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Review Article

A Review of Artificial Intelligence Applications in Epilepsy: From Misdiagnosis to Precision Care

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ABSTRACT

Background and Objective The misdiagnosis of epilepsy is a problem that 25-30% of patients all around the world have to deal with, which results in the use of incorrect treatments, imposing restrictions on life unnecessarily, and making other underlying conditions' care delayed. The limitations of the classic techniques are the subjectivity of EEG interpretation, 20-30% inter-observer variability, and ictal phenomena being only partially captured. This review evaluates thoroughly the potential of using artificial intelligence (AI) for detection of seizures and epilepsy management individually in order to tackle the diagnostic problems. Methodology: A detailed review of the literature has been done to consider the AI interventions in different areas, including deep learning-based EEG signal processing, computer vision for semiological characterization, new wearable biosensors, and machine learning methods to improve personalized treatment. The assessments of effectiveness focused on diagnostic accuracy, clinical validity, and the practicality of real-world implementation Results: AI offers a practical solution for addressing misdiagnosis and advancing precision medicine in epilepsy treatment. There is enough evidence to support the prompt use of validated AI technology in clinical settings. This can enhance diagnosis accuracy, help tailor treatments for individual patients, and ensure broad access to quality epilepsy care. The presence of enforceable regulations, demonstrated effectiveness in clinical trials, and the pressing need to improve the lives of those impacted by epilepsy all support a teamwork-based approach to incorporating AI into regular clinical practice for epilepsy care. Conclusions: AI marks a paradigm shift from misdiagnosis to precision medicine to maximize care for patients with epilepsy. There is evidence to support the immediate utilization of innovative AI technology developed to improve diagnostic accuracy, specify and optimize treatment for individuals with epilepsy, and disseminate high-quality expert care to all patients, regardless of geography.

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The convergence of regulatory approval, proof of utility, and synthesized clinical need compel us to adopt a systematic integration of AI into daily practice for epilepsy.

INTRODUCTION

Seizure disorders include a wide collection of neurologic disorders which are characterized by paroxysmal events, mainly involving alterations in awareness and/or motor activity. For purposes of this article, seizure disorders are differentiated into two broad groups, specifically epileptic seizures or non-epileptic seizures, as defined by the International League Against Epilepsy (ILAE). Epileptic seizures are caused by abnormal neuronal activity, while non-epileptic seizures demonstrate seizure signs and symptoms, although the events do not have a distinct correlate to the electroencephalogram (EEG) (1).

Around the world, epilepsy is a condition that impacts about 50 million individuals, with a global incidence of 658 per 100,000 population (2). The diagnostic burden is heavier in low- and middle-income countries, where childhood epilepsy is diagnosed three times as often as in high-income countries (3). This burden of ill health is compounded by the greater difficulty in diagnosing epilepsy, and diagnostic challenges resulting in substantial healthcare resource utilization and morbidity for patients.

The diagnosis involves several challenges that lead to a heavy misdiagnosis rate. Among patients with treatment-resistant epilepsy, at least 26.1% are misdiagnosed (4). One of the most common causes of misdiagnosis is psychogenic non-epileptic seizures (PNES), which look like seizure events but do not show abnormal electrical brain activity (5). cardiovascular events related to syncope, migraine-type phenomena, movement disorders, and metabolic disorders. PNES can be especially complex, as they appear remarkably similar to epilepsy, and the existence of both epileptic and non-epileptic seizures can further complicate the diagnosis (6).

All currently available diagnostic measures have clear limitations. EEG is considered the gold standard, but only reflects a short segment of time and may miss an ictal event. Additionally, inter-ictal abnormalities may not occur in more than 50% of patients with epilepsy (7). Video-EEG monitoring is typically needed to provide a definitive diagnosis but is not always available (8). Clinical diagnosis is based on subjective reporting of the patient and/or bystanders, which can be unreliable. Neuroimaging can also appear normal in many patients with epilepsy, and there remains considerable interrater variability between epilepsy experts, with disagreement rates of 20 to 30% (9).

The last decade has seen explosive growth in the application of artificial intelligence (AI) in epilepsy, which holds great promise for increasing the accuracy and efficiency of diagnosis (10). AI technologies would contribute increased pattern recognition, standardized analysis to reduce inter-rater variability, real-time analysis and detection of seizure occurrence, and multimodal integration of multiple sets of information. These advantages suggest that AI may offer a transformative solution to the diagnostic problems that exist now (11).

