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Review Article

Epileptic detection based on deep learning: A review

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Abstract
Epilepsy, a neurological disorder characterized by recurring seizures, necessitates early and precise detection for effective management. Deep learning techniques have emerged as powerful tools for analyzing complex medical data, specifically electroencephalogram (EEG) signals, advancing epileptic detection. This review comprehensively presents cutting-edge methodologies in deep learning-based epileptic detection systems. Beginning with an overview of epilepsy's fundamental concepts and their implications for individuals and healthcare are present. This review then delves into deep learning principles and their application in processing EEG signals. Diverse research papers to know the architectures—convolutional neural networks, recurrent neural networks, and hybrid models—are investigated, emphasizing their strengths and limitations in detecting epilepsy. Preprocessing techniques for improving EEG data quality and reliability, such as noise reduction, artifact removal, and feature extraction, are discussed. Present performance evaluation metrics in epileptic detection, such as accuracy, sensitivity, specificity, and area under the curve, are provided. This review anticipates future directions by highlighting challenges such as dataset size and diversity, model interpretability, and integration with clinical decision support systems. Finally, this review demonstrates how deep learning can improve the precision, efficiency, and accessibility of early epileptic diagnosis. This advancement allows for more timely interventions and personalized treatment plans, potentially revolutionizing epilepsy management.

Keywords
Epileptic seizures, Deep Learning, Electroencephalogram, Convolution Neural Networks, Detection.

I. Introduction

Epilepsy, a neurological disorder affecting approximately 50 million people worldwide, is characterized by spontaneous and recurrent seizures [1]. These unpredictable seizures can profoundly affect an individual's quality of life, impacting their daily activities, mobility, and social interactions. Timely and accurate detection of seizures is paramount for managing the disorder and enhancing patients' overall well-being. Electroencephalogram (EEG), a non-invasive technique used to monitor brain activity, is pivotal in diagnosing and managing epilepsy. However, interpreting EEG signals poses a significant challenge due to their inherent complexity and noise. This complexity often hinders the precise detection of seizures. In recent years, the emergence of deep learning techniques has offered a promising avenue for improving epileptic seizure detection from EEG signals. This paper comprehensively reviews the latest advancements in epileptic seizure detection using deep learning methodologies. By harnessing the power of deep learning, researchers have made substantial progress in enhancing the accuracy of seizure detection. The paper contributes to the ongoing efforts to advance the quality of epilepsy management and the lives of individuals affected by this condition. The main contributions to this review are:

1. **Comprehensive Review:** This review provides a comprehensive overview of the current state of epileptic detection methodologies, explicitly focusing on deep learning techniques applied to EEG signals. Covering fundamental concepts and their implications offers readers a holistic understanding of the topic.
2. **Deep Learning Principles:** present various deep learn-

ing architectures used in previous research, including convolutional neural networks, recurrent neural networks, and hybrid models. By emphasizing their strengths and limitations to provide insights into the technical aspects of these methodologies.

3. **Preprocessing Techniques:**The review addresses preprocessing techniques used in previous research to improve EEG data quality, such as noise reduction, artifact removal, and feature extraction. This practical information is crucial for researchers and practitioners working in the field.

4. **Dataset Challenges:**The problem of limited labeled epileptic EEG datasets and present potential solutions. Addressing this challenge is crucial for the advancement of research in this area.

5. **Anticipation of Future direction:**By highlighting challenges like dataset size and diversity, model interpretability, and integration with clinical decision support systems, this review not only discusses current issues but also anticipates future challenges in the field. This forward-looking approach is valuable for researchers.

6. **Contributing to Healthcare Advancements:**Ultimately, the papers comprehensive review and analysis contribute to ongoing efforts to advance the quality of epilepsy management. By showcasing the potential of deep learning techniques, it paves the way for future research and innovations in epileptic seizure detection.

II. Epilepsy Types

Epilepsy might be one of four kinds: focal, generalized, unknown, or unclassified. A focal seizure begins with a single point of attention [2]. The term ”focal” has replaced the phrase ”partial”. The name ”focal” was used since it was deemed more accurate and natural than seizures that begin with a focus [3]. When both brain hemispheres are active at once, it leads to a ”generalized” seizure. A seizure is categorized as having an unknown onset if the history and supporting research do not provide enough information to classify it as focal or generalized. Including ”unknown onset” in the classification has the advantage that it” allows” classification of the remainder of the seizure ”even ”if the onset is unknown [4]. An unclassifiable category is still used in seizure classification; although ”unknown” has been included as a seizure onset type, it is anticipated that it will be used less frequently [5]. Epilepsy affects people of all ages differently, with one peak around the age of 5 to 9 years and the other around the age of 80. There is no gender difference in epilepsy prevalence [6]. Patients can benefit from early detection of epileptic seizures since it improves their quality of life and lowers their risks [7–9]. Epilepsy is a clinical diagnosis based solely on a patient’s medical history, as healthcare providers rarely view the patients seizure activity.

