Systematic Review Article

Artificial Intelligence and Machine Learning Approaches in Seizure Forecasting and Detection: A Comprehensive Review

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ABSTRACT

A seizure is a sudden, uncontrolled surge of electrical activity in the brain that affects millions of people leading to serious impairments. Seizures can be caused by many factors commonly attributed to epilepsy; however, other factors, such as brain tumors and drugs, can induce seizures as well. Such seizures, especially in early childhood, can have a devastating impact on a child's development, or induce physical harm due to the immediate loss of consciousness and other severe side effects. Currently, seizure treatments are limited, with medications and surgery being the two main points. However, models based on artificial intelligence and machine learning have emerged as newer prevention methods for seizure treatments, allowing for forecasting ahead of time to apply treatments in case a seizure can happen. This systematic review paper investigates recent literature, from 2022 to 2025, and explores the application of artificial intelligence and machine learning to seizure forecasting and detection. The sources are screened through the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) flowchart. Additionally, the review addresses the limitations, reliability, accuracy, and barriers to widespread use indicating that seizure care is shifting from reaction to prediction. Through artificial intelligence and machine learning, seizures can now be detected before they occur, allowing earlier intervention and improved patient safety. This review establishes the state of the art in models, performance, and challenges, and will help researchers continue to advance in the realm of seizure forecasting, thereby improving the quality of life of many people around the globe.

Keywords: Seizure; Forecasting; Artificial Intelligence; Machine Learning; Prediction

INTRODUCTION

Seizures impact over 50 million people around the world, and one in ten people has a seizure at one point in their lives (1). A seizure is a sudden, uncontrolled surge of electrical activity in the brain that causes temporary changes in muscle control, behavior, sensation, or awareness (2). This occurs through mechanisms such as increased activity of the excitatory neurotransmitter glutamate and reduced activity of the inhibitory neurotransmitter GABA, which are typically attributed to epilepsy but can also result from other factors (3). Consequently, a single stimulation triggers repetitive, high-frequency firing (a paroxysmal depolarization shift) that can spread to other neurons through synchronized activity and failed inhibition (4). Symptoms of seizures can include, but are not limited to, confusion, uncontrollable movement, nausea, and loss of consciousness (5). Seizures can happen to anyone

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and can happen anywhere, and even minor seizures in muscles may lead to bigger consequences.

There are a multitude of types of seizures as well, such as focal seizures, which happen in one part of the brain and the patient will be confused or in a dream-like state and may lose consciousness along with generalized seizures, occurring due to abnormal activity on both hemispheres of the brain and will lead to body stiffening, loss of consciousness, and jerking movements (6). These are the two types of seizures that encompass additional subtypes. A person of any age can experience a seizure, whether a child, a teenager, an adult, or an older adult (7).

Treatment options for seizures include antiseizure medications such as levetiracetam and carbamazepine, as well as surgical interventions like lobectomy to remove seizure-generating brain tissue. Other approaches include vagus nerve stimulation, which delivers electrical impulses to reduce seizure activity, and dietary therapies (8). For immediate treatment of acute seizures, diazepam (9) or midazolam (10) can be administered by injection or nasal spray.

Seizures may be prevented depending on the strength, amplitude, and energy of the seizure (11). There is also no single threshold for preventable seizures, as individuals differ (12). Historically, seizure detection relied primarily on visual observation, detailed written logs, or visual/audio recordings of the event (13). These methods, however, were not very accurate due to their subjective nature, false alarms, and inaccurate visual/sensory detection. Additionally, limited technology meant that logs or recordings could only be viewed after the seizure had occurred, thereby being ineffective for prevention (14). Moving on to modern methods, seizures can be monitored using cameras, electroencephalography (EEG) (15), bed sensors (16), and other wearable devices (16).

In recent years, integration of artificial intelligence and medical devices reinforced capabilities to analyze brain waves and correlate them to forecast a seizure. Accordingly, the waves can be used to train specialized models, such as Generative Adversarial Networks (GANs) (17), Deep Learning Models, and others. Such models can also be incorporated into wearable devices that are then worn to allow early detection of seizures, and immediate notification will facilitate timely intervention. For instance, a person can be rushed to emergency care, administered antiseizure medications (as previously mentioned), or prepared to minimize seizure-related harm, such as physical injury to others. Benefits of early intervention include reduced risk of injury and brain damage from prolonged seizures, immediate assistance, peace of mind, and improved quality of life for the caregiver or affected person, among others (18). Therefore, in recent years, artificial intelligence and machine learning have become state-of-the-art for seizure detection (13), providing detailed reports of seizures before they occur. Nowadays, artificial intelligence or machine learning can achieve 80-99% accuracy and detect seizures up to an hour before they occur, and some devices will even contact emergency services without manual input (20).

