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REVIEW ARTICLE

THE USE OF ARTIFICIAL INTELLIGENCE IN EPILEPSY DIAGNOSIS – AN OVERVIEW OF CONTEMPORARY TOOLS

WYKORZYSTANIE SZTUCZNEJ INTELIGENCJI W DIAGNOSTYCE PADACZEK – PRZEGLĄD WSPÓŁCZESNYCH NARZĘDZI

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ABSTRACT

Introduction

Epilepsy is a common neurological disorder in which diagnostic accuracy is often limited by subtle or magnetic resonance imaging (MRI)-negative abnormalities as well as non-specific electroencephalography (EEG) findings. Conventional interpretation of imaging and EEG is time-consuming and depends on experience. Recent advances in artificial intelligence (AI) offer new opportunities for automating and improving the detection, classification and prediction of epileptic activity. This review aimed to summarise recent evidence on AI-based diagnostic applications in epilepsy.

Materials and methods

A PubMed search (2015–2025) identified almost 50 studies meeting predefined quality and relevance criteria. Included works examined AI models applied to MRI/functional MRI, EEG analysis, seizure detection and prediction, and multimodal diagnostic systems.

Results

AI significantly improves detection of subtle MRI abnormalities, including hippocampal sclerosis and focal cortical dysplasia, with performance often exceeding expert radiologists. Multimodal approaches combining EEG with MRI/resting state MRI show high accuracy in seizure-onset localization. Deep-learning systems – including convolutional neural networks (CNN), long short-term memory, combined models and transformer-enhanced architectures – achieve sensitivity and specificity above 90% in seizure detection and short-term prediction, with continuous wavelet transform-based CNN models reporting > 95% accuracy.

Conclusions

AI enhances diagnostic precision, reduces review time, and assists in seizure classification and localization. Ongoing advances suggest that AI will soon play a meaningful role in routine epilepsy diagnostics and clinical decision-support.

Keywords: epilepsy, artificial intelligence, seizure detection, seizure prediction, machine learning

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STRESZCZENIE

Wstęp

Padaczka to częste schorzenie neurologiczne, w którym dokładność diagnostyczna jest często ograniczona przez subtelne lub niewidoczne w badaniu rezonansu magnetycznego (*magnetic resonance imaging* – MRI) nieprawidłowości, a także niespecyficzne wyniki elektroencefalografii (EEG). Konwencjonalna interpretacja wyników obrazowania i EEG jest czasochłonna i zależy od doświadczenia. Najnowsze postępy w dziedzinie sztucznej inteligencji (*artificial intelligence* – AI) oferują nowe możliwości automatyzacji i usprawnienia wykrywania, klasyfikacji i przewidywania aktywności padaczkowej. Celem niniejszego przeglądu jest podsumowanie najnowszych dowodów dotyczących zastosowań diagnostycznych opartych na AI w padaczce.

Materiały i metody

Wyszukiwanie w bazie PubMed (2015–2025) zidentyfikowało niemal 50 badań spełniających wcześniej określone kryteria jakości i trafności. Uwzględnione prace analizowały modele AI stosowane do oceny MRI/funkcjonalnego MRI, analizy EEG, detekcji i predykcji napadów padaczkowych oraz systemów diagnostycznych opartych na danych multimodalnych.

Wyniki

AI znacząco poprawia wykrywanie subtelnych nieprawidłowości w badaniach MRI, w tym stwardnienia hipokampa oraz ogniskowej dysplazji korowej, osiągając wyniki często przewyższające skuteczność doświadczonych radiologów. Podejścia multimodalne łączące EEG z MRI/*resting state* MRI charakteryzują się wysoką dokładnością w lokalizacji strefy początku napadu. Systemy oparte na uczeniu głębokim, w tym splotowe sieci neuronowe, długa pamięć krótkotrwała, modele łączone oraz architektury wzbogacone o transformatory, uzyskują czułość i swoistość powyżej 90% w detekcji napadów i krótkoterminowej predykcji, przy czym modele z wykorzystaniem konwolucyjnych sieci neuronowych opartych na ciągłej transformacji falkowej osiągają dokładność przekraczającą 95%.