III. Epilepsy Diagnosis Techniques

Effective therapy for epilepsy and seizures depends on a correct diagnosis. Diagnostic testing can assist in identifying whether and where a brain injury produces seizures. Examples of epilepsy diagnosis techniques include:

A. Electroencephalogram EEG:

EEG is the most important diagnostic tool for epilepsy diagnosis [10–14]. It measures brainwaves dynamics and the brains electrical activity [15–17]. Electrodes are placed on various brain areas to record EEG signals, as shown in Fig.1. Different types of seizures are associated with specific EEG patterns:

1. **Interictal Spikes:**
   Brief bursts of high-frequency activity between seizures, indicating an increased risk of seizure occurrence.

2. **Ictal Activity:**
   EEG patterns during a seizure vary based on the seizure type and location.

3. **Slow Waves:**
   Low-frequency waves indicating decreased brain activity after a seizure.

4. **High-Frequency Oscillations (HFOs):**
   Fast EEG oscillations associated with epileptic activity are often observed with interictal spikes.

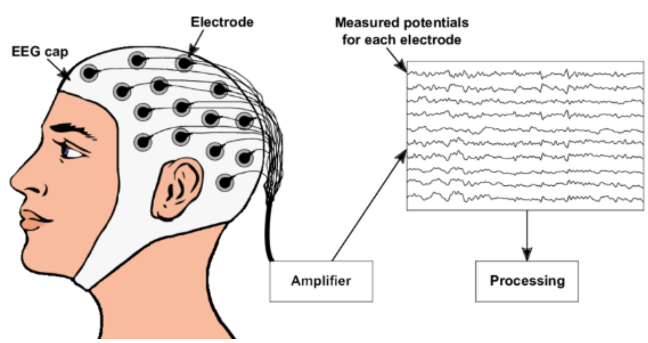

Fig. 1. EEG recording system [12].

Table I describes the key frequencies and amplitudes of human EEG waves. EEG recordings can be obtained through standard EEG, sleep EEG, ambulatory EEG, and video telemetry. However, it's important to note that EEG has limitations in precisely recording deep brain cortex layers.

TABLE I.
BASIC BRAIN WAVES CHARACTERISTICS

Freq. Band	Details		
	Frq. HZ	Amp. mv	states
Gamma	More than 30	5-10	Concentration
Beta	15-30	2-20	Anxiety is prevalent, energetic, focused on others, and calm.
Alpha	9-14	20-60	very calm, unresponsive focus
Theta	4-8	2-100	internally concentrated and deeply relaxed
Delta	1-3	20-200	Sleep

B. Magnetic Radiographic Imaging MRI:

MRI is a radiographic imaging technique used to study the structural and functional problems of epilepsy [18, 19]. Functional MRI (fMRI) observes the brain's reaction to stimuli and helps identify epilepsy etiology. MRI maps the brain's white and grey matter distribution and blood flow rate. While MRI provides detailed images, it is a costly procedure requiring advanced instruments and expertise. [20–23].

C. Modern Techniques for Epileptic Diagnosis:

Technology advancements have led to the integration of Artificial Intelligence (AI) in health systems [24–29]. Machine learning (ML) and deep learning (DL) methodologies are used for epileptic diagnosis [30–35]. ML models require iterative processes of feature selection and classification. In contrast, DL models, such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), demand a large amount of data for effective training [35–39]. Epileptic diagnosis using deep learning involves several stages, as shown in Fig. 2. Here's an outline of the typical stages involved in using deep learning techniques for diagnosing epilepsy: First of all, there may be a need for some process for the dataset, Like :

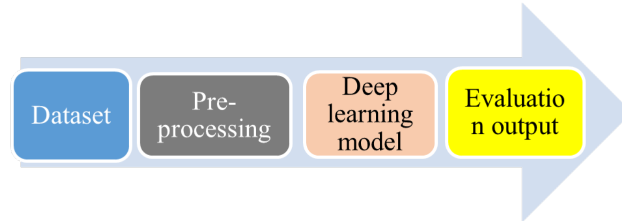

Fig. 2. Stages of epileptic diagnosis by deep learning.

1) Data Preprocessing:

- Clean the EEG data to remove noise and artifacts that might interfere with the analysis.
- Segment EEG signals into smaller epochs for analysis.
- Convert EEG signals into a format suitable for input into deep learning models, such as numerical arrays.

2) Feature Extraction:

- Extract relevant features from EEG signals that indicate different types of epileptic activity.
- Common features include spectral features, statistical measures, and time-domain features.

3) Data Augmentation (Optional):

Augment the dataset by applying transformations like rotation, scaling, or adding noise. This step helps generate more diverse training samples, especially when the original dataset is limited.
Secondly, the Deep learning model needs the following:

1. Model selection:
    - Choose an appropriate deep-learning architecture for the task.
    - Experiment with various architectures to find the most suitable one for the specific EEG classification task.
2. Model Training:
    - Train the selected deep learning model using the pre-processed and augmented data.
    - Utilize appropriate loss functions and optimization techniques for training the model.
    - Monitor the training process, validating the models performance on a separate validation dataset to prevent over-fitting. the specific EEG classification task.

Finally the Evaluation: Evaluate the trained model on a separate test dataset to assess its performance metrics, including accuracy, sensitivity, specificity, and F1 score. Deployment step (Optional):

- If the model performs satisfactorily, deploy it in clinical settings to assist healthcare professionals in epilepsy diagnosis.
- Implement necessary security and privacy measures if the model involves patient data.