2. Epidemiology of Misdiagnosis

The incorrect diagnosis of epilepsy and seizure disorders is an important clinical issue that has significant variation by healthcare contexts. Previous studies that have been conducted by various clinical sectors have reported similar error rates for misdiagnosis of between 4.6% and 30% for the difficulties and uncertainty involved in making a diagnosis for convulsive disorders (12). A review of patients at specialized epilepsy clinics report up to 26.1% of patients were misdiagnosed. This was due to misinterpretation of retrospective, incomplete history taking, and/or interpretation of electroencephalogram (EEG) results (13). Compounding the issue, as many as 20-30% of patients classified as having an epilepsy diagnosis may be misdiagnosed, with a high percentage of these patients having cardiovascular syncope with movement that led to cerebral hypoxia, which can be clinically indistinguishable (14). The challenge is that despite the advances in technology for clinical diagnosis and knowledge about mechanisms that underlie the condition, epilepsy remains predominantly a clinical diagnosis as the evaluation methods have simply not worked their way into outpatient methods. Continued high rates of misdiagnosis reflect the persistent reliance on clinical judgement and also highlight the challenges for differentiating seizures

from other paroxysmal events, including the clinical environment emergency department for both the general practitioner and emergency medical practitioner (15).

3. Causes of Misdiagnosis

3.1 Limitations of EEG interpretation and subjective history

One of the main contributors to epilepsy misdiagnosis is overreading of electroencephalogram (EEG) recordings. By far the most common patterns that are overread as epileptiform are nonspecific fluctuations of background in the temporal regions that are overinterpreted as temporal sharp waves (16). Overinterpretation of EEG recordings is troubling, as overinterpretation of an EEG is a significant contributor to misdiagnosis of epilepsy, and it is important to recognize normal variants and artifacts that are mistaken for pathological patterns (17).

The tendency to overread normal EEG tracings as abnormal is usually due to misinterpretation of normal variants or simple fluctuations of background rhythms, and misdiagnosis may be particularly difficult when it is put in the medical record as a reality.

Subjective seizure histories can overlap with EEG misreading to create more variability in diagnosis. Seizure-related histories are more nebular at times making it more difficult for the clinician to decide between actual epileptic seizure types and other paroxysmal events (18). Additionally, a reliance on patients to report symptoms or the circumstances of witness accounts contribute to variability and inaccurate results.

3.2. Psychogenic Nonepileptic Seizures (PNES)

Psychogenic nonepileptic seizures (PNES), while relatively common, are poorly understood and frequently misdiagnosed as epilepsy. This can result in unnecessary procedures and treatments, as well as the chance of not engaging the patients in behavioral health care which is needed (19,20). PNES is one of the most common causes of convulsive misdiagnosis within epilepsy centers. Up to 25% of people who have received a prior diagnosis of epilepsy and do not respond to drug therapy have been found to be misdiagnosed; PNES accounts for 20–30% of referrals/ appointments/wait lists to epilepsy centers (21,22).

This issue is further complicated by the fact that epilepsy is a risk factor for developing psychogenic non-epileptic seizures (PNES) and comorbid epilepsy is also identified as a comorbidity in about 10–30% of patients with PNES (23).

3.3 Syncope and Cardiovascular Causes

Syncope (cardiac or non-cardiac) may appear similar to atonic and even convulsive seizures (24,25). Myoclonus/myoclonic jerks (sometimes tonic spasms) may be the most confounding symptom in the differential diagnosis between seizures and syncope (26,27). Convulsive syncope, especially when it presents with brief tonic-clonic movements, can be difficult to differentiate from an epileptic seizure, often leading to an inaccurate diagnosis and ineffective antiepileptic medication management (28,29).

3.4 movement disorders and sleep-related events

Movement disorders, sleep-related events, and other paroxysmal episodes may present with similar symptoms; as such, they are included in the differential diagnosis of transient spells (30). Nocturnal movement disorders, parasomnias, or periodic limb movements may be particularly difficult to differentiate from nocturnal seizures, especially when being reported and described inadequately or mistakenly (31).

4. The Impact of Misdiagnosis

An accurate diagnosis of a convulsion is one of the indispensable components of management; however, it is a prominent challenge in clinical practice. A convulsion is defined as an abrupt, violent, irregular movement of a limb or of the body; more often than not, this is a movement that occurs during an epileptic seizure, but can also occur due to other types of medical conditions. The diagnosis of convulsions is remarkably common with studies demonstrating to have rates between 4.6% to upwards of 30% in clinical practice (32).

