Epilepsy & Behavior 166 (2025) 110327

Contents lists available at ScienceDirect

Epilepsy & Behavior

journal homepage: www.elsevier.com/locate/yebeh

Perspective

Unlocking new frontiers in epilepsy through AI: From seizure prediction to personalized medicine

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ARTICLE INFO

Keywords:
Artificial Intelligence
Epilepsy
Seizure Detection
Personalized Medicine
Machine Learning
Deep Learning
EEG Analysis
Ethical Considerations
Neurology
Clinical Integration

ABSTRACT

Artificial intelligence (AI) is revolutionizing epilepsy care by advancing seizure detection, enhancing diagnostic precision, and enabling personalized treatment. Machine learning and deep learning technologies improve seizure monitoring, automate EEG analysis, and facilitate tailored therapeutic strategies, addressing the complexities of epilepsy management. However, challenges remain, including issues of model accuracy, interpretability, and applicability across diverse patient populations. Ethical considerations, such as safeguarding patient privacy, ensuring data security, and mitigating algorithmic bias, underscore the importance of responsible AI integration. Collaborative efforts among neurologists, data scientists, and regulatory authorities are critical to refining models, establishing ethical guidelines, and ensuring safe clinical adoption. This review examines AI's transformative potential, its current limitations, and the multidisciplinary initiatives driving its effective implementation in epilepsy care.

1. Introduction

Epilepsy, affecting over 50 million people worldwide, is a complex neurological disorder characterized by recurrent, unprovoked seizures [1]. It presents significant diagnostic and treatment challenges due to the wide variability in seizure phenotype and etiologies. The disorder significantly impacts children and older adults. It is associated with psychological, social, and economic hurdles, including stigma, reduced quality of life, and sudden unexpected death in epilepsy (SUDEP), which is notably higher in individuals with poorly controlled seizures [2,3].

Despite advanced medical technology, diagnosing epilepsy remains resource-intensive and complex [4]. Accurate diagnosis requires distinguishing between epileptic and non-epileptic events such as psychogenic non-epileptic seizures (PNES) or syncope [5]. Traditional diagnostic EEG and MRI often have limitations in sensitivity and specificity, particularly during the interictal phase when seizures are absent [6]. Approximately one-third of epilepsy is drug-resistant, limiting therapy with standard anti-seizure drugs requiring alternative strategies [12].

Artificial Intelligence (AI) has emerged as a tool to address healthcare challenges [7]. AI refers to the simulation of human intelligence in machines, enabling tasks that typically require human cognition, such as reasoning, learning, and decision-making [12]. Using of AI in healthcare began with expert systems like INTERNIST-1 and MYCIN in the 1970 s and 1980 s, which used rule-based logic to assist in diagnosis but lacked adaptability [20,21]. Machine Learning (ML), Deep Learning (DL), Natural Language Processing (NLP), and Robotic Process Automation (RPA) are key advance AI technologies that play a significant role in epilepsy care [13]. ML employs algorithms to analyze data, identify patterns, and make predictions as shown in Fig. 1. In epilepsy management, ML algorithms are crucial for detecting and predicting seizure activity through EEG analysis, enabling the development of personalized seizure prediction models trained on patient-specific data [11]. While larger datasets improve ML performance by capturing seizure pattern variability, smaller datasets can still be effectively utilized through techniques like data augmentation and transfer learning [11]. DL, a more advanced subset of ML, leverages deep neural networks to process complex, high-dimensional data such as EEG recordings and neuroimaging scans (MRI, PET) [22]. Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) are commonly applied in epilepsy care to identify epileptogenic zones and enhance seizure detection as shown in Fig. 2 [23]. However, NLP facilitates the interpretation of unstructured clinical data, including electronic health records (EHRs), physician notes, and research articles, helping clinicians

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https://doi.org/10.1016/j.yebeh.2025.110327
Received 2 November 2024; Received in revised form 19 January 2025; Accepted 18 February 2025
Available online 4 March 2025