Research papers have proposed various deep learning models for EEG classification, each with specific objectives, datasets, preprocessing techniques, classification methods, and software/tools used present in Table II. These papers focus on different EEG classification approaches with varying preprocessing techniques and achieve different levels of accuracy based on their specific objectives and datasets. Every research endeavor has limitations that researchers should strive to mitigate for more precise diagnoses. Simultaneously, there are also advantages that researchers can leverage to enhance their work. These advantages and limitations are detailed in the accompanying Table II. Fig. 3 illustrates the frequency with which distinct deep learning neural network (DNN) methods were employed across the reviewed papers.

IV. Datasets for Epileptic Detection

Recording EEG signals is a challenging and laborious process. Nowadays, numerous internet datasets may be utilized in research. Recording EEG signals is a challenging and laborious process. Additionally, it takes a lot of time to evaluate complex, slow, and fast-varying EEG patterns. Various used certain freely available web datasets, while others require permission from the owners. Table III contains a list of the most popular EEG datasets. The description of the most popular datasets and the website for each one is given in Table IV.

V. Discussions

Deep learning techniques have exhibited remarkable advancements in recent years when applied to epileptic detection, employing methods such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Deep Belief Networks (DBNs) to analyze Electroencephalogram (EEG) signals. These techniques have demonstrated the capability to identify epileptic activity from EEG data with notable accuracy automatically. A fundamental strength of deep learning methods lies in their capacity to extract pertinent features from complex EEG signals autonomously. Unlike traditional methods that necessitate manual feature extraction, deep learning obviates this step, mitigating the risk of human error and reducing subjectivity. Moreover, using extensive datasets for training purposes empowers deep learning models to learn from diverse examples, progressively refining their accuracy and performance. Despite the considerable potential of deep learning approaches in epileptic detection, several challenges demand attention. Foremost among these is the absence of standardized datasets for training and evaluating deep learning models. While several publicly accessible datasets exist, they often exhibit variation in terms of patient numbers, seizure types, and recording equipment employed. This variability poses difficulties in comparing outcomes across different studies and hinders the generalizability of deep learning models. Another pertinent challenge pertains to the interpretability of deep learning models. While these models can attain impressive accuracy in detecting epileptic events, deciphering the underlying rationale for their predictions can prove intricate. The intricate nature of deep learning architectures often makes it challenging to gain insights into the decision-making process of these models. In summary, the recent strides made by deep learning techniques in epileptic detection, facilitated by their automatic feature extraction and extensive learning capabilities, hold substantial promise for improving diagnosis and treatment. Nevertheless, addressing issues such as dataset standardization and model interpretability is essential to fully realize the potential benefits of deep learning in enhancing epileptic detection.

VI. Conclusion

This review has conducted a thorough examination of the use of deep learning techniques in the detection of epileptic seizures. The advances in using deep learning to identify epileptic seizures using electroencephalogram (EEG) signals are promising. Combining different deep learning architectures, such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), and hybrid models, has greatly improved the precision and efficiency of epileptic detection systems. With the growing integration of electronic healthcare, the clinical imperative of an accurate, automated, computer-assisted seizure diagnosis system is more important than ever. However, this pursuit is not without its difficulties. The inherent weakness, instability, and noise of EEG signals—the most commonly used diagnostic signal in this context—underscores the need for novel approaches. Dealing with scarce datasets emphasizes the importance of addressing data scarcity through augmentation techniques. Furthermore, the possibility of automatic EEG signal recording via synchronized camera monitoring and artifact removal to isolate seizure-related activity holds promise for improved diagnostic accuracy. These developments are critical, given the lengthy recording times frequently required for definitive diagnosis. Deep learning-based epileptic detection has enormous poten-

TABLE II.
EPILEPTIC DETECTION FROM EEG SIGNALS

Ref	Objective	Dataset	Pre-processing	Classification Model	Tools	Results
[40]	To assess the accuracy of the model on ictal and interictal EEG recordings.	REPO 2MSE cohort	Downscaled Raw EEG to 256 Hz and split into 5-second overlapping pieces.	CNN for binary classification 2-fully linked layers with a single output are placed after 3 blocks of convolutional layers. Stochastic Gradient Descend SGD optimizer.	Python computer with two A 500 GB of Memory, 32-core AMD EPYC 7551 processors, and Nvidia Tesla T4 GPU. Keras and TensorFlow v1.4. Are used.	Accuracy for 3×131 model = 0.869 while the model 3×5 accuracy = 0.825.
[41]	To evaluate different evaluation techniques on the accuracy of the model.	Bonn University	To divide the signal into segments using the Hamming window with length 128.	CNN with 16 kernels and kernle size is 31 × 1 The batch size is set to 6 and 100 epochs. With Adam optimizer.	Python/ NVIDI NVIDIA GeForce RTX 2080 tests were run with Keras 2.3.1.	Accuracy is: originalEEG =0.949 DWT =0.9595, FFT=0.9371, STFT=0.943, Hybrid =0.9639 EEG _LSTM =0.9787 Hybrid _ LSTM =0.9908.
[42]	To achieve high accuracy in 2-class, 3-class, and 5-class EEG classification.	Bonn University.	Standardize the raw input EEG data to a mean of 0 and a variation of 1.	1D CNN (3- blocks of convolutional, each block consists of 5 layers, then 3 fully connected layers). Batch size =100 with Adam optimizer.	Python Keras, a package built on top of TensorFlow.	DCAE+ Bi-LSTM model has sensitivity =98.72%, specificity =98.86%, accuracy =98.79%, F1-score = 98.79%.
[43]	To achieve high accuracy, sensitivity, specificity, and F1-score in EEG classification.	CHB–MIT.	Signals are filtered between 0 and 128 Hz and sampled at 256 Hz. Use down sampling to reduce dimensionality channel-by-channel z-score normalization.	2D-DCAE using 4 models, 2D-DCAE+MLP, 2D-DCAE+ Bi-LSTM, 2D-DCNN+MLP, 2D-DCNN+ Bi-LSTM) ., Adam optimizer.	Python Google Colaboratory	DCAE+ Bi-LSTM model has sensitivity =98.72%, specificity =98.86%, accuracy =98.79%, F1-score = 98.79%.