The implications of diagnostic errors are significant and produce an adverse cascade of events for the patient, the family, and the healthcare system. This

review includes the recent literature on the multifactorial sequelae of misdiagnosing convulsions.

The most immediate and serious consequence of misdiagnosis is the application of an incorrect medical management plan, primarily consisting of anti-epileptic drugs (AEDs). When an individual is misdiagnosed with a seizure disorder, they will endure prolonged ineffective therapy and, additionally, serious adventitious effects. The repercussions of AEDs can vary in severity from mild (e.g. fatigue, dizziness) to critical (e.g. cognitive impairment, in and of itself), if psychogenic non-epileptic seizures (PNES) are misdiagnosed, and are interpreted as status epilepticus, this may lead to excessive and unwarranted invasive interventions such as the need for intubation and admission to the critical care unit validating extraneous harm (33).

The misdiagnosis of epilepsy also represents not just direct medical harm, but also considerable psychosocial and economic harm, in that the categorization of epilepsy can advance significant stigma and affect relationships and social inclusion. Patients would have been exposed to significant pain, suffering, and unnecessary restrictions influencing aspects of their lives (e.g. revocation of driving license, employment or securing employment) (34).

Misdiagnosis of epilepsy often leads to the misprescribing of antiepileptic drugs (AEDs) to patients that do not have epilepsy. The former patient's use of inappropriate AED therapies presents an economic and clinical burden incurring average medical costs for the patient per year of misdiagnosis of 316 pounds sterling with the majority of costs attributable to inpatient admissions (45%), inappropriate prescribing of AEDs (26%), outpatient attendances (16%) and general practitioner (GP) care (8%) (35). The misprescribing of unnecessary AEDs places the patient theoretical adverse effects without clinical gains, which is an increased additional health complication and risk.

However, beyond the economic consequences, misdiagnosis creates serious personal and social implications for patients. Patients who are misdiagnosed are often prescribed unnecessary medications, which expose them to the potential adverse effects of a suggested antiepileptic drug therapy which may or may not be appropriate or efficacious. A misdiagnosis would often entail unwarranted restrictions on driving, and incurs employment issues among other effects which ultimately impact the patient socially in their day-to-day life. (36)

5. Traditional Methods for Convulsion Diagnosis

While accurate diagnostic classification of convulsive disorders may be considered among the bedrock of neurological practice, the primary means by which clinicians would diagnose convulsive disorders depend on clinical judgement supported by observed or monitored electrophysiology. Traditional methods of diagnosing convulsive disorders have remained relatively unchanged for decades; remaining unable to provide distinction between epileptic or non-epileptic episodes.

5.1 Clinical Assessment and History Taking

The process of diagnosing a convulsion starts with an extensive clinical evaluation, which includes a detailed collection of seizure semiology, a witness account, clinical history, and a physical exam. The clinical evaluation is important in identifying events that could lead to seizure activity, classifying the seizure type, and describing post-ictal phenomena. When witnesses are describing seizures, diagnostic uncertainty or confusion can arise, especially when distinguishing between epileptic seizures, psychogenic non-epileptic seizures (PNES) or other paroxysmal events (37).

5.2 Electroencephalography (EEG)

Standard electroencephalography is the principal tool for diagnosing convulsive disorders, while also providing clinically relevant information regarding brain electrical functioning during both interictal and ictal periods. The primary purpose in assessing a case in which there is a known seizure is to confidently characterize the seizure into a type, an epilepsy syndrome, and potentially even an eventual treatment, while assessing an individual having paroxysmal events that seem consistent with seizure and do not have a known seizure diagnosis. The routine recording of EGG usually lasts between 20-30 minutes of EEG activity, while conforming to the international 10-20 configuration.

While routine EEG is a frequently utilized diagnostic tool it has limitations. It has been noted that the first EEG finding is normal in approximately 50% of

patients who have epilepsy, thus necessitating redundant studies or a longer duration of monitoring. (38). The diagnostic yield is increased when EEG recordings are obtained serially, with 80-90% sensitivity shown after several recordings. Nonetheless, the temporal sampling limitation of routine EEG is a major obstacle to characterizing spontaneous seizure events, particularly in patients who have infrequent seizures (39).