This comprehensive review examines the use of artificial intelligence and machine learning for seizure detection. Additionally, the overview of the current research landscape in state-of-the-art seizure detection and prevention serves as an initial reference for researchers seeking to pursue further work in this area. This review will also include summarized datasets for seizure forecasting applications, state-of-the-art detection models, primary issues in artificial intelligence and machine learning, the number of published articles on seizure detection, and the future reliability of artificial intelligence and machine learning for early seizure detection.

METHODS AND MATERIALS

Study Design

This study was conducted as a systematic review of the literature examining artificial intelligence (AI) and machine learning (ML) approaches in seizure detection and forecasting. The review was guided by the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework to ensure transparency and reproducibility. The research was structured around five predefined research questions, summarized in Table 1.

Search Strategy

A structured literature search was performed using Google Scholar. The following search query was applied: (“Seizure”) AND (“Detection” OR “Prediction” OR “Diagnosis” OR “Forecast”) AND (“Machine Learning” OR “Artificial Intelligence” OR “Algorithms” OR “Brainwaves” OR “Reliability” OR “Accuracy” OR “Performance”). The survey employed multiple criteria, as listed below.

Inclusion criteria

Studies were selected based on predefined inclusion and exclusion criteria to ensure relevance and quality.

Table 1. *Overview of Research Questions explored in this Research Paper.*

Research Questions	Research Question 1 (RQ1)	Research Question 2 (RQ2)	Research Question 3 (RQ3)	Research Question 4 (RQ4)	Research Question 5 (RQ5)
Question	Available datasets accessible for seizure forecasting applications.	State-of-the-art performance of seizure detection models.	Primary issues regarding artificial intelligence in its ability to be used within a seizure detection application.	The current number of published articles regarding seizure detection.	The paths artificial intelligence will take to become more reliable and dependable for early seizure forecasting.
Why should it be explored	The question helps identify datasets to review.	The performance of state-of-the-art models is useful for comparing with traditional models and for estimating future performance.	Artificial Intelligence is not always reliable, and several key issues need to be addressed for it to be used correctly.	This will help identify when the articles were published and whether they are more prevalent now.	New paths help increase awareness and future proof, so people will have more trust in this idea.

Eligible studies were required to be original research articles published between 2022 and 2025, with a minimum of 25 citations to indicate credibility. In addition, included studies had to present quantitative results, address at least one of the predefined research questions, and contain at least one relevant keyword in the article title.

Exclusion criteria

Studies were excluded if they were duplicate records, review articles, or contained misleading or non-original content. Articles that did not focus on machine learning applications in seizure detection were also excluded. Furthermore, studies without publicly accessible full texts and those not written in English were omitted from the analysis.

RESULTS AND DISCUSSION

The results of the study are presented below. Figure 1 is the PRISMA flow diagram outlining the phases of the article review, retrieved from Google Scholar via the search query. Initially the SCOPUS search resulted in 902,000 results, however they were screened for the exclusion criteria with 876,500 records identified as not being between 2022-2025 and the keywords not in the title leading to excluding 24,688 records, also removing 75 unoriginal records, 622 non-specific records, and 60 records that did not provide full text. Out of the remaining 55 records that were screened, 0 were excluded. The 55 records were then sought to be retrieved, 42 were not retrieved, leading 13 to be assessed for eligibility and eventually having those 13 studies included in the review.