TABLE II.
EPILEPTIC DETECTION FROM EEG SIGNALS *(Continued)*

Ref	Objective	Dataset	Preprocessing	Classification Model	Tools	Results
[44]	To achieve high accuracy, sensitivity, and specificity in EEG classification using phase synchronize.	CHB–MIT.	Using the Pauta criterion, reduce the impact of noise. ICA4 for filtering out 95% of the noise. Analysis of variance by P-value method. Phase Synchronization.	Random forest model The outcome is determined by voting or averaging the results optimized parameters by using the grid search.	N/A.	Accuracy =91.78%, sensitivity =91.27%, and specificity =93.61%.
[45]	To achieve high accuracy in EEG classification using short temporal Fourier transforms (STFT).	CHB–MIT.	The short temporal Fourier transforms (STFT) contain time and frequency.	CNN with LeNet-5, the network Two pooling layers and two convolutional layers make up the model.	N/A.	Accuracy in a single channel is 86%. In multichannel the accuracy increased to 90%.
[46]	To achieve high accuracy in binary and ternary EEG classification using spectrogram data.	Bonn University.	A spectrogram is used to translate the EEG signal into visual data.	AlexNet CNN model Convolutional neural network in two dimensions and the idea of transfer learning.	Matlab N/A.	Accuracy for binary classification = 100% and for ternary classification = 100%
[47]	To achieve high classification accuracy in multiple classes using the Epileptic-Net model.	Bonn Universitys.	Splitting EEG signal with a set size window into several smaller signals.	Epileptic-Net model which integrates DCB, FAM, RB, and HT Adam optimizer.	N/A PC with NVIDIA Titan XP Pro GTX1080Ti 12 GB GPU, 1 TB HDD, and 8 GB RAM with an Intel Core i7 3.90 GHz CPU.	classification accuracy in the 2class =99.95%, 3class =99.98%, 4class =99.96%, and 5class = 99.96%.
[48]	To achieve high accuracy in EEG classification using oversampling, sliding window, FFT.	CHB-MIT.	Oversampling method, Sliding window, FFT, and WPD.	3D-CNN. Three distinct CNNs are built to separate deep and beginning features.	N/A	Accuracy = 98.33±0.18

TABLE III.
THE ADVANTAGES AND DISADVANTAGES OF THE RECHERCHE LITERATURE

Ref	Advantages	Disadvantages
[40]	1. The kernel size in the first layer controls retrieved features interpretability and the trained models sensitivity. 2. Amplitude is the most significant feature in ictal prediction. 3. Learning more complex frequency patterns would require a larger patient population.	1. Ignores the correlation between decision probability and crucial frequency components in the internal states of the network. 2. Mishandling the categorization of distinct seizure sub-populations. 3. Signals from improperly classified segments are often totally ictal or entirely interictal, with no clear transition between the immediately preceding pre-itcal segments and seizure onsets.
[41]	1. The smallest variance and the best classification accuracy are produced by hybrid input. 2. Depth-wise separable convolution to reduce the parameters in the network. 3. Utilize regularization.	The classification accuracy performance deteriorated as the training sample count decreased.
[43]	1. The supervised deep convolutional autoencoder (SDCAE) training is faster than typical semi-supervised systems. 2. The number of parameters is reduced because it uses convolutional layers instead of fully connected layers to learn features. 3. Auto Encoder (AE) supervised training is more effective in learning. 4. Plotting with s(1s, 2s, 4s) time segments.	1. Deep learning requires a large dataset; selecting 16 out of the 23 pediatric patients will increase the detection ratio. 2. Do Not use any de-noising method to clean EEG signals.
[44]	1. Increased phase synchronization and the sample entropy improve detection. 2. Using ICA and correlation p-value.	1. Detecting epilepsy by traditional methods. 2. select 23 from 24 pediatric patients using a small dataset. 3. The noise type is not mentioned.
[45]	1. The results demonstrate that the single channel algorithm has an accuracy=86%. 2. The multichannel combination technique improves accuracy by about 4% and raises the TPR to 96.5%.	1. Training Parameters: affect the training process's speed. 2. The Time-size frequency. It's unclear whether the scaling process impacts how the model was trained.
[46]	1. Using 2-dimensional visual data based on graphical monitoring ensures high accuracy rates. 2. The extraction of features is done automatically. 3. With 14 million data points in 1,000 categories, the Alex Net CNN model was successfully trained.	1. The requirement for a GPU computer with significant memory and processing capability and accompanying computational expense 2. Image noise suppression was skipped. 3. A small quantity of training and testing data was used.
[47]	1. Provide patients with epilepsy with a trustworthy diagnosis of their seizures. 2. The Epileptic-Net model performs well when data are added.	1. Performance declines in the absence of augmentation. 2. The difficulty in labeling EEG samples and their rarity.
[48]	1. Low detection delay (1.0431s) is a feature of the suggested technique. 2. The detection success rate is 99.95%, meaning all epileptic events may be identified in less than 10 seconds.	1. Among other pertinent aspects, statistical and nonlinear patterns in EEG data can be employed to enhance detection. 2. A more effective multi-view learning process is required.