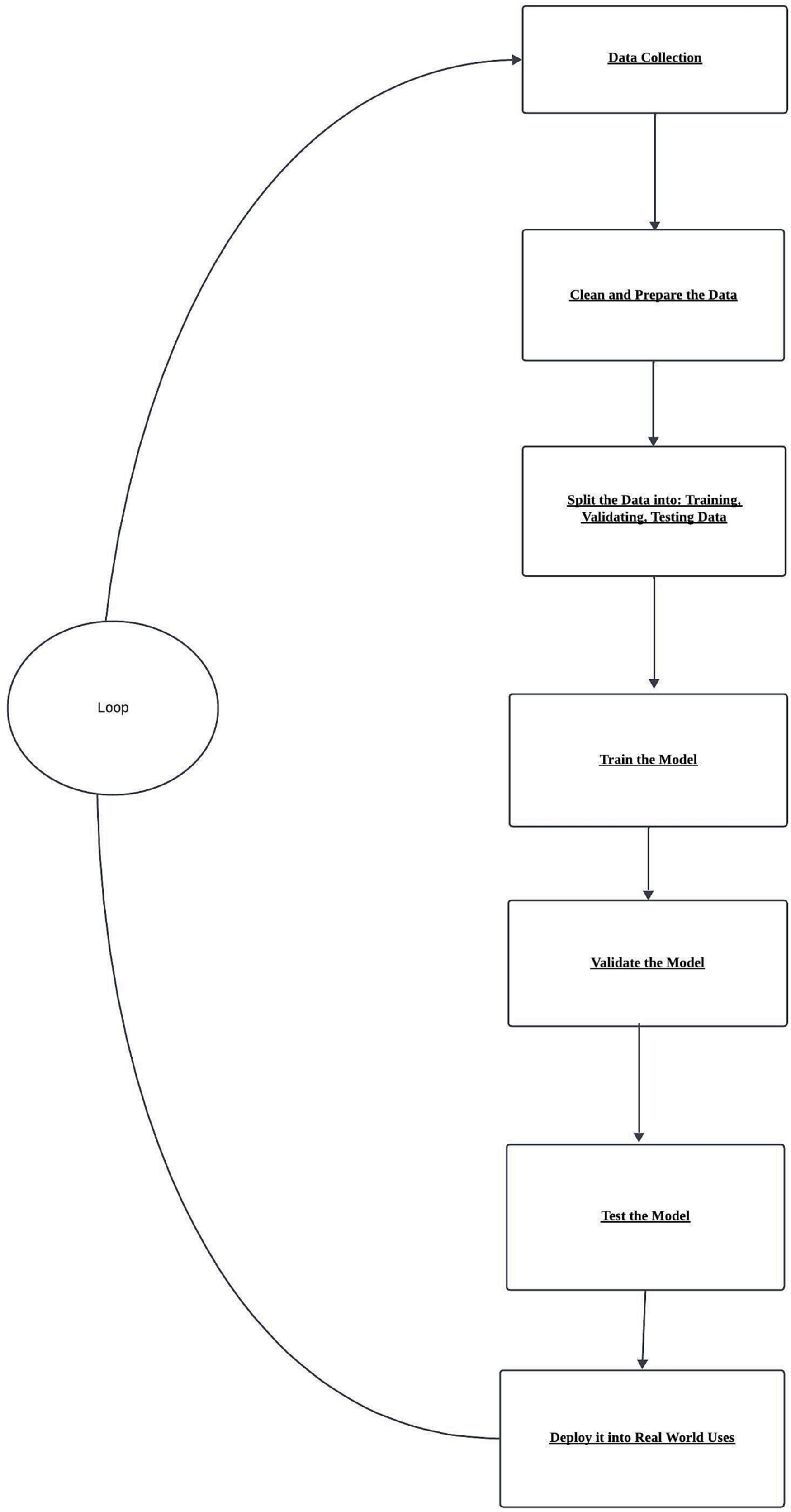

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Fig. 1. Workflow of machine learning in healthcare. Overview of the Machine Learning Workflow. The figure illustrates the iterative process involved in developing a machine learning model. The steps include: 1. Data Collection: Gathering relevant data from various sources. 2. Clean and Prepare the Data: Preprocessing the data to handle missing values, remove noise, and ensure quality for modeling. 3. Split the Data into Training, Validation, and Testing Sets: Dividing the data into subsets for training, tuning, and evaluating the model. 4. Train the Model: Using the training data to teach the machine learning algorithm. 5. Validate the Model: Fine-tuning the model using the validation set to ensure it generalizes well. 6. Test the Model: Evaluating the model's performance on an unseen testing dataset to assess its accuracy and robustness. 7. Deploy into Real-World Uses: Applying the trained and tested model to practical applications. 8. Iterative Loop: Feedback from the deployment or testing phase is used to refine the model by revisiting earlier steps (e.g., improving data collection or retraining the model).

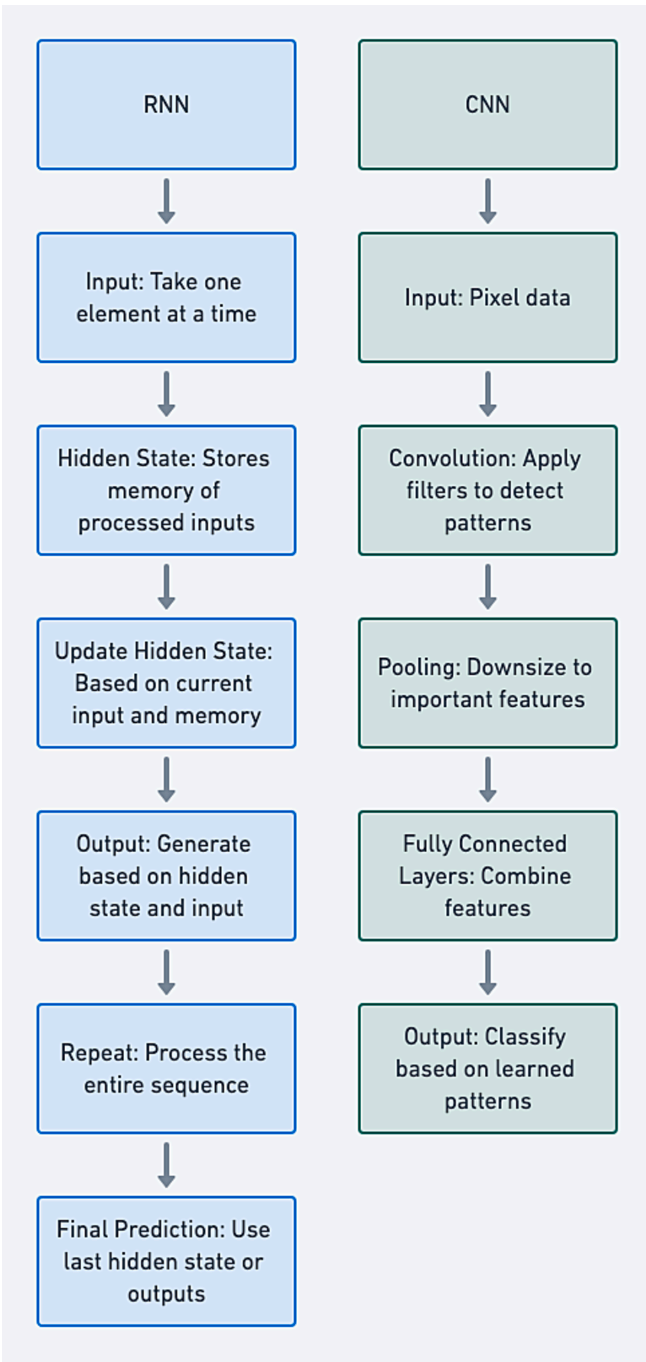

Fig. 2. Comparative workflows of CNNs and RNNs for epilepsy-related tasks. This figure compares the workflows of Recurrent Neural Networks (RNNs) and Convolutional Neural Networks (CNNs). RNNs process sequential data one element at a time, maintaining memory through hidden states to produce outputs based on temporal dependencies. In contrast, CNNs process pixel data by applying convolutional filters to detect spatial patterns, followed by pooling to reduce dimensionality and fully connected layers for classification.