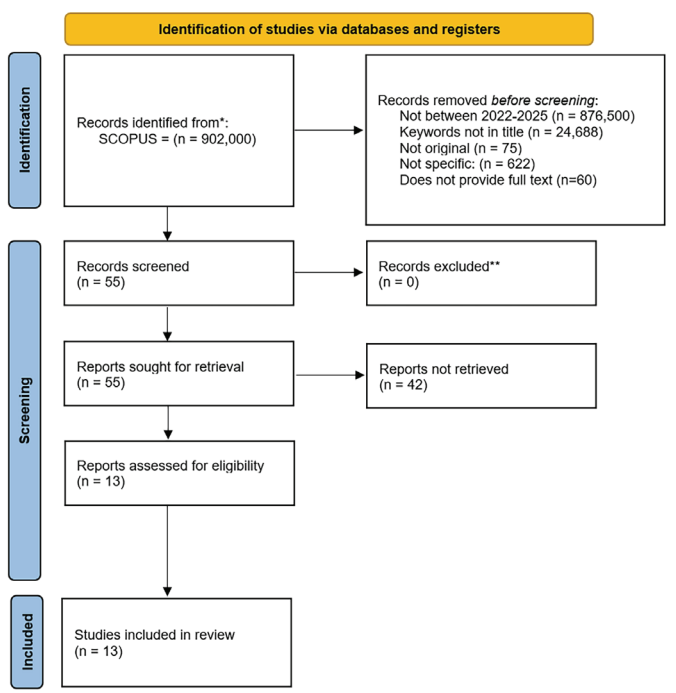

Figure 1. *Prisma Flowchart. The diagram shows the route data taken from the initial search towards the final selected papers.*

RQ1: Available datasets accessible involving seizure forecasting applications

Table 2 presents four datasets covering a range of subjects, collected in a controlled environment. The table identifies each dataset by name, its modality, how it gains data, the amount of data, quantifiable in hours or number of files, the year the dataset was published, the number of subjects participating in the dataset, the authors of the dataset, examples of where the dataset is used in published works, and a description of the datasets information.

Table 2. *Datasets with data related to seizure patients.*

Dataset	CHB-MIT Scalp EEG Dataset	Freiburg Hospital iEEG Dataset	EPILPSIAE Dataset	Empatica EpiMonitor Study
Modality	EEG	Intracranial Electroencephalography (iEEG)	sEEG & iEEG	Wearables
Amount of data	664 EDF files with recordings from 22 pediatric patients	509 hours of intracranial EEG data from 21 patients, including about 87 seizures	40,000 hours of recording; documenting 2,700 seizures across over 300 patients; a subset of data focusing on temporal lobe epilepsy includes 5,600 hours of recording with 227 seizures from 41 patients.	Ongoing, estimated thousands of hours of patient recordings
Year	2010	2012	2012	2024
Number of subjects	22 subjects	21 patients (focal epilepsy)	Over 300 patients	Varies, some studies report in the hundreds, while others in the thousands
Author(s)	Jack Connolly, REEGT; Herman Edwards, REEGT; Blaise Bourgeois, MD; and S. Ted Treves, MD. Investigators from MIT include Ali Shoeb, PhD and Professor John Guttag.	Andreas Schulze-Bonhage, Michael Dümpelmann, R. Winterhalder, B. Schelter, J. Timmer,	Matthias Ihle, Hinnerk Feldwisch-Drentrup, Andreas Schulze-Bonhage, César A. Teixeira, Adrien Witon, Björn Schelter, Jens Timmer	Rosalind W. Picard, Matteo Z. Poh, Tanusri Pal Attia, Tomás Loddenkemper, Giacomo Regalia, Maurizio Onorati, Caterina Carboni
Used in literature	Machine Learning approaches, Deep Learning Methods, CNNs, RNNs, LSTMs, (20,21)	Machine Learning and Deep Learning, Epileptic Seizure Prediction and Detection, feature extraction, Epileptic Seizure Prediction and Detection, SVMs, LNNs, (22,23), (24).	Clinical Trials, Artificial Intelligence approaches, epilepsy research, seizure detection or prediction, and machine learning in EEG, (25),(26),(27),(28)	Clinical trials, SUDEP, algorithm validation, seizure forecasting, major pharmaceutical companies for treatments, and other extensive scientific papers
Description	A widely used dataset for seizure detection and prediction, offering continuous EEG recordings from pediatric patients.	Contains intracranial EEG recordings from adult patients, useful for high-resolution seizure analysis.	Provides data on patients with drug-resistant epilepsy, aiding the development of forecasting models.	A real-world dataset collected via a wearable device, aiming to develop seizure forecasting algorithms.