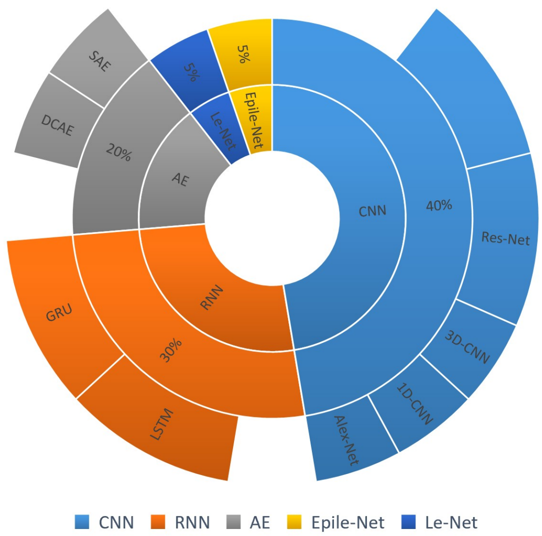

Fig. 3. DNN models percentage used in paper.

TABLE IV.
POPULAR EEG DATASETS

Ref	Dataset	Participant	Channels
[49]	Siena Scalp EEG Database	14	29
[50]	Neurologists at Nilratan Sircar Medical College and Hospital (NRSMCH)	150	21
[51]	Seoul National University Hospital (SNUH) Scalp EEG database	25	21
[52]	Ramaiah Medical College and Hospital (RMCH)	115	19
[53]	NICU of Helsinki University Hospital , Finland	79	19
[54]	Neurology and sleep center New Delhi EEG	10	57
[55]	Children's Hospital Boston–MIT database	22	23-26
[56]	Bonn EEG time-series database	5	100

TABLE V.
DESCRIPTION FOR POPULAR DATASETS

Ref	Description	Website
[56]	Bonn University: contains five classes and 11500 EEG samples, and at 173.61 Hz, it is sampled and recorded. A, B, C, D, and E represent the five categories that make up the dataset. Using the common 10-20 electrode placement approach, each category has 100 recorded EEG data. Each EEG signal is 4097 bytes long.	www.upf.edu/web /ntsa/downloads/
[55]	CHB–MIT contains 24 people with epileptic seizures, ranging in age from 3 to 22. A total of 23 channels are used to monitor each patient for 46 hours. 18 women and 5 men. 256 Hz is the sample rate employed.	physionet.org /content/chbmit /1.0.0/
[40]	REPO2MSE cohort: Consists of 568 epileptic patients multichannel scalp EEG recordings with annotations about the start of seizures provided by a knowledgeable epileptologist. EEG data were captured at 256 Hz, 512 Hz, or 1024 Hz.	www.response studie.nl/

tial for revolutionizing epilepsy diagnosis and management. By seamlessly integrating these techniques into healthcare systems, we have the potential to unlock the benefits of early detection, tailored treatment strategies, and improved quality of life for people living with epilepsy. As progress continues, sustained collaboration between deep learning and epilepsy experts will be critical in realizing these transformative possibilities. Anticipating future directions in epilepsy diagnosis using deep learning involves considering emerging technologies and novel methodologies and addressing current limitations. Here are some potential directions:

1. Incorporating Multi-Modal Data: Integrate data from multiple sources such as EEG, functional MRI (fMRI), genetic information, and patient clinical histories. Combining these data types could provide a more comprehensive understanding of epilepsy and improve diagnostic accuracy.

2. Exploring Advanced Neural Network Architectures: Investigate newer neural network architectures such as transformers, graph neural networks, and attention mechanisms. These architectures have shown promise in various domains and might offer improved performance in EEG analysis for epilepsy detection.

3. Utilizing Explainable AI (XAI) Techniques: Develop models that provide accurate predictions and insights into the reasoning behind these predictions. Explainable AI techniques, such as attention maps and saliency maps, can enhance the interpretability of deep learning models, making them more reliable for clinical use.

4. Addressing Data Imbalance: Research methodologies to handle class imbalance in EEG datasets, especially for rare seizure types. Techniques like data augmentation, transfer learning, and ensemble methods can help mitigate the challenges of imbalanced datasets.