Wnioski

AI zwiększa precyzję diagnostyczną, skraca czas analiz oraz wspomaga klasyfikację i lokalizację napadów padaczkowych. Postęp w tym zakresie wskazuje, że AI odegra wkrótce istotną rolę w rutynowej diagnostyce padaczki oraz systemach wspierania decyzji klinicznych.

Słowa kluczowe: padaczka, epilepsja, sztuczna inteligencja, wykrywanie napadów, przewidywanie napadów, uczenie maszynowe

Introduction

Epilepsy remains one of the most common neurological disorders. Epilepsy diagnosis continues to pose significant clinical challenges, particularly in patients with subtle, magnetic resonance imaging (MRI)-negative structural abnormalities or non-specific electroencephalography (EEG) findings. Traditional interpretation of neuroimaging and EEG recordings is time consuming, requires experienced specialists and is limited by inter-observer variability. As a result, diagnostic delays remain a persistent clinical problem.

However, over the past decade, artificial intelligence (AI) has introduced new possibilities for enhancing diagnostic accuracy and efficiency in epilepsy. A wide spectrum of AI-based tools has been developed, such as convolutional neural networks (CNN) for MRI feature extraction, support vector machines (SVM) for automated epileptiform pattern recognition, and long short-term memory (LSTM) networks capable of modeling temporal EEG dynamics. Therefore, multimodal systems integrating MRI, functional MRI (fMRI), EEG and AI-based algorithms have shown particular promise in localizing seizure onset zones and assisting in presurgical evaluation. Recent solutions also extend beyond static analysis – deep learning (DL)-based seizure detection and prediction models, brain-computer interface (BCI) systems provide real-time monitoring with high sensitivity and efficiency in clinical environments.

This review aimed to systematize current knowledge on the contemporary applications of AI-based diagnostic methods in epilepsy, as well as to critically evaluate their effectiveness (accuracy, sensitivity, specificity), clinical relevance, and potential for integration into routine neurological practice. Over the past ten years, a substantial increase has been observed in both the importance and the feasibility of using AI in medicine, as evidenced by the steadily growing number of publications addressing this topic. The scientific literature reports not only on the effectiveness of AI models but also on the ongoing need to refine AI systems for diagnosing, classifying, and predicting epileptic seizures. These developments hold the potential to markedly enhance the verification of diagnostic findings and enable the detection of seizures before they occur, thereby reducing complications and improving disease management. The involvement of AI in routine practice could help relieve the burden on the medical sector and improve access to timely diagnostic assessment, following verification of results by medical specialists.

Materials and methods

A comprehensive literature search was conducted using the PubMed scientific database, with a primary focus on studies published between 2015 and 2025. Keywords included "convolutional neural network," "support vector machine," "epilepsy," and "diagnosis." Furthermore, original research articles and review papers describing the use of AI in EEG analysis, neuroimaging interpretation, and seizure prediction were included in the analysis. Sixty peer-reviewed publications meeting both inclusion and quality criteria were selected for in-depth discussion. The data were organized thematically to illustrate the functioning and diagnostic capabilities of hybrid models (CNN and SVM), DL approaches, and their integration with conventional data sources such as MRI/fMRI and EEG.

Results

AI in MRI analysis for epilepsy diagnosis

Neuroimaging plays an essential role in assessing epilepsy, and MRI is the most effective imaging method for identifying epileptogenic lesions. However, in almost 30% of patients with epilepsy, MRI is unremarkable [1].

AI-based image analysis, especially DL, enhances detection of subtle structural abnormalities in epilepsy patients, the most common being hippocampal sclerosis (HS), cortical malformations, neoplasms and vascular malformations [2]. Accurate interpretation of these scans demands high quality standards of imaging studies [3], therefore, in 2019 The International League Against Epilepsy issued official guidelines for an MRI protocol intended for epilepsy evaluation. It should include 3D T1-weighted images, 3D fluid-attenuated inversion recovery (FLAIR) sequences, and 2D coronal T2-weighted images. CNN and SVM analyze and extract hidden structural and textural features from MRI, fMRI or diffusion-weighted imaging scans, such as volume, thickness of cortex, asymmetry, and texture of the brain [4].