identify seizure trends, treatment responses, and adverse events [24]. Additionally, NLP supports medical coding and documentation, optimizing administrative workflows [24]. Lastly, RPA automates repetitive, rule-based administrative tasks such as scheduling, billing, and data entry, reducing clinicians' workload and improving healthcare system efficiency [25]. Although RPA does not directly contribute to epilepsy diagnosis or treatment, it enhances overall patient care by streamlining hospital operations and improving access to resources [26]. Together, these AI technologies contribute to more effective epilepsy management, advancing both clinical decision-making and healthcare efficiency [10].

In the context of epilepsy, AI technologies enable more accurate detection, prediction, and personalized treatment plans. AI-driven seizure detection algorithms, for example, can analyze EEG patterns in real time, improving monitoring for patients who need continuous surveillance [10]. In healthcare, ML is especially valuable for data analysis, such as predicting seizure occurrences and identifying patterns in EEG signals, allowing for proactive management and enhancing patient safety [11]. Unlike traditional AI, which may rely on rule-based systems, ML models improve their accuracy as they are exposed to more data [10]. DL can play a transformative role in **personalized medicine;** by using patient-specific data—including clinical profiles, genetic markers, and previous treatment responses—AI can tailor treatment plans more effectively [9]. This personalized approach can reduce the trial-and-error process typically associated with anti-seizure medication (ASM) selection, especially in resistant cases, minimizing side effects and improving patient outcomes [10].

This review explores the transformative potential of Artificial Intelligence (AI) in epilepsy diagnosis, treatment, and management. It begins by examining AI's role in seizure detection and prediction, where machine learning and deep learning algorithms improve the identification of seizure onset and patient monitoring. The review also highlights AI's contribution to personalized treatment, tailoring plans based on patient data such as genetic markers, clinical history, and medication responses. It then addresses the ethical challenges of implementing AI in epilepsy care, including concerns around privacy, data security, transparency, and algorithmic bias. These issues are crucial for maintaining trust in AI-driven decision-making. Lastly, the review discusses regulatory considerations, particularly the role of the FDA and other bodies in ensuring AI tools meet safety and efficacy standards. Emphasizing the need for collaboration among neurologists, data scientists, and regulators, this review provides a comprehensive overview of AI's potential, its current limitations, and the steps for responsible clinical integration in epilepsy care.

2. Epilepsy overview and clinical challenges

Epilepsy is a complex neurological disorder characterized by recurrent, unprovoked seizures due to abnormal electrical activity in the brain [12]. The condition's pathophysiology is highly heterogeneous, arising from diverse etiologies, including genetic, structural, metabolic, and traumatic factors, leading to varied clinical manifestations [13]. Seizures can be focal, generalized, or absent, presenting different challenges for accurate diagnosis and treatment [12]. For a more in-depth discussion of epilepsy's pathophysiology and epidemiology, see Supplementary Materials.

Epilepsy affects approximately 1 % of the global population, with a higher prevalence in children and older adults [14]. The disease poses significant clinical challenges, particularly in accurately diagnosing epilepsy and distinguishing it from conditions with similar symptoms, such as psychogenic non-epileptic seizures (PNES), syncope, and certain types of migraines [16]. This difficulty is compounded by the limited sensitivity and specificity of traditional diagnostic tools like electroencephalography (EEG), magnetic resonance imaging (MRI), and positron emission tomography (PET), especially when seizures are infrequent or absent during testing [17]. Epilepsy patients are considered drug-resistant, meaning that they do not respond to conventional antiseizure medications (ASMs) [15]. These patients often require alternative treatments such as neurostimulation, surgery, or dietary therapies, which may not be universally effective or suitable for all individuals [18]. Despite the conventions, they often involve complex decision-making and considerable risks. The trial-and-error approach for selecting the most effective ASM for patients remains a significant hurdle in epilepsy care [19].

AI offers promising solutions by improving the accuracy and efficiency of epilepsy diagnosis and management. Machine learning (ML) and deep learning (DL) algorithms can assist in automating EEG analysis, predicting seizure onset, and personalizing treatment plans based on individual patient data. These advancements in AI are particularly crucial in epilepsy, where personalized treatment strategies may reduce the reliance on trial-and-error methods and improve patient outcomes.

3. AI applications in epilepsy diagnostics

3.1. Automated EEG analysis

Automated EEG analysis, powered by AI, has brought significant advancements to epilepsy diagnostics, enabling the detection of seizure patterns with improved speed and accuracy. **Convolutional neural networks (CNNs)** and **support vector machines (SVMs)** are widely used in analyzing EEG data, each offering unique strengths in capturing the complex patterns associated with epileptic activity. CNNs are especially effective in identifying spatial patterns within EEG signals, while SVMs excel in handling high-dimensional data and are robust against overfitting, which is crucial for medical applications. These models aid clinicians by processing vast amounts of EEG data quickly, which reduces diagnostic times and improves seizure monitoring, especially in patients requiring long-term, real-time monitoring.[27].