5. Real-time Seizure Prediction: Focus on developing real-time seizure prediction systems that provide timely alerts to patients or caregivers. Integrating wearable devices and mobile applications with deep learning models can facilitate early warnings and improve patient safety.

6. Personalized Medicine: Investigate the potential of personalized deep learning models tailored to individual patients. Utilize patient-specific data to train models uniquely tuned to each person's brain patterns, thereby enhancing the accuracy of predictions and treatment recommendations.

7. Integration with Clinical Workflow: Collaborate with healthcare professionals to integrate deep learning models into clinical workflows. User-friendly interfaces and seamless integration with existing hospital systems are crucial for adopting AI technologies in real-world medical settings.

8. Longitudinal Data Analysis: Analyze longitudinal EEG data to understand the progression of epilepsy over time. Long-term studies can provide valuable insights into the evolution of the disease, leading to more effective treatment strategies.

9. Ethical and Privacy Considerations: Investigate ethical implications, patient privacy concerns, and data security issues associated with deploying deep learning models in healthcare. Addressing these ethical challenges is crucial for the responsible implementation of AI technologies in the medical domain.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest in relation to this paper and the published research results, including the financial aspects of conducting the research, obtaining and using its results, and any non-financial personal relationships.

REFERENCES

[1] J. Falco-Walter, "Epilepsy—definition, classification, pathophysiology, and epidemiology," in *Seminars in neurology*, vol. 40, pp. 617–623, Thieme Medical Publishers, Inc. 333 Seventh Avenue, 18th Floor, New York, NY . . . , 2020.

[2] T. Vos, C. Allen, M. Arora, and R. Barber, "A systematic analysis for the global burden of disease study 2016," *Lancet*, vol. 390, no. 2017, pp. 1151–1210, 2017.

[3] E. CERULLI IRELLI *et al.*, "Phenotypic spectrum and prognostic factors in epilepsy with eyelid myoclonia," *Rev Neurol (Paris)*, vol. 179, 2023.

[4] S. Makkawi, F. S. Alshehri, A. A. Malaikah, A. M. Alghamdi, R. M. Al-Zahrani, R. J. Nahas, M. A. Khan, A. Y. Hakami, D. A. Babaer, R. M. Al-zahrani, *et al.*, "Prevalence of etiological factors in adult patients with epilepsy in a tertiary care hospital in the western region of saudi arabia: A cross-sectional study," *Cureus*, vol. 15, no. 1, 2023.

[5] M. A. de Bruijn, A. Van Sonderen, M. H. van Coevorden-Hameete, A. E. Bastiaansen, M. W. Schreurs, R. P.

Rouhl, C. A. van Donselaar, M. H. Majoie, R. F. Neuteboom, P. A. Sillevis Smitt, *et al.*, "Evaluation of seizure treatment in anti-lgi1, anti-nmdar, and anti-gababr encephalitis," *Neurology*, vol. 92, no. 19, pp. e2185–e2196, 2019.

[6] S. S. Abdulwahab, H. K. Khleaf, M. H. Jassim, and S. Abdulwahab, "A systematic review of brain-computer interface based eeg," *Iraqi J. Electr. Electron. Eng*, vol. 16, no. 2, pp. 1–10, 2020.

[7] A. Shoeibi, M. Khodatars, N. Ghassemi, M. Jafari, P. Moridian, R. Alizadehsani, M. Panahiazar, F. Khozeimeh, A. Zare, H. Hosseini-Nejad, *et al.*, "Epileptic seizures detection using deep learning techniques: A review," *International Journal of Environmental Research and Public Health*, vol. 18, no. 11, p. 5780, 2021.

[8] A. Omidvarnia, M. A. Kowalczyk, M. Pedersen, and G. D. Jackson, "Towards fast and reliable simultaneous eeg-fmri analysis of epilepsy with automatic spike detection," *Clinical Neurophysiology*, vol. 130, no. 3, pp. 368–378, 2019.

[9] I. S. Al-Furati and A. I. AL-Mayoof, "Design and implementation of an injury detection system for corona tracker," *Iraqi Journal for Electrical And Electronic Engineering*, vol. 18, no. 2, 2022.

[10] P. Thangavel, J. Thomas, N. Sinha, W. Y. Peh, R. Yuvaraj, S. S. Cash, R. Chaudhari, S. Karia, J. Jing, R. Rathakrishnan, *et al.*, "Improving automated diagnosis of epilepsy from eegs beyond ieds," *Journal of Neural Engineering*, vol. 19, no. 6, p. 066017, 2022.

[11] M. Liu, B. Liu, Z. Ye, and D. Wu, "Bibliometric analysis of electroencephalogram research in mild cognitive impairment from 2005 to 2022," *Frontiers in Neuroscience*, vol. 17, p. 1128851, 2023.

[12] H. B. Hawsawi, P. J. Allen, T. Warbrick, R. Störmer, G. Iannotti, F. Grouiller, S. Vulliemoz, and L. Lemieux, "Eeg instrumentation and safety in the mri environment," in *EEG-fMRI: Physiological Basis, Technique, and Applications*, pp. 141–166, Springer, 2023.

[13] G. A. Buzzell, Y. Niu, S. Aviyente, and E. Bernat, "A practical introduction to eeg time-frequency principal components analysis (tf-pca)," *Developmental Cognitive Neuroscience*, vol. 55, p. 101114, 2022.