Early investigations began appearing around 2019–2020, exploring the use of machine learning (ML) applied to MRI and fMRI in temporal lobe epilepsy (TLE). Since then, an increasing number of studies – including recent publications in *Frontiers in Psychiatry* [4] and *Nature Communications* [5] – have confirmed the feasibility and promise of these approaches. TLE is the most common type of drug-resistant focal epilepsy in adults, and its most frequent cause is HS. In this condition, the hippocampus typically shows volume loss, disrupted internal architecture, and increased signal intensity on T2-weighted and FLAIR images [6]. These abnormalities are often very mild, particularly in the early stages, making them challenging to detect during routine neuroimaging. For this reason, several studies have applied ML to aid in identifying HS, creating models that integrate clinical and imaging data to automatically detect the condition. Highest performance was achieved using MPRAGE + 3D-FLAIR data with mean accuracy 1.0, and confidence interval (CI) = 0.939 – 1.0; MPRAGE + 2D-FLAIR with mean accuracy = 0.950, CI = 0.772 – 0.999 and MPRAGE alone with mean accuracy = 0.986, CI = 0.925 – 1.0 [7]. Notably, the tool proved especially valuable in patients whose MRI scans appeared normal, as it was able to detect imaging patterns related to HS that were too subtle for conventional visual assessment. The classifier detected 90.1% of unilateral HS patients and lateralized lesions in 97.4%. In patients with MRI-negative histopathologically-confirmed HS, the classifier detected 79.2% and lateralized 91.7% [8].

ML-based methods have high potential applications in diagnosis, localization of the epileptogenic focus, prognosis prediction, and pre-surgical assessment. Although current data do not yet allow us to quantify how much AI improves diagnostic sensitivity in epilepsy, existing findings are encouraging. Consequently, once key limitations are resolved, ML algorithms may become integrated into routine clinical practice [9].

Multimodal AI for seizure localization

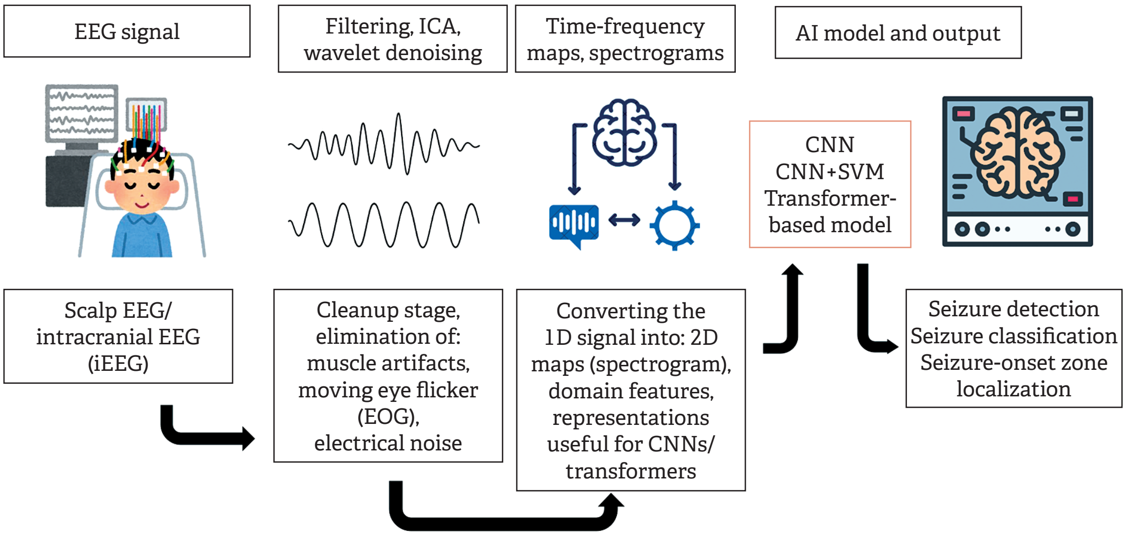
Functional alterations in the brain can precede structural abnormalities and may be detected using non-invasive techniques. In TLE, analyses of functional connectivity using fMRI and resting state MRI (rs-fMRI), supplemented with diffusion tensor imaging, have provided valuable insights [10]. Effective therapeutic intervention in epileptogenic regions depends on accurate identification of seizure onset. Computers already play a significant role in supporting clinicians with acquisition, processing, storage, and interpretation of EEG data. Several computer-assisted detection tools rely on BCI technology. For an autonomic computing system to function reliably, robust computational algorithms are essential [11].