Models such as **SPaRCNet (Seizure Prediction and Reliable Control Network)** and **SCORE-AI (Standardized Computer-based Organized Reporting of EEG)** are examples of advanced AI systems designed for epilepsy. SPaRCNet has shown potential in predicting seizure onset with high sensitivity, while SCORE-AI offers a standardized system for reporting EEG results, improving consistency and accuracy across diagnostic settings. However, these models have limitations. While SPaRCNet performs well in controlled environments, its sensitivity can drop in diverse, real-world clinical settings. SCORE-AI, despite its benefits, may sometimes produce false positives, which can lead to unnecessary treatment adjustments.[28,29].

3.2. Sensitivity and specificity Metrics

Performance metrics like sensitivity (the model's ability to correctly identify actual seizures) and specificity (its ability to avoid false alarms) are essential for assessing AI effectiveness in epilepsy diagnostics. In recent studies, CNN-based models achieved sensitivity rates up to **85–90 %** and specificity rates around **80–85 %** in controlled datasets, illustrating their accuracy in detecting seizures. [30]However, in real-world scenarios, where factors like signal noise and patient variability affect readings, these metrics often fluctuate, underscoring the need for continuous refinement and validation. SVM-based models also show high sensitivity but may struggle with specificity, especially in complex cases with overlapping seizure-like symptoms.[31].

3.3. AI for functional imaging (MRI, PET)

AI has also demonstrated considerable utility in analyzing functional imaging data, such as MRI and PET scans, to identify epileptogenic zones—the areas in the brain responsible for generating seizures. **Deep learning models** like CNNs and **autoencoders** are particularly effective in processing high-resolution imaging data, capturing subtle abnormalities that can be difficult for clinicians to identify manually. For example, AI models trained on large sets of MRI data can identify hippocampal sclerosis, cortical dysplasia, and other structural brain anomalies associated with epilepsy, which are often missed by traditional visual analysis.[32].

Compared to traditional imaging techniques, AI-driven approaches offer several advantages. Traditional methods rely on manual interpretation by radiologists and neurologists, which can be subjective and influenced by clinician experience. AI models, on the other hand, can process thousands of images quickly, providing consistent and objective assessments that aid in pinpointing epileptogenic zones with higher precision. In clinical studies, AI models analyzing MRI data achieved diagnostic accuracy rates between **75 % and 90 %**, significantly higher than the typical accuracy rates of manual interpretation alone. [33] However, AI's reliance on large, high-quality datasets for training is a limitation, as variations in scanner quality, imaging protocols, and patient populations can affect model performance.[34].

3.4. Comparison with traditional diagnostic Methods

The integration of AI with traditional diagnostic methods like EEG, MRI, and PET improves diagnostic accuracy by combining the strengths of automated pattern recognition with conventional expert analysis. In traditional methods, the accuracy of epilepsy diagnosis can be influenced by various factors, including clinician experience, the duration and quality of EEG monitoring, and the availability of advanced imaging technologies. AI algorithms, by contrast, systematically analyze EEG and imaging data, identifying patterns that may escape human detection, thus enhancing the reliability of diagnostic results.[35].

Studies comparing AI-augmented EEG and imaging with traditional diagnostics reveal that AI improves overall diagnostic sensitivity, especially in cases with atypical presentations. For instance, AI-integrated systems can increase seizure detection rates by **20–30 %** compared to conventional EEG analysis alone, making it a valuable tool for complex cases or when expert resources are limited [70–75]. Despite these advantages, AI models face challenges related to data generalization, as models trained on one dataset may not perform consistently across different patient demographics or clinical settings. Additionally, the "black box" nature of many AI models, where decision-making processes are not fully transparent, can hinder clinician trust and adoption.[36].

3.5. Limitations of AI diagnostics

The effectiveness of AI diagnostics in epilepsy is contingent upon access to large, diverse datasets for training and validation. However, gathering such data is challenging due to differences in equipment, EEG and imaging protocols, and population demographics across institutions. Additionally, the complexity of some AI models creates "black box" issues, where the internal decision-making processes of models are not fully interpretable. This lack of transparency can make it difficult for clinicians to validate AI recommendations and raises ethical questions about responsibility in cases of misdiagnosis. Finally, generalizing AI models across varied clinical settings remains a hurdle, as model performance may drop when applied to patient populations or environments different from those in the training data.[37].

4. AI in epilepsy treatment and management

4.1. Ai-driven personalized Treatments

Personalized medicine is a crucial area where AI can significantly impact epilepsy treatment by customizing antiseizure medication (ASM) plans to individual patients' needs. Traditional ASM selection often involves a trial-and-error process, where patients cycle through various drugs and dosages to find an effective regimen, which can be a lengthy and frustrating process. AI models analyze large sets of patient-specific data, including genetic information, seizure history, and treatment responses, to predict the most effective ASM regimen for a particular individual. By leveraging this data, AI can help clinicians make more informed decisions, reducing the need for repeated trial-and-error treatments.[38,39].

In this context, **predictive models** have shown promising results. For instance, machine learning algorithms trained on genetic markers and clinical data have demonstrated accuracy rates of up to **70–80 %** in predicting ASM efficacy for specific patient profiles. However, implementing these models in clinical practice requires robust regulatory oversight to ensure that predictions are reliable and that models do not introduce biases based on incomplete or skewed datasets.[40].

4.2. Regulatory Guidelines

The FDA has introduced guidelines for AI and machine learning in healthcare, specifically regarding tools that are intended for direct clinical use. For epilepsy, the FDA requires that AI-based treatment models meet rigorous safety, efficacy, and transparency standards before they can be implemented in patient care. These guidelines emphasize the importance of real-world validation, model interpretability, and patient safety, all of which are critical in high-stakes areas like epilepsy treatment. Additionally, continuous monitoring and updating of AI models are recommended to ensure that predictive tools remain accurate as new data becomes available.[41,42].