5.3 Video-EEG Monitoring

Video electroencephalogram (EEG) monitoring is the gold standard diagnostic test that provides a definitive distinction between psychogenic nonepileptic seizures and epilepsy. Long-term video-EEG monitoring (LTM) overcomes many limitations of routine EEG by providing surveillance that lasts for many consecutive days (3-7) and continuous recording of events. LTM also allows for synchronous recordings of clinical events with associated electrographic changes, which aids in exact characterization of behavioral and electrical phenomena.

LTM video-EEG monitoring can improve the accuracy of diagnosis when assessing if events are epileptic in nature. In the literature, video-EEG monitoring has diagnostic yields during long-term monitoring of clinical events greater than 80-95% (40). The diagnostic technique can greatly assist with more complicated cases where seizure semiology alone does not allow for a reliable diagnostic determination.

Limitations and Challenges

Numerous significant limitations affect clinical decision-making in the traditional diagnostic paradigms. These limitations provide several obstacles including artifacts, ocular migration, and electrical interferences, which depend on correctly diagnosing and then classifying the episode in order to ensure errors are avoided in detection of epileptic seizures. Interictal abnormal EEG patterns are absent in the EEG for up to 50% of patients who have a definitive diagnosis of epilepsy, while healthy individuals can show non-specific abnormal patterns which cause results to be misread as false negatives or false positives.

In addition, the limitations of video-EEG (VEEG) monitoring are extensive when also factoring aspects such as availability, cost, and discomfort from prolonged monitoring. A VEEG must occur in the hospital environment where trained epilepsy unit staff can monitor and interpret the EEG in a highly specialized staff area which often a barrier to access for many patients. Even in the hospital setting, the surroundings may not fully recreate the seizure triggers which limits the diagnostic yield in certain cases.

Additionally, EEG readings are subject to significant inter-observer variability, evidenced through studies showing considerable agreement between experienced electroencephalographers, particularly in cases when the abnormality is subtle or there are atypical EEG patterns (41).

6. Prevention of Misdiagnosis-Approach to Improving Diagnostic Accuracy

Mistakes in diagnosis represent an important issue of patient safety in contemporary health care with estimates suggesting that hundreds of thousands of patients are misdiagnosed in the United States each year making this an important public health issue (42,43). Efforts to address the prevention of misdiagnosis will require systemic attention to provider level issues and the limitations of the health care system in facilitating evidence-informed actions and organizational process change (44).

6.1 Systematic Approaches to Reducing Diagnostic Errors

Preventing misdiagnosis, we can start by adopting a multimodal effort diagnostic safety program in health care organizations. This could involve embedding robustness into EHR workflows, improving testing protocols, monitoring results, and establishing multidisciplinary diagnostic safety event teams to analyze safety events for each respective discipline. A diagnostic safety program should have the ability to facilitate a high reliability error reporting system to allow for clinicians to report diagnostic errors and near misses freely with no consideration for blame or punitive action. This creates a culture of safety that will promote the quality of care and continuous improvement (45,46).

Clinical decision support systems (CDSS) are a potential solution and have been implemented as a useful method for decreasing diagnostic errors by offering

another intervention with prompts based on evidence, or up to date EMR during the diagnostic process. A growing body of literature has developed on artificial intelligence and machine learning capabilities for the use of CDSS, and studies have shown that CDSS can offer useful assistance in support of different diagnosis or decreasing diagnostic errors (47) An AI CDSS is a possibility to examine in dynamically generating an action list that promotes clinical reasoning, improving the clinical reasoning process through a CDSS tool, decreasing cognitive bias error conditions that can lead to misdiagnoses. (48,49).

6.2 Individual and Team-Based Interventions

At the clinician level, diagnostic error prevention requires targeted educational interventions and implementation of structured diagnostic processes. Clinicians have been provided with diagnostic mnemonics to create a structured approach to complex cases to reduce the frequency of cognitive errors (45). Effective communication is also important for reducing misdiagnosis, as some experts note that physicians will need time to both meet with patients and to have a clear discussion on what to do with abnormal results (46).