RQ2: State-of-the-art performance of seizure detection models

In a study aimed at assessing the accuracy of advanced mathematical models in seizure forecasting, researchers developed a seizure-prediction wearable model based on electrocardiogram, electroencephalogram, and photoplethysmography (19). The developed seizure-prediction model has been validated only under static, fixed conditions. To compare with clinical data, a model based on Boosted Trees (19)using eight predictors achieved 91.5% prediction accuracy using only data from the wearable device. Based on the accuracy of the predictive model, the developed state-of-the-art device, the best technology, can potentially serve as a support tool to determine status epilepticus, a severe seizure classified as being over 5 minutes (23), and prevent a seizure, thereby improving the lives of people with epilepsy. Deep Learning Models, complex networks to identify patterns in large amounts of data, using raw EEG signals, such as fully convolutional neural networks (CNN), have achieved an area under the curve (AUC) of 98.5% in neonatal seizure detection (19). A model using the CHB-MIT dataset achieved a true-positive rate of 92.23% and an average prediction time (time before seizure onset) of 23.60 minutes on the scalp of patients, consistent with the findings of (25). Table 3 lists model types, their seizure-detection task (whether to detect a seizure after it has occurred or to predict future seizures), performance quantified as accuracy percentages, publication year, and the resources required for model operation. Due to the limited data and models, Table 3 draws models from outside the inclusion criteria (2022-2025) to provide thorough information.

RQ3: Primary issues regarding artificial intelligence in its ability to be used within a seizure detection application

There are several issues related to artificial intelligence in seizure detection applications. These include accuracy, the amount of data needed in datasets, the quality of those datasets, the usefulness of detection relative to forecasting, regulatory approval (FDA), and real-time/latency issues (29). Accuracy is a major concern; if many false positives are generated, this would lead the patient to overuse emergency medications and to distrust the artificial intelligence's reliability (13). Another major issue identified is the large volume of data required; researchers concluded that the volume is overwhelming and must be of such high quality that it is not yet fully developed (30). Additionally, some models are designed solely for detection, which is less helpful than forecasting because no preventive measures can be taken (13). Furthermore, FDA approval is difficult to obtain, particularly given the invasive nature of iEEG (31), which requires placement within the brain; although the procedure is generally considered safe, constant monitoring of EEG signals is still required. Finally, real-time and latency issues arise because no technology has yet been developed to reliably transmit data from an iEEG to a patient-monitoring device; this process can also be harmful, as radio waves may interfere with brain function and even cause internal damage (32).

RQ4: The current number of published articles regarding seizure detection

There is a substantial body, over 40, of published datasets on seizure detection. Evaluation using these

Table 3. *Machine Learning Models for Seizure Forecasting presents a comparison of model types that can be used for seizure forecasting/detection, along with their performance metrics to each other with their publishing date, with the required resources needed to function the model.*

Model type	Detection vs Forecast	Performance	Year of Publishing	Required resources
Deep learning models	Detection	AUC of 98.5% in neonatal seizure detection.	2020	Raw EEG signals need to be attached to the machine
Feature Embedding Approaches	Detection	Embedding raw EEG data has led to 100% sensitivity and 99% specificity in seizure detection tasks.	2012	Continuous monitoring with iEEG
Generative Adversarial Networks	Forecast	Performance varies; 77.68% accuracy for the CHB-MIT dataset and 65.05% for the EPILEPSIAE dataset.	2014	Require EEG signals after being trained with multiple datasets

datasets demonstrates that Machine Learning and artificial intelligence are becoming increasingly effective and approaching perfection in the modern era. As explored in Table 2 and reference (33), the SH-SDU and CHB-MIT EEG datasets achieve an accuracy of 95% or higher. Furthermore, the current media landscape in the scientific world is shifting its focus toward artificial intelligence and machine learning approaches. These approaches now require ever more training data and a constant feed of information, leading to the rise of iEEG (34). Additionally, multimodal approaches are emerging as a new direction in external hospital monitoring (35). Currently, these are the only available approaches, constrained by technological limitations and federal regulations, that permit data collection only via EEGs and EMGs (36). Finally, there is an emerging interest in wearables, with the seizure prediction wearable market projected to reach 1.41B in 2025, such as those from Empatica (37), which enable easy, real-time data collection for both the company's research and direct data feed to a person's cellular device for monitoring. Wearables are a promising future, as they can be always worn without discomfort and provide real-time data feedback. Figure 2 shows a medical signal chart from (37) using variable data to make diagnostic decisions. The figure uses electrodermal activity (EDA), and it is relevant towards seizure forecasting, as EDA is a marker for the sympathetic nervous system and data shows EDA is increased during pre-ictal, ictal, and postictal periods (39). Additionally, wearables are able to gain this information, which is why companies like Empatica use this technology to have non-invasive monitoring, providing people seizure forecasting.