4.3. Responsive neurostimulation (RNS)

Responsive neurostimulation (RNS) systems represent an innovative application of AI in epilepsy treatment, particularly for patients with drug-resistant epilepsy. RNS devices, such as the NeuroPace RNS System, are implantable devices that monitor brain activity in real-time and deliver electrical stimulation to interrupt seizure activity. AI enhances these systems by analyzing EEG data to identify seizure onset patterns, enabling the device to provide timely interventions that may prevent seizure progression.[43].

Recent studies have demonstrated the effectiveness of RNS systems in reducing seizure frequency among patients with refractory epilepsy, with some patients achieving seizure reductions of **up to 50 %**. However, the efficacy of RNS devices can be limited by factors such as patient-specific seizure patterns and the need for precise device programming, which often requires continuous adjustments. Regulatory approvals for RNS devices highlight the importance of long-term safety data, particularly because these devices are invasive and require surgical implantation. Additionally, the cost and complexity of RNS systems can limit their accessibility, creating practical barriers to widespread adoption.[44].

4.4. Predicting drug Responses

AI also has the potential to predict individual responses to ASMs, a critical capability given that approximately one-third of epilepsy patients are resistant to commonly used medications. By analyzing genetic data, clinical history, and seizure characteristics, AI models can estimate the likelihood of a patient's response to specific ASMs, potentially reducing the time and cost associated with ineffective treatments. This approach aligns with precision medicine, as it customizes treatment based on each patient's unique biological and clinical profile.[45].

Challenges in predictive modeling for ASM response include data heterogeneity and the need for continuous validation as new genetic and clinical data emerge. Patient genetics, for instance, play a significant role in drug metabolism and efficacy, but current datasets may not capture the full range of genetic variability across diverse populations. [46] As a result, predictive models must be regularly updated to ensure that they remain relevant and accurate for broader patient populations. Additionally, differences in treatment protocols and drug formulations across institutions can further complicate model generalization, underscoring the need for adaptable models that can be fine-tuned to individual healthcare settings.[47].

4.5. Challenges in predictive Modeling

While predictive modeling holds great promise, it faces several technical and logistical hurdles. **Data heterogeneity**, or the variation in data types and sources, is a primary challenge. AI models rely on diverse datasets that encompass genetic, clinical, and demographic information, but inconsistencies in these data points can limit model accuracy. For instance, genetic markers may vary across ethnicities, making it difficult for a single model to generalize across diverse populations. Similarly, models trained in one clinical environment may not perform equally well in another, where treatment protocols and patient demographics differ.[48].

Another challenge is the need for **continuous validation and recalibration**. Predictive models are dynamic and must be frequently updated with new patient data to maintain their accuracy. This ongoing validation is resource-intensive and requires collaborations across institutions to aggregate high-quality data. Furthermore, as predictive models become more integral to treatment planning, there is a need for ethical oversight to ensure that decisions remain patient-centered and that AI predictions do not inadvertently reinforce biases or exacerbate healthcare disparities.[49].

5. Ethical and practical challenges

5.1. Interpretability of AI models

One of the critical ethical concerns in AI applications for epilepsy is the interpretability of AI models, especially in clinical neurology. Many AI models, particularly deep learning algorithms, function as "black boxes" with complex inner workings that even experts struggle to fully understand. While these models can offer highly accurate predictions, their opacity raises concerns in a clinical context where understanding the rationale behind diagnostic or therapeutic recommendations is crucial. [50]Clinicians and patients alike require transparency to trust AI-driven outcomes, particularly in high-stakes conditions like epilepsy, where treatment decisions carry substantial risks. Transparent models allow healthcare providers to understand the reasoning behind AI-generated insights, fostering informed decision-making that is aligned with patient safety and ethical standards.[51].

To improve interpretability, several techniques are emerging, including **explainable AI (XAI)**, which aims to create models that provide clear explanations for their outputs. [51]XAI frameworks use tools like heat maps, feature importance scores, and simplified surrogate models that approximate complex models while remaining interpretable. By providing clinicians with insights into how AI models reach their conclusions, these methods aim to bridge the gap between high performance and transparency, ensuring that AI-enhanced decision-making remains clinically and ethically sound.[52,53].

5.2. Algorithm bias and Equity

Bias in AI algorithms presents another significant ethical challenge, with potential to exacerbate existing health disparities in epilepsy care. AI models are highly dependent on the quality and diversity of their training data. When data from certain demographic groups are underrepresented, AI algorithms may develop biases that reduce the accuracy and reliability of predictions for those populations. [54]For instance, if an AI model for epilepsy diagnosis is trained primarily on data from adults, its accuracy may decrease when applied to children, who exhibit different seizure characteristics. Similarly, ethnic minorities and low-income patients are often underrepresented in clinical datasets, which can lead to AI models that are less effective or even harmful when applied to these groups.[55].

Mitigating bias requires concerted efforts to ensure diverse and representative datasets. Strategies to reduce bias include **data augmentation**, collecting data from underrepresented groups, and employing fairness-enhancing algorithms that actively counteract learned biases. Collaborative research efforts across institutions are also essential to create large, representative datasets that capture a wide range of patient characteristics.[56] Additionally, **algorithmic auditing**—regular evaluations to identify and correct biases in AI models—can help ensure that these technologies are equitable and do not contribute to systemic inequalities in healthcare.[57].

5.3. Data Privacy

Data privacy is paramount when implementing AI systems that use sensitive patient information, such as EEG recordings, genetic data, and clinical history. The large-scale data requirements of AI often necessitate pooling information from multiple sources, increasing the risk of data breaches and unauthorized access. Moreover, the sensitive nature of epilepsy-related data, which may include information on seizure history, treatment responses, and personal health behaviors, makes it essential to maintain robust privacy protections to safeguard patient trust.[58].