6.3 Technology Integration and Quality Improvement

Institutions in contemporary healthcare should draw on technology to establish resilient methods for tracking diagnostic results and error trends (45). Result notification systems (RNS) are utilized to transmit abnormal, and critical findings of results to the appropriate healthcare provider in order to prevent delay in diagnosis, and possibly delay in treatment and results (46.) Optimizing the electronic health record is key to this process because it allows for data sharing, and creates a complete dataset that the clinician may reference for an accurate diagnosis (42,45)

7. AI Interventions in the Differential Diagnosis of Convulsions

7.1 AI in EEG Signal Analysis

Current State and Methodological Approaches

The implementation of artificial intelligence (AI) in evaluating electroencephalography (EEG) signals has revolutionized the differential diagnosis of seizures by resolving the challenges of a visual assessment, which is labor-intensive, subjective, and excessively reliant on clinical experience (50). Recently, AI has applied deep learning models that automatically extract meaningful coefficients from EEG signals, resulting in enhanced accuracy of diagnosis and decreased inter-observer variability (51).

Deep learning architectures in seizure detection

Schirrmeister et al., created end-to-end convolutional neural networks (ConvNets) that decode the raw EEG signals without hand-crafted features. They researched deep, shallow, and residual ConvNet architectures suitable for multi-channel EEG. In addition to cropping training data, cutting-edge approaches, such as batch normalization and exponential linear units, were applied to maximize performance improvements. Using deep ConvNets exceeded traditional approaches, including FBCSP, with better decoding accuracy. First-hand visualization methods demonstrated that ConvNets learn physiologically meaningful features like alpha, beta, and gamma band modulation, which shows promise for clinical applications in EEG decoding and brain–computer interface applications (52,53). Several recent works have demonstrated that CNN-based approaches coupled with shallow classifiers outperform existing automated seizure recognition (54,55).

Combining spatial and temporal feature extraction through CNN-LSTM hybrid models has yielded particularly favorable results demonstrating high accuracy rates of advanced architectures at recognizing epilepsy through space-time algorithms (56,57).

Advanced architectures of neural networks including spiking neural architectures have reported impressive performance metrics. For example, multi-channel Long- and Short-Term Memory-Like Spiking Neural Networks experienced an accuracy of 98.25%, specificity of 98.22%, and sensitivity of 97.59% based on the CHB-MIT dataset which demonstrated meaningful competitive levels of detection for clinical utility (58,59).

7.2 AI in Video and Motion Analysis (Semiology)

Semiological Analysis And Clinical Significance

The new semiological seizure classification (SSC) system developed purely based on clinical semiology and not EEG phenomena and classifies seizures into five categories: aura, autonomic seizures, dialeptic seizures, motor seizures, and special seizures with negative features. The authors create a new term, "dialeptic" seizures, to refer to changes in consciousness without EEG correlates a welcome term that delineates events away from traditional absence and complex partial seizures. The hallmark of the classification system is a thorough somatotopic map and mapped out seizure evolution, which represents a significant change away from classifying seizures via purely clinical observation. This approach calls into question the ILAE classification system since the proposed approach might provide adequate diagnostic precisions based on clinical semiology alone and without corresponding electrographic correlates. The SSC might be particularly beneficial in clinical situations where high-level EEG monitoring is not practical or not available. The straightforward implementation and validation of this semiological system would probably require expansive clinical validation to address reliability and diagnostic accuracy compared to currently validated electroclinical classification systems (60,61).

Deep Learning to Recognize Movement

Deep learning and computer vision methodologies have become applications that allow a semiological method of analysis to take place in an automated fashion. Deep motion analysis algorithms that may have the ability to summarize facial expressions, body motion, and body postural changes should be treated as natural semiological variables for capturing seizure activity. They have shown to be successful in capturing seizure appearance across a range of aspects both for differences within patients, and in differing patients (62,63).

Advanced Video Methods

Advancements in 3D video action recognition represent a generational change in the ability to classify seizures from normality with recent advances in accuracy and the ability to apply it more closely to true real-time scenarios (54). New deep learning methods can identify specific epilepsy syndromes and specific/non-specific non-epileptic differential diagnoses based on the semiology of seizures solving an aspect not easily solved through clinical observation (64).

8. Multi-sensor AI wearable devices for seizure setup

The evolution of combining artificial intelligence with wearable biosensor technology has created an epiphany in the type and quality of real-time patient monitoring through seizure detection and monitoring creating a new standard of care and improved quality of life of patients with epilepsy (65). This emergence of multi-sensor AI wearable devices has represented a shift from episodic clinical care and detailed clinical assessments to entirely continuous ambulatory monitoring systems that detect seizures as they happen, in the natural environment rather than reality

8.1 Smartwatch-Based Seizure Detection Systems

The emergence of modernized smartwatch technology has introduced a front-line solution in seizure detection, such as the Empatica Embrace series that presents the only commercially sold product. The Embrace is the first FDA-cleared wrist-worn wearable in epilepsy that is designed to notify caregivers of detected possible convulsive seizures. The new EpiMonitor with EmbracePlus is the first seizure-detection FDA-approved wearable for adults and kids, creating a historic opportunity for better management of pediatric epilepsy.