[14] S. Beniczky, H. Aurlien, J. C. Brøgger, L. J. Hirsch, D. L. Schomer, E. Trinka, R. M. Pressler, R. Wennberg, G. H. Visser, M. Eisermann, *et al.*, "Standardized computer-based organized reporting of eeg: Score–second version," *Clinical Neurophysiology*, vol. 128, no. 11, pp. 2334–2346, 2017.

[15] S. W. Roberson, P. Shah, V. Piai, H. Gatens, A. M. Krieger, T. H. Lucas II, and B. Litt, "Electrocorticography reveals spatiotemporal neuronal activation patterns of verbal fluency in patients with epilepsy," *Neuropsychologia*, vol. 141, p. 107386, 2020.

[16] S. Abdulwahab, H. Khleaf, and M. Jassim, "Eeg motor-imagery bci system based on maximum overlap discrete wavelet transform (modwt) and machine learning algorithm," *Iraqi Journal for Electrical and Electronic Engineering*, vol. 17, no. 2, pp. 38–45, 2021.

[17] R. Bandopadhyay, T. Singh, M. M. Ghoneim, S. Alshehri, E. Angelopoulou, Y. N. Paudel, C. Piperi, J. Ahmad, N. A. Alhakamy, M. A. Alfaleh, *et al.*, "Recent developments in diagnosis of epilepsy: scope of microrna and technological advancements," *Biology*, vol. 10, no. 11, p. 1097, 2021.

[18] A. S. Konar, A. D. Shah, R. Paudyal, M. Fung, S. Banerjee, A. Dave, V. Hatzoglou, and A. Shukla-Dave, "Quantitative synthetic magnetic resonance imaging for brain metastases: a feasibility study," *Cancers*, vol. 14, no. 11, p. 2651, 2022.

[19] H. Odéen and D. L. Parker, "Magnetic resonance thermometry and its biological applications–physical principles and practical considerations," *Progress in nuclear magnetic resonance spectroscopy*, vol. 110, pp. 34–61, 2019.

[20] B. Heim, S. Mangesius, F. Krismer, G. K. Wenning, A. Hussl, C. Scherfler, E. R. Gizewski, M. Schocke, R. Esterhammer, A. Quattrone, *et al.*, "Diagnostic accuracy of mr planimetry in clinically unclassifiable parkinsonism," *Parkinsonism & Related Disorders*, vol. 82, pp. 87–91, 2021.

[21] A. Z. Atiyah and K. H. Ali, "Brain mri images segmentation based on u-net architecture," *IJEEE Journal*, pp. 21–27, 2021.

[22] J.-G. Yoo, D. Jakabek, H. Ljung, D. Velakoulis, D. van Westen, J. C. Looi, and K. Källén, "Mri morphology of the hippocampus in drug-resistant temporal lobe epilepsy: Shape inflation of left hippocampus and correlation of right-sided hippocampal volume and shape with visuospatial function in patients with right-sided tle," *Journal of Clinical Neuroscience*, vol. 67, pp. 68–74, 2019.

[23] A. Massot-Tarrús and S. M. Mirsattari, "Roles of fmri and wada tests in the presurgical evaluation of language functions in temporal lobe epilepsy," *Frontiers in Neurology*, vol. 13, p. 884730, 2022.

[24] O. S. Atiyah and S. H. Thalij, "A comparison of coivd-19 cases classification based on machine learning approaches," *Iraqi Journal for Electrical and Electronic Engineering*, vol. 18, no. 1, pp. 139–143, 2022.

[25] E. Tuncer and E. D. Bolat, "Classification of epileptic seizures from electroencephalogram (eeg) data using bidirectional short-term memory (bi-lstm) network architecture," *Biomedical Signal Processing and Control*, vol. 73, p. 103462, 2022.

[26] G. Y. Abbass and A. F. Marhoon, "Iraqi license plate detection and segmentation based on deep learning," *Iraqi Journal for Electrical and Electronic Engineering*, vol. 17, no. 2, pp. 102–107, 2021.

[27] E. B. Assi, D. K. Nguyen, S. Rihana, and M. Sawan, "Towards accurate prediction of epileptic seizures: A review," *Biomedical Signal Processing and Control*, vol. 34, pp. 144–157, 2017.

[28] J. B. Romaine, M. Pereira Martín, J. R. Salvador Ortiz, and J. M. Manzano Crespo, "Eeg—single-channel envelope synchronisation and classification for seizure detection and prediction," *Brain Sciences*, vol. 11, no. 4, p. 516, 2021.

[29] M. Abdulla and A. Marhoon, "Deep learning and iot for monitoring tomato plant," *Iraqi Journal for Electrical and Electronic Engineering*, vol. 19, 2023.

[30] S. A. Thamer and M. A. Alshmmri, "Detection of covid-19 using cad system depending on chest x-ray and machine learning techniques," *Iraqi Journal for Electrical And Electronic Engineering*, vol. 18, no. 2, 2022.

[31] A. Craik, Y. He, and J. L. Contreras-Vidal, "Deep learning for electroencephalogram (eeg) classification tasks: a review," *Journal of neural engineering*, vol. 16, no. 3, p. 031001, 2019.