Guidelines and regulations like the **General Data Protection Regulation (GDPR)** in Europe and the **Health Insurance Portability and Accountability Act (HIPAA)** in the United States outline strict requirements for data security and patient privacy in healthcare. [59] These regulations mandate data anonymization, controlled access, and encryption to protect patient information. Privacy-preserving AI techniques, such as **federated learning** and **differential privacy**, are emerging solutions that allow AI models to train on data without directly accessing patient information. These approaches ensure that sensitive data remains on local devices, and only aggregated insights are shared, minimizing privacy risks. For AI in epilepsy to gain widespread acceptance, it is essential to adopt these privacy-preserving technologies and comply with established guidelines to protect patient data and maintain public trust.[60].

5.4. Regulatory and legal Concerns

The rapid integration of AI into healthcare has raised regulatory and legal challenges, particularly concerning the accountability and safety of AI-driven decisions. The **U.S. Food and Drug Administration (FDA)**, along with similar regulatory bodies globally, has recognized the need to develop standards for AI applications in clinical settings. [61]The FDA's framework for AI-based software in healthcare emphasizes the need for transparency, real-world validation, and continuous monitoring to ensure that AI systems perform safely and effectively. However, regulatory guidelines are still evolving, and inconsistencies between countries can complicate the deployment of AI models in epilepsy care.[62].

A major regulatory concern is the issue of accountability. In cases where AI-driven decisions result in adverse outcomes, it is unclear whether the responsibility lies with the developers, the healthcare providers, or the institution. Establishing standardized guidelines that clarify accountability in such cases is critical to protect both patients and providers. Additionally, ensuring that AI models undergo rigorous testing across diverse patient populations before clinical deployment is essential to prevent unintended consequences. As AI continues to advance, regulatory frameworks will need to evolve in tandem to ensure that AI applications in epilepsy are both effective and ethically sound. [63].

6. Future Directions and research needs

6.1. Improving model accuracy and generalizability

To enhance the clinical utility of AI in epilepsy care, ongoing research must address the challenges of model accuracy and generalizability. Current AI models may perform well in controlled settings but often struggle with the variability encountered in real-world clinical environments. For instance, seizure detection models trained on specific patient data may not generalize effectively to patients with different seizure characteristics or comorbid conditions. To improve accuracy, future research should focus on developing more robust algorithms capable of adapting to diverse patient populations and handling data variability. Techniques such as **transfer learning**, which allows models to apply knowledge from one domain to another, could be instrumental in improving generalizability.[64].

Further, research into interpretability-focused AI, such as **explainable models** and **transparent neural networks**, can provide clinicians with insights into model reasoning. This is particularly relevant in epilepsy, where understanding the basis for a model's prediction (e.g., seizure prediction or drug response) is crucial for clinical decision-making. Developing models that are both accurate and interpretable will be key to fostering trust and acceptance among healthcare providers.[52].

6.2. Closed-Loop Systems

Closed-loop neurostimulation devices represent a promising future direction for epilepsy treatment, allowing real-time, adaptive intervention based on AI-driven insights. Unlike open-loop systems, which provide continuous or intermittent stimulation without feedback, closed-loop systems monitor brain activity and deliver targeted stimulation when abnormal patterns are detected.[65] **AI algorithms** embedded within these devices analyze EEG data in real-time to detect early signs of seizure onset, enabling immediate intervention that can potentially halt seizure progression.[66].

As AI-driven closed-loop systems evolve, they offer a high level of personalization, tailoring interventions to each patient's unique brain activity patterns. Research into adaptive algorithms that learn from patient responses over time will be critical in enhancing these systems. Such systems could eventually revolutionize epilepsy care by providing a continuous, personalized approach to seizure management. However, challenges remain in refining these algorithms to ensure high accuracy, reliability, and regulatory approval, as real-time therapeutic decisions carry significant risks.[67].

6.3. AI in genomics and Wearables

The integration of AI with genomics and wearable devices offers significant potential for enhancing epilepsy management. Genomic data can reveal insights into an individual's predisposition to certain types of epilepsy, drug responses, and potential adverse reactions. AI algorithms can analyze genetic markers to help predict epilepsy onset and customize treatment plans, tailoring interventions to each patient's unique genetic profile. This precision-medicine approach could prove invaluable for patients with drug-resistant epilepsy, where standard treatments are often ineffective.[55].

Wearable devices, such as smartwatches equipped with EEG sensors, heart rate monitors, and accelerometers, provide a continuous stream of physiological data, enabling real-time seizure detection and monitoring. When integrated with AI, these devices can predict seizure onset, alerting patients and caregivers to take preventive action. As wearable technology becomes more advanced, research into combining genomic data with real-time physiological monitoring could allow AI to create comprehensive patient profiles, resulting in even more precise and responsive epilepsy management.[8].

6.4. Advancements in ethical and regulatory Frameworks

For AI to reach its full potential in epilepsy care, advancements in ethical and regulatory standards are essential. Current frameworks, while foundational, often lack specific guidelines for the nuances of AI in neurology, such as interpretability, bias mitigation, and patient privacy in epilepsy-related data. Developing ethical frameworks that address these issues will ensure that AI technologies are used responsibly and equitably.[68].

Further, regulatory bodies need to establish clear guidelines that address the accountability and transparency of AI systems. With AI systems increasingly involved in clinical decision-making, it is crucial to ensure that these systems meet rigorous standards for safety, efficacy, and equity. Collaboration between regulatory authorities, healthcare professionals, and AI developers is key to creating adaptable standards that can keep pace with technological advancements. By establishing comprehensive ethical and regulatory frameworks, the field can foster an environment where AI technologies enhance patient care while upholding the highest standards of safety and ethics.[69].