Wearable devices utilize multimodal sensor arrays to capture physiological hallmarks that are associated with generalized tonic-clonic seizures (GTCS). The Embrace wristbands and E4 wristband have available machine learning models that are intended to detect the physiological hallmarks of ongoing GTCS (66)

Advanced machine-learning algorithms provide the foundation for these detection systems to ultimately characterize and identify seizure-like activity across patient populations. Custom deep-learning seizure detection models have shown detection of a large variety of seizure types utilizing wearable signals, thus expanding beyond simple GTCS detection capabilities to also identify focal seizures with a secondary generalization and other seizure subtypes (67).

8.2 Real-Time Data Processing and Notification Mechanisms

The foundation of successful wearable seizure detection stems from the real-time data processing capabilities of the devices. Contemporary devices demonstrate an ability to use edge computing architectures that allow for the instantaneous processing of physiological signals without needing cloud-based computing resources (68). Real-time epileptic seizure detection through the use of lightweight deep learning models such as LightSeizureNet (LSN) are particularly relevant to battery-constrained use cases as they allow for real-time detection from raw EEG data on ultra-low power wearable seizure detection devices (69).

8.3 Clinical Need for Accuracy In Distinguishing Non-Epileptic Events

The distinction between epileptic seizures (ES) and non-epileptic events (NEE) is arguably one of the most difficult hurdles clinical neurology faces. NEEs, particularly psychogenic non-epileptic seizures (PNES), are episodes that have clinical features consistent with ES, however, do not feature epileptiform electroencephalographic (EEG) activity (70).

PNES are as similar devastating to patients' quality of life as their diagnosis can also lead to serious secondary iatrogenic harms to patients during their journey seeking proper diagnosis and treatment. Patients can go years after their symptom onset until a correct diagnosis of PNES is made during which time the complications of iatrogenic harm and treatment everyday while being misdiagnosed.

9. AI Seizure Prediction and Personalized Medicine: Changing Care for Epilepsy with Intelligent Technologies

Artificial intelligence (AI) is revolutionizing epilepsy management through better monitoring of seizure activity more precise diagnosis and individualized treatment (71). The utilization of machine learning and deep learning technologies in the spectrum of epilepsy care represents a fundamental departure from a casuist lens of a "one-size-fits-all" management plan for all patients to a more tailored process for managing treatment protocol focusing on the electroencephalographic patterns and clinical presentation of each patient (72,73). The technology revolution directly addresses the most frustrating and problematic aspect of epilepsy care which is the great degree of inter-patient variability with respect to treatment regimens and the inherent complexities that surround seizure management (74).

9.1 Machine Learning Solutions for Seizure Prediction

Solutions derived from machine learning (ML) and ML deep learning (DL) enhance the monitoring of seizures, enhance the efficiency of EEG analysis, personalize treatment approaches, and confront the nuances of care associated with epilepsy. Novel methodologies utilizing AI capabilities have demonstrated impressive ability to identify minute changes in electroencephalogram (EEG) data as individuals approach seizure activity and those subtle brain changes even go unnoticed by clinician and caregivers (75). These algorithms leverage intricate feature extraction techniques to apply temporal patterns in the EEG, then build predictions of impending seizures and the time in which the seizure can occur, often from a clinical perspective from minutes to hours in advance allowing patient and families to be in position to respond to an event and anticipate the impending experience (76).

The advancement of wearable devices that leverage AI algorithms for seizure prediction have promoted the possibilities of continuous monitoring and immediate alertness as warranted (77). Many of these systems provide multi-physiological state signals, including EEG, heart rate variability, movement, and autonomic markers to create models that are comprehensive and reflect the multidimensional construct of seizure onset mechanisms (78).