CNN and SVM process and integrate large multimodal datasets – neurophysiological from EEG records and neuroimaging data from rs-fMRI – to improve localization of the seizure-onset zone and seizure classification (Figure 1). The DL framework was designed to extract higher-order features for preictal detection and localization, distinguishing preictal state from non-preictal periods, making use of emerging mobile-edge computing technologies. The combination of rs-MRI and EEG/intracranial electroencephalography can reveal more information about dynamic functional connectivity. Experimental and simulation results based on real patient data validate the effectiveness of the proposed AI-based model [12].

This AI-based model is very promising for surgical planning and treatment of drug-resistant epilepsy. This algorithm is expected to be implemented first in specialized epilepsy treatment centers within the next few years [13]. The current and future challenge for ML-based tools is to develop methods and systems to remove noise, extract meaningful features, and learn from huge datasets [14].

Seizure prediction and proactive monitoring

Traditional ML techniques, such as SVM and random forest, increase the efficiency of EEG analysis by enabling automated classification and feature extraction, thereby mitigating the need for laborious and time-consuming manual interpretation



CNN – convolutional neural network, EEG – electroencephalography, EOG – electrooculography, ICA – independent component analysis, iEEG – intercranial EEG, SVM – support vector machine

Figure 1. Signal and image preprocessing workflow for artificial intelligence (AI)-based epilepsy diagnostics

by experts [15]. More advanced DL models – including CNN, LSTM, and hybrid CNN-LSTM-Gated Recurrent Unit architectures – further improve outcomes with reported classification accuracies frequently reaching up to 99% for critical tasks like automated seizure detection [16–18]. However, the results often fall into the 76–90% sensitivity range when models are tested on real-world, multi-patient, and non-optimized clinical datasets [19–21].

Seizure prediction has become one of the most rapidly advancing areas of AI research in epilepsy, driven by the need for more effective prevention strategies and continuous monitoring solutions. Although seizure detection is now well established, prediction – identifying preictal patterns minutes to hours before seizure onset – remains a substantially more challenging task due to the heterogeneous nature of preictal EEG dynamics. Recent AI methods, especially those using DL, have significantly improved the sensitivity and specificity of short-term seizure forecasting [9].

The preictal period preceding the seizure is characterized by subtle, but detectable alterations in neuronal synchrony, spectral composition, and functional connectivity [22]. Traditional ML methods – such as SVM – have shown moderate effectiveness, typically achieving 70–85% prediction accuracy in controlled settings [23, 24]. However, the variability of preictal patterns between individuals and even within the same patient complicates prediction efforts, making hand-engineered features insufficient for clinical assessment [9].

DL approaches, especially CNN, have redefined the field by enabling automated extraction of hierarchical EEG features. CNN can process unprocessed or minimally preprocessed EEG data and uncover non-linear interactions that traditional methods tend to miss [25,26].

Additionally, the incorporation of continuous wavelet transform (CWT) into CNN models, has been a major improvement. CWT is a technique that decomposes a signal into components at different scales and positions, providing both time and frequency information at the same time [27]. In a 2024 study, a landmark model using CWT-based depthwise CNN was used and reported scores such as 95.99% accuracy, 94.27% sensitivity, 97.29% specificity, and 96.34% precision [28]. Consequently, similar high scores were reported in other studies, published across 2023–2025 [29–32]. The most recent research demonstrates incorporation of transformer blocks and attention mechanisms into CNN models, which significantly improve resilience against EEG noise in ambulatory environments [33–35].