7. Conclusion

Artificial intelligence is transforming the landscape of epilepsy care by enabling more accurate diagnosis, personalized treatment, and proactive management strategies. Through advanced data analytics and machine learning algorithms, AI offers the potential to improve seizure detection, automate EEG interpretation, predict patient-specific drug responses, and support real-time intervention with closed-loop systems. These applications address many of the persistent challenges in epilepsy care, such as the complexity of accurate diagnosis, the trial-and-error approach of antiseizure medication selection, and the need for continuous monitoring in drug-resistant cases.

Despite these advancements, significant challenges remain in integrating AI safely and effectively into clinical practice. Issues related to model interpretability, algorithmic bias, and data privacy highlight the need for transparent and equitable AI solutions. Furthermore, regulatory and ethical frameworks must evolve alongside AI technologies to ensure patient safety, accountability, and fairness. Regulatory bodies like the FDA are beginning to establish guidelines for AI applications in healthcare, but ongoing collaboration between neurologists, data scientists, and policymakers is essential to develop comprehensive standards for AI in epilepsy.

Looking forward, future research should prioritize model generalizability, the development of interpretable AI systems, and the integration of multimodal data from genomics, imaging, and wearables. By advancing these areas and addressing ethical and regulatory considerations, the field of epilepsy care can harness AI's full potential to provide safer, more effective, and personalized patient care. Through a multidisciplinary effort, AI-driven epilepsy management could shift from potential to practice, offering a profound impact on patient outcomes and quality of life.

CRediT authorship contribution statement

Majd A. AbuAlrob: Writing – original draft, Conceptualization. **Adham Itbaisha:** Writing – original draft, Conceptualization. **Boulenouar Mesraoua:** Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] "Global Epilepsy Report; 2019".
[2] Assadsangabi R et al. Update on adult epilepsy: what neuroradiologists should know.
[3] Devinsky O, Friedman D, Cheng JY, Moffatt E, Kim A, Tseng ZH. Underestimation of sudden deaths among patients with seizures and epilepsy.
[4] Harris L, Angus-Leppan H. Epilepsy: diagnosis, classification and management.
[5] Atwood AC, Drees CN. Seizure detection devices.
[6] Benbadis SR et al. Putting it all together: options for intractable epilepsy.
[7] Tveit J et al. Automated interpretation of clinical electroencephalograms using artificial intelligence.
[8] Saeizadeh A et al. SeizNet: an AI-enabled implantable sensor network system for seizure prediction.
[9] M. I. Ahmed, B. Spooner, J. Isherwood, M. A. Lane, E. Orrock and A. R. Dennison, "A Systematic Review of the Barriers to the Implementation of Artificial Intelligence in Healthcare".
[10] Alowais SA et al. Revolutionizing healthcare: the role of artificial intelligence in clinical practice.
[11] A. L. N. Al-hajjar and A. K. M. Al-Qurabat, "An overview of machine learning methods in enabling IoMT-based epileptic seizure detection".
[12] Falco-Walter J. Epilepsy—definition, classification, pathophysiology, and epidemiology.
[13] Beghi E. The epidemiology of epilepsy.
[14] Sen A, Jetté N, Husain M, Sander JW. Epilepsy in older people.
[15] M. M. Watila, S. A. Balarabe, O. Ojo, M. R. Keezer and J. W. Sander, "Overall and cause-specific premature mortality in epilepsy: A systematic review".
[16] M. Zhou et al., "Epileptic Seizure Detection Based on EEG Signals and CNN".
[17] K. Lee, H. Jeong, S. Kim, D. Yang, H. Kang and E. Choi, "Real-Time Seizure Detection using EEG: A Comprehensive Comparison of Recent Approaches under a Realistic Setting".
[18] C. Santana-Gomez, J. Engel and R. J. Staba, "Drug-resistant epilepsy and the hypothesis of intrinsic severity: What about the high-frequency oscillations?".
[19] D. Guery and S. Rheims, "Clinical Management of Drug Resistant Epilepsy: A Review on Current Strategies".
[20] R. A. Miller, H. E. Pople and J. D. Myers, "Internist-I, an Experimental Computer-Based Diagnostic Consultant for General Internal Medicine".
[21] V. L. Yu et al., "Evaluating the performance of a computer-based consultant".
[22] F. Wei, J. Mo, Q. Zhang, H. Shen, S. S. Nagarajan and F. Jiang, "Nested Deep Learning Model Towards A Foundation Model for Brain Signal Data".
[23] A. Saeizadeh et al., "SeizNet: An AI-enabled Implantable Sensor Network System for Seizure Prediction".
[24] W. Ge et al., "Improving Neurology Clinical Care With Natural Language Processing Tools".
[25] "Robotic Process Automation: An Overview and Comparison to Other Technology in Industry 4.0".
[26] R. Swetha, P. Pavithra, S. Prathiksha and S. Selvakanmani, "Robotic Process Automation (RPA) in Healthcare".
[27] R. C. Hogan et al., "Scaling convolutional neural networks achieves expert-level seizure detection in neonatal EEG".
[28] J. Jing et al., "Development of Expert-Level Classification of Seizures and Rhythmic and Periodic Patterns During EEG Interpretation".
[29] S. Beniczky et al., "Standardized Computer-based Organized Reporting of EEG: SCORE".
[30] H. Albaqami, G. M. Hassan and A. Datta, "MP-SeizNet: A multi-path CNN Bi-LSTM Network for seizure-type classification using EEG".
[31] Z. Wang, J. Yang, H. Wu, J. Zhu and M. Sawan, "Power efficient refined seizure prediction algorithm based on an enhanced benchmarking".
[32] M. M. R. Siddiquee et al., "Brainomaly: Unsupervised Neurologic Disease Detection Utilizing Unannotated T1-weighted Brain MR Images".
[33] C. A. J. R. R. B. E. R. T. K. S. S. D. D. L. G. R. E. W. J. A. A. C. V. K. I. K. E. W. B. M. C. G. E. B. Leonardo, "MRI-based deep learning can discriminate between temporal lobe epilepsy, Alzheimer's disease, and healthy controls - Communications Medicine".
[34] N. G. Nia, E. Kaplanoğlu and A. Nasab, "Evaluation of artificial intelligence techniques in disease diagnosis and prediction".
[35] K. Saab, S. Tang, M. Taha, C. Lee-Messer, C. Ré and D. L. Rubin, "Towards trustworthy seizure onset detection using workflow notes".
[36] A. Aldoseri, K. Al-Khalifa and A. Hamouda, "Re-Thinking Data Strategy and Integration for Artificial Intelligence: Concepts, Opportunities, and Challenges".
[37] M. A. AbuAlrob and B. Mesraoua, "Harnessing artificial intelligence for the diagnosis and treatment of neurological emergencies: a comprehensive review of recent advances and future directions".
[38] I. G. Malone et al., "Machine Learning Methods Applied to Cortico-Cortical Evoked Potentials Aid in Localizing Seizure Onset Zones".
[39] S. An, C. Kang and H. W. Lee, "Artificial Intelligence and Computational Approaches for Epilepsy".