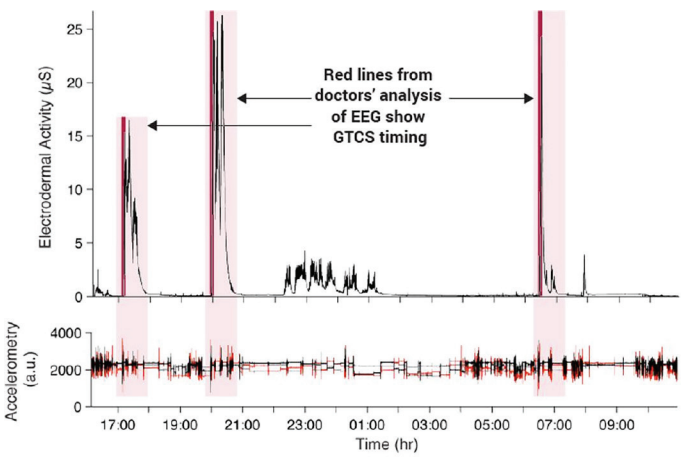

Figure 2. *Seizure Analysis. The figure presents a chart comparing data-collection modalities and their accuracy relative to analysis, providing electrodermal activity and its effect on autonomic disruption over time. Figure from (38).*

RQ5: The paths artificial intelligence will take in the future to become more reliable and dependable for early seizure forecasting

In the future, artificial intelligence will require further improvements before it can be used on a scale in commercial settings. Such changes concern accuracy and reliability, as patients need to trust that what they are using is correct and provides reliable information that can be acted upon. As a solution, additional data will be obtained through increased model training and testing, as well as reliability testing with research participants. This is consistent with patients' experiences with wearables, including negative experiences (40). There is also an emerging interest in personalized models (41), similar to OpenAI's ChatGPT, that use a person's data to augment existing datasets and improve prediction accuracy. Regulatory compliance is also a consideration that must be addressed and requires approval from the FDA's medical device division, the Center for Devices and Radiological Health (CDRH). As a result, some experiments are still conducted in hospitals, particularly with multimodal approaches (42). Finally, clinician trust is required for these wearables and other devices, through exposure and trustable data, as physicians must be able to prescribe them and have full confidence in the performance of artificial intelligence or machine learning, therefore hospitals in China, have multiple physicians exposed to this technology (43) which allows physicians to already know if the technology works and whether or not to prescribe it. Lastly, to guide future research, it is heavily important for it to cover accuracy, as it is a major factor when considering if people will choose the modern over traditional methods.

Some limitations in this study were the lack of access to Empatica data systems along with this paper being a systematic review and not having experimental knowledge to base this review off of. Furthermore, there were difficulties in finding accessible data, as most data was not in the subject timeframe as found in Figure 1, along with recent works not being included due to not having enough citations (<25), with 2026 papers not being included. Another area for future researchers is to incorporate and encompass the significance of these methods' comparative to the effects if not used.

CONCLUSION

The use of artificial intelligence and machine learning has shown significant potential in enabling seizure prevention by improving monitorization methods and streamlining care for patients who require or prefer alternatives to traditional treatments. Continuing this, future work should focus on improving the clinical translation of seizure forecasting models by prioritizing the development of streamlined and generalized models; capable of performing consistently across diverse patient populations, accounting for variability in seizure types and data quality. Expanding and standardizing both large-scale and high-quality datasets will be essential to improving model accuracy and reproduction, whilst also allowing for comparison between researchers. In parallel, research should emphasize the integration of these models into real-time clinical and wearable monitoring systems, such as hospital-based neurological equipment and portable devices, like watches accessible by cellphones; should allow for both continuous and nonintrusive early seizure forecasting allowing for timely intervention by healthcare providers. Ensuring model interpretability and transparency is critical for building clinician trust and allowing for adoption in healthcare workflows, alongside careful prospective clinical checks to evaluate safety, accuracy, and impact on patient outcomes. Furthermore, collaboration between data scientists, neurologists, biomedical engineers, and other healthcare providers in this field, technology, seizure related, or parallel, will play a central role in bridging the gap between simple technological innovation and healthcare implementation. Future research should also explore personalized and adaptable learning approaches that tailor individualized predictions to patients, as well as address the ethical, regulatory, and data privacy considerations associated with artificial intelligence driven decision making in seizure care. By going headfirst against these challenges, this paper can help guide the next generation of research toward clinically viable, patient centered solutions that not only improve seizure forecasting accuracy but also reduce treatment load, minimize physical and psychological effects, and ultimately enhance the quality of life for individuals living with seizures or epilepsy.

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CONFLICT OF INTEREST

The author declares that there are no conflicts of interest related to this work.

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