Finally, AI-driven prediction is increasingly embedded into practical monitoring systems, such as:

- implantable devices – neurostimulation platforms such as responsive neurostimulation incorporate ML algorithms that detect early signs of seizure activity and deliver targeted electrical stimulation to prevent the events [9],
- cloud-based ambulatory EEG – modern long-term EEG systems leverage cloud computing and AI-based detection/prediction engines capable of high-accuracy analysis in real time [36,37],
- wearable sensor systems – AI-enabled platforms that integrate accelerometry, photoplethysmography and behavioral metrics to find use in clinical seizure detection [38,39].

Early clinical evidence suggests that proactive monitoring systems may reduce uncontrolled seizure burden by 20–40% in selected patient cohorts [40].

All the above seizure detection systems can find a clinical implementation and be a useful tool for proactive epilepsy monitoring.

Recent AI methods in epilepsy diagnostics – performance and clinical translation

ML is used to automatically detect hidden patterns in large amounts of data. DL is a subfield of ML whose structure is based on multilayered networks composed of nodes [4].

Among the many applications of ML and DL, they are used in the diagnosis of epilepsy, including the identification of epileptic patterns in EEG signals, the detection and classification of epileptic seizures, the automatic analysis of long-term EEG recordings, distinguishing between epileptic and functional seizures, and analyzing time-frequency signals and subcutaneous and scalp EEG monitoring to aid clinical decision-making [28,41,42].

DL segmentation has a very important application in preoperative planning for the treatment of drug-resistant epilepsy [43].

DL models outperform neuroradiologists in the diagnosis of discrete lesions [44–46]. Radiologists often overlook focal cortical dysplasia (FCD) foci when the lesions are minimal, blurred, difficult to distinguish from anatomical variants, and in MRI-negative patients due to drug-resistant epilepsy or lesions in areas that are difficult to assess [44,46]. In an inter-center study, the DL network detected 62.9% of foci in patients who had ever been labeled MRI-negative by radiologists [46].

In studies evaluating the accuracy of ML and DL assessment using ^{18}F-FDG positron emission tomography to evaluate patients with TLE, higher detection accuracy was also observed than in visual analysis by experienced neuroradiologists, with 90% accuracy for DL compared to 56% accuracy for assessment [47], and 82.6% accuracy for ML detection compared to 75.3% accuracy for visual analysis [48].

Observations show that DL models outperform visual image analysis, especially for sites where lesions are masked by artifacts or where structures are difficult to assess due to anatomical distortions, such as postoperative assessment of TLE [45]. This is based on the fact that U-shaped CNN (CNN/U-Net) models detect FCD and epileptic foci by analyzing textural and voxel features that are not visible macroscopically [44].

In our review, we analyzed several new, promising ML and DL models that are used in the diagnostic imaging of epilepsy.

In the publication by Amiri *et al*., a hybrid 1D CNN–LSTM model using DL was proposed for any input signal (single-channel and multi-channel) for the automatic analysis of epileptic EEG signals [41]. The performance of the new method was compared with that of other standard algorithms and was shown to be more effective in terms of accuracy and sensitivity, with results of 94–97 % accuracy and 79–99 % sensitivity, respectively. The 1D CNN–LSTM + DWT model outperformed support vector classifier, k-nearest neighbours (KNN), Gaussian naive Bayes, DT (Decision Tree), and Multi-Layer Perceptron (MLP) models in terms of accuracy, but if the goal is to maximize sensitivity on a specific multi-channel set (CHB-MIT), MLP in this configuration achieved a marginally better result.

An example of a DL model used to interpret EEG recordings is the method presented by Dişli *et al*. [28], in which EEG signals from 35 electrodes were subjected to CWT. The approach used achieved very high effectiveness in the classification of EEG signals, obtaining accuracy, sensitivity, specificity, and precision values presented in the overview table (Table 1), with each parameter having a value of at least 94%.

