use these to reach the diagnosis
Can alert the patient about dysautonomia
Barriers:
Disruption of traditional doctor–patient relationship
Physician reluctance to adopt novel technology in practice
Limitations to billing and reimbursement for time spent
Additional costs for technology and highly educated experts of AI
Licensing, credentialing issues for out-of-state physicians
Concern for malpractice liability
Consistency and availability of mobile phones and electronic gadgets

with the manufacturer or the physician [95–97]. We need to develop standard practices for evaluation of AI tools [98]. It is debatable whether AI will replace physicians, but AI will definitely be playing a greater role in integrating health care [94].

Future directions

Deep brain stimulation (DBS) is an effective surgical treatment option and improves quality of life in patients with tremor manifestation, including Parkinson's (PD) and essential tremor (ET) [99–102]. Currently, determination of DBS leads is done by a neurologist, and is therefore affected by interpersonal variability. AI may help in this regard to make an objective evaluation, subject to fulfilling the regulatory requirements and getting medical clearance [17].

Using open data portals can be in the best shared interest to develop data standards and smart devices [86]. Some researchers have made the study models, frameworks, codes, and anonymized data samples open source, which makes it easier to reproduce in future studies [17]. Using devices that are affordable with customizable apps that are available to the masses increases their applicability [17]. For example, Kardiaband app by AliveCor is the first FDA-cleared smartwatch-based ECG reader [103].

Standard auditing and statistics only can test known hypotheses, but newer algorithms can test multiple hypotheses in a reasonable time frame and make a priori assumptions [28] beyond the scope of human capabilities. This has the potential to be applied across other diseases and specialties [28]. ML specifically is able to analyze large datasets at much quicker speeds and at higher accuracy to investigate unexplained phenomena [15]. ML algorithms like self-organizing map (SOM) can be extended to include non-vestibular parameters, including previous concussions, neuropsychological outcomes, and multiple other variables to validate studies in a more complicated context [29]. This also help to improve diagnostic criteria by identifying features among varied patient populations [16].

Conclusion

The current neurological care not only places a burden on the US economy by imposing higher overall costs, but also affects disability-adjusted life years. The ability of AI and ML to analyze medical data in disease prevention, diagnosis, patient monitoring, and development of new protocols will help clinicians to deal with voluminous data in a more accurate and efficient manner. AI has the ability to limit interobserver variability, screen for asymptomatic atrial fibrillation, diagnose epilepsy, PNES, concussions, and movement disorders, and identify abnormal autonomic functions to prevent SUDEP. Though AI utilization is limited for a wide variety of reasons including physician's reluctance to adopt novel technology, billing and reimbursement issues, pan-USA licensing problems, malpractice lawsuits, and the initial cost of technological establishment, it has the potential to serve as a powerful tool for neurological care.

Author contributions Conceptualization, UP; methodology: none; formal analysis and investigation, UP, AA, SS; writing—original draft preparation, KA, AA, SS, UP; writing—review and editing, PM, KP, RY, AS, MY, BR; supervision, KA; project administration, UP; resources, UP; funding acquisition, none.

Funding The study had no internal or external funding source.

Compliance with ethical standards

Conflicts of interest The authors report no disclosures relevant to the manuscript. The authors declare that there is no conflict of interest. Robert Yao is the founder and CEO of EpiFinder, Inc.

Informed consent This review article does not have direct or indirect involvement of humans or animals, so permission from IRB or ethics committee was not applicable or required.

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