9.2 Personalized Medicine via AI Approaches

The concept of personalized medicine in the field of epilepsy has picked up traction due to AI technologies which can facilitate the processing and analysis of large datasets for personalized biomarkers and treatment responses. In fact, machine learning methods applied to imaging datasets can predict outcomes on an individual basis through MRI features that have been described as informing temporal lobe epilepsy phenotype and outcomes (79). This type of technology will allow the

clinician to systematically transition from the traditional trial-and-error medication process toward a methodology to select individualized treatment protocols based on evidence, using genetic, neuroimaging, and clinical phenotypes to ultimately inform which treatments are considered based on the evidence available (80).

AI-directed methods for drug selection protocols would assess patients' individual seizure semiology, EEG patterns, neuroimaging information, and genetic markers to determine likelihood of medication effectiveness and potential side effects prior to initiating treatment (81).

This model of precision medicine can greatly decrease time required to achieve optimum seizure control and limit the time that may be unnecessarily spent on treatment that may not be effective, maximizing overall health related quality of life (82). Additionally, machine learning methods may incorporate information to identify biomarkers that may have prognostic value in determining surgical candidacy and outcomes, thus allowing clinicians more information to make a meaningful decision to utilize invasive measures (83).

The use of AI in epilepsy care will use integrated digital health platforms that combine seizure prediction, medication optimization, and remote monitoring into a holistic approach to patient management in the future (84). These platforms will also facilitate the generation of real-world evidence, continuous learning algorithms, and the use of patient-reported outcomes to improve treatment recommendations and long-term seizure control (85).

DISCUSSION:

Misdiagnosing epilepsy is still one of the key issues in neurology and countless of individuals are exposed to inappropriate treatment, even to the risk of extra and unrecognized disorders. The very wide use of antiepileptic drugs renders an individual compromised in their driving, employment and quality of life. Diagnosis of epilepsy based on clinical intuition and limited EEG, is confronted with either inter-observer variability and a narrow temporal sampling of events. Video-EEG has improved the accuracy and precision of the diagnosis of epilepsy; however, the great cost and limited availability has hampered it as an option for many around the world. The clear and present challenge is distinguishing epilepsy from psychogenic non-epileptic seizures or syncope.

Recently, regulators have approved FDA-cleared AI-based wearables (e.g Empatica Embrace and EpiMonitor), signifying an absolute breakthrough in conducting real-time continuous seizure monitoring. These devices will also work within the community to create and innovate new avenues and allow for more independence by those individuals with epilepsy, as well as provide alerts to the appropriate caregivers at the right time. While not directly involved, AI will help move the field closer to precision antiepileptic drug treatment, for example considering genetic, EEG and imaging where AI could begin estimating potential treatment response, and help eliminate ineffective therapies and determination of treatment resistance.

In addition, AI can potentially facilitate access to epilepsy services through cloud software and mobile diagnosis. AI will expand the potential access to specialists in low resource contexts and mitigate the inequities and disparities witnessed globally. The implementation of AI must be considered cautiously, with a number of well-documented challenges including algorithmic bias, protecting sensitive data, and the potential to undermine physician oversight. Success with AI will depend on trained clinicians using a strong infrastructure, validated algorithms and AI that is designed to be explainable and transparent. Should AI be successfully implemented, there is the potential convergence of AI with genetic profiling, advanced imaging techniques and biomarker discovery that could support personalized diagnosis and management of therapy.

Thus, AI presents a paradigm shift in the delivery of care for people with epilepsy with immediate potential for improved reduction of misdiagnosis, improved management of therapy and improvement of quality of life for people living with epilepsy around the world

CONCLUSION:

Artificial Intelligence (AI) represents a game-changing paradigm to combat the global issue of misdiagnosis in epilepsy, easily surpassing traditional, specifically

advanced pattern recognition and multimodal data analysis-based diagnostics. The recent entry of FDA-cleared AI-enabled wearables translates into preparedness for clinical practice. Deep learning allows for standardized analyses that can eliminate subjectivity and variability. Personalized AI-enabled medicine is a means to anticipate what a person with epilepsy will experience with antiepileptic drugs and their possible future outcome, thereby reducing time wasted in delay with trial and error-based therapies. Smartphone applications and cloud bearing or cloud-based platforms democratize access to standards of expert care especially in under-resourced regions and areas of low access to quality care. For the millions of severely impacted individuals living with seizure disorders, AI technologies will improve their opportunity for accurate diagnosis, education, outcome measures, and quality of life. With ample evidence, regulatory validation and agreement with the need, the time to integrate the tools of AI into person-centered care of epilepsy is now.

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