In one of the latest studies, DL was used to distinguish between epileptic seizures and functional/dissociative seizures [42]. The authors analyzed EEG activity in a six-minute window covering the period from three minutes before to three minutes after the onset of an epileptic seizure. A total of 106 mesial TLE seizures and 100 focal dyscognitive seizures were differentiated. A key element of the proposed solution was analysis using a 34-layer residual neural network (ResNet34) convolutional network. The model developed in this way proved to be highly effective in classifying seizure types, indicating that DL-based density spectral array analysis can serve as a screening tool, particularly useful in conditions where the number of electrodes is limited or access to specialist interpretation of EEG recordings is restricted.

Table 1. Overview of machine learning (ML) and deep learning (DL) models applied in epilepsy diagnostics

Source	AI model	Application area	Performance metrics	Sensitivity/ specificity
Seizure detection using ultra-long-term subcutaneous EEG: a DL CNN–BiLSTM approach [49]	CNN–BiLSTM	Automated seizure detection in ultra-long subscalp EEG	AUROC = 0.98; AUPRC = 0.50	Sensitivity ~94%
Epileptic seizure detection from EEG signals based on 1D CNN–LSTM DL model using DWT [41]	1D CNN–LSTM + DWT	Seizure detection in EEG signals, EEG classification	Accuracy: CHB-MIT 96.94%; TUSZ 94.32%	Specific sensitivity/ specificity values not uniformly reported
Epilepsy diagnosis from EEG signals using CWT-based depthwise CNN model [28]	CWT + depthwise CNN	Detection of epileptiform patterns in EEG	Accuracy = 95.99%; Precision = 96.34%	Sensitivity = 94.27%; Specificity = 97.29%
Differentiation between epileptic and functional/dissociative seizures using DSA of ictal single-channel EEG with DL [42]	ResNet34 (CNN)	Differentiation of mTLE vs. FDS using DSA EEG	AUROC = 0.941	Not reported; high performance for Cz DSA

AUPRC – the area under the precision-recall curve, AUROC – area under the ROC curve, BiLSTM – bidirectional long short-term memory, CHB-MIT – Children's Hospital Boston and the Massachusetts Institute of Technology, CNN – convolutional neural network, CWT – continuous wavelet transform, Cz – central midline electrode, DSA – density spectral array, DWT – discrete wavelet transform, EEG – electroencephalography, FDS – functional dissociative seizures, LSTM – long short-term memory, mTLE – mesial temporal lobe epilepsy, TUSZ – Temple University Seizure Corpus

Conclusions

AI technologies demonstrate significant potential to transform the diagnostic process in epilepsy by enhancing the analysis of neurophysiological and neuroimaging data. Moreover, AI models – particularly CNN, LSTM, and hybrid architectures (e.g., CNN–SVM) – have achieved accuracy, sensitivity, and specificity exceeding 90% in selected studies, surpassing traditional manual interpretation and thereby offering superior diagnostic performance compared with conventional methods. In clinical application, AI supports clinicians in the objective detection of epileptic patterns, classification of seizure types, and localization of epileptogenic zones, contributing to faster, more accurate and consistent diagnostic workflows. In the coming years, AI is expected to be integrated into routine clinical practice, which will increase the personalization of care for people with epilepsy, but also optimize and reduce the burden on neurologists.

AI-based tools are expected to evolve from decision-support systems to real-time diagnostic assistants. Nevertheless, this technology still needs refinement. AI models require large, well-labeled datasets, and in epileptology, data is often small in number and heterogeneous (different EEG/MRI protocols, lack of standardization of clinical data), leading to poor generalization of other patients and lower effectiveness for rare types of epilepsy. Lack of data explainability makes legal accountability difficult and complicates the assessment of whether the algorithm is analyzing pathological features or artifacts. In addition, clinical validation is limited because most studies are retrospective, do not include multicenter trials, and do not test algorithms in real clinical conditions.

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