[40] W. L. Cava et al., “A flexible symbolic regression method for constructing interpretable clinical prediction models”.
[41] S. E. Labkoff et al., “Toward a responsible future: recommendations for AI-enabled clinical decision support”.
[42] “Predetermined Change Control Plans for Machine Learning-Enabled Medical Devices: Guiding Principles”.
[43] M. Ronchini, Y. Rezaeiyan, M. Zamani, G. Panuccio and F. Moradi, “NET-TEN: a silicon neuromorphic network for low-latency detection of seizures in local field potentials”.
[44] B. Jarosiewicz and M. J. Morrell, “The RNS System: brain-responsive neurostimulation for the treatment of epilepsy”.
[45] V. Gawade, K. S. Apar, R. D. Mapari, H. S. Lahane and D. R. Pawar, “From Data to Drugs a Review: Harnessing AI for Accelerated Pharmaceutical Development”.
[46] K. Wong et al., “Towards a reference genome that captures global genetic diversity”.
[47] J. Cohen et al., “Problems in the deployment of machine-learned models in health care”.
[48] Y. Yang, H. Zhang, J. W. Gichoya, D. Katabi and M. Ghassemi, “The limits of fair medical imaging AI in real-world generalization”.
[49] D. A. Dorr, L. Adams and P. J. Embí, “Harnessing the Promise of Artificial Intelligence Responsibly”.
[50] X. Li et al., “Interpretable deep learning: interpretation, interpretability, trustworthiness, and beyond”.
[51] E. Kyrimi et al., “Explainable AI: Definition and attributes of a good explanation for health AI”.
[52] S. Martin, F. J. Townend, F. Barkhof and J. H. Cole, “Interpretable machine learning for dementia: A systematic review”.
[53] X. Li, J. Gu, Z. Wang, Y. Yuan, B. Du and F. He, “XAI for In-hospital Mortality Prediction via Multimodal ICU Data”.
[54] “A toolbox for surfacing health equity harms and biases in large language models”.
[55] B. Singhal and F. Pooja, “Unveiling Intractable Epileptogenic Brain Networks with Deep Learning Algorithms: A Novel and Comprehensive Framework for Scalable Seizure Prediction with Unimodal Neuroimaging Data in Pediatric Patients”.
[56] A. Retzer et al., “A toolkit for capturing a representative and equitable sample in health research”.
[57] M. D. Abràmoff et al., “Considerations for addressing bias in artificial intelligence for health equity”.
[58] “Toward a 21st Century National Data Infrastructure: Managing Privacy and Confidentiality Risks with Blended Data”.
[59] J. W. T. M. D. Kok et al., “A guide to sharing open healthcare data under the General Data Protection Regulation”.
[60] H. Cho et al., “Privacy-Enhancing Technologies in Biomedical Data Science”.
[61] “Artificial Intelligence and Medical Products”.
[62] “WHO outlines considerations for regulation of artificial intelligence for health”.
[63] A. Saenz, Z. Harned, O. Banerjee, M. D. Abràmoff and P. Rajpurkar, “Autonomous AI systems in the face of liability, regulations and costs”.
[64] M. Moor et al., “Foundation models for generalist medical artificial intelligence”.
[65] L. F. H. Contreras et al., “Neuromorphic Neuromodulation: Towards the next generation of on-device AI-revolution in electroceuticals”.
[66] Tang J et al. Seizure detection using wearable sensors and machine learning: Setting a benchmark.
[67] Khambhati AN, Chang EF, Baud MO, Rao VR. Hippocampal network activity forecasts epileptic seizures.
[68] “Ethics and governance of artificial intelligence for health: guidance on large multi-modal models”.
[69] Oniani D et al. Adopting and expanding ethical principles for generative artificial intelligence from military to healthcare.
[70] Artificial intelligence system, based on mjn-SERAS algorithm, for the early detection of seizures in patients with refractory focal epilepsy: A cross-sectional pilot study.
[71] Chen W, Wang Y, Ren Y, et al. An automated detection of epileptic seizures EEG using CNN classifier based on feature fusion with high accuracy. *BMC Med Inform Decis Mak* 2023;23:96.
[72] “Using Explainable Artificial Intelligence to Obtain Efficient Seizure-Detection Models Based on Electroencephalography Signals”.
[73] Cao X, Zheng S, Zhang J, et al. A hybrid CNN-Bi-LSTM model with feature fusion for accurate epilepsy seizure detection. *BMC Med Inform Decis Mak* 2025;25:6.
[74] “Generative AI with WGAN-GP for boosting seizure detection accuracy, https://doi.org/10.3389/frai.2024.1437315”.
[75] Artificial intelligence-enhanced epileptic seizure detection by wearables, https://doi.org/10.1111/epi.17774.