[32] M. Natu, M. Bachute, S. Gite, K. Kotecha, A. Vidyarthi, *et al.*, "Review on epileptic seizure prediction: machine learning and deep learning approaches," *Computational and Mathematical Methods in Medicine*, vol. 2022, 2022.

[33] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "Imagenet classification with deep convolutional neural networks," *Communications of the ACM*, vol. 60, no. 6, pp. 84–90, 2017.

[34] W. H. Park, N. M. F. Qureshi, and D. R. Shin, "An effective 3d text recurrent voting generator for metaverse," *IEEE Transactions on Affective Computing*, 2022.

[35] S. K. Jawad and M. Alaziz, "Human activity and gesture recognition based on wifi using deep convolutional neural networks," *Iraqi Journal for Electrical And Electronic Engineering*, vol. 18, no. 2, 2022.

[36] R. Chai, S. H. Ling, P. P. San, G. R. Naik, T. N. Nguyen, Y. Tran, A. Craig, and H. T. Nguyen, "Improving eeg-based driver fatigue classification using sparse-deep belief networks," *Frontiers in neuroscience*, vol. 11, p. 103, 2017.

[37] L. Vařeka and P. Mautner, "Stacked autoencoders for the p300 component detection," *Frontiers in neuroscience*, vol. 11, p. 302, 2017.

[38] A. Ditthapron, N. Banluesombatkul, S. Ketrat, E. Chuangsuwanich, and T. Wilaiprasitporn, "Universal joint feature extraction for p300 eeg classification using multi-task autoencoder," *IEEE access*, vol. 7, pp. 68415–68428, 2019.

[39] N. A. Noori and A. A. Yassin, "Towards for designing intelligent health care system based on machine learning.," *Iraqi Journal for Electrical & Electronic Engineering*, vol. 17, no. 2, 2021.

[40] V. Gabeff, T. Teijeiro, M. Zapater, L. Cammoun, S. Rheims, P. Ryvlin, and D. Atienza, "Interpreting deep learning models for epileptic seizure detection on eeg signals," *Artificial intelligence in medicine*, vol. 117, p. 102084, 2021.

[41] Y. Pan, X. Zhou, F. Dong, J. Wu, Y. Xu, S. Zheng, *et al.*, "Epileptic seizure detection with hybrid time-frequency eeg input: a deep learning approach," *Computational and Mathematical Methods in Medicine*, vol. 2022, 2022.

[42] W. Zhao, W. Zhao, W. Wang, X. Jiang, X. Zhang, Y. Peng, B. Zhang, G. Zhang, *et al.*, "A novel deep neural network for robust detection of seizures using eeg signals," *Computational and mathematical methods in medicine*, vol. 2020, 2020.

[43] A. Abdelhameed and M. Bayoumi, "A deep learning approach for automatic seizure detection in children with epilepsy," *Frontiers in Computational Neuroscience*, vol. 15, p. 650050, 2021.

[44] Y. Ru, J. Li, H. Chen, J. Li, *et al.*, "Epilepsy detection based on variational mode decomposition and improved

sample entropy," *Computational Intelligence and Neuroscience*, vol. 2022, 2022.

[45] Y. Cao, Y. Guo, H. Yu, and X. Yu, "Epileptic seizure auto-detection using deep learning method," in *2017 4th International Conference on Systems and Informatics (ICSAI)*, pp. 1076–1081, IEEE, 2017.

[46] H. S. Nogay and H. Adeli, "Detection of epileptic seizure using pretrained deep convolutional neural network and transfer learning," *European neurology*, vol. 83, no. 6, pp. 602–614, 2021.

[47] M. S. Islam, K. Thapa, and S.-H. Yang, "Epileptic-net: an improved epileptic seizure detection system using dense convolutional block with attention network from eeg," *Sensors*, vol. 22, no. 3, p. 728, 2022.

[48] X. Tian, Z. Deng, W. Ying, K.-S. Choi, D. Wu, B. Qin, J. Wang, H. Shen, and S. Wang, "Deep multi-view feature learning for eeg-based epileptic seizure detection," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 27, no. 10, pp. 1962–1972, 2019.

[49] P. Detti, "Siena scalp eeg database," *PhysioNet. doi*, vol. 10, 2020.

[50] K. Das, D. Daschakladar, P. P. Roy, A. Chatterjee, and S. P. Saha, "Epileptic seizure prediction by the detection of seizure waveform from the pre-ictal phase of eeg signal," *Biomedical Signal Processing and Control*, vol. 57, p. 101720, 2020.

[51] G. Choi, C. Park, J. Kim, K. Cho, T.-J. Kim, H. Bae, K. Min, K.-Y. Jung, and J. Chong, "A novel multi-scale 3d cnn with deep neural network for epileptic seizure detection," in *2019 IEEE International Conference on Consumer Electronics (ICCE)*, pp. 1–2, IEEE, 2019.

[52] S. Raghu, N. Sriraam, Y. Temel, S. V. Rao, A. S. Hegde, and P. L. Kubben, "Performance evaluation of dwt based sigmoid entropy in time and frequency domains for automated detection of epileptic seizures using svm classifier," *Computers in biology and medicine*, vol. 110, pp. 127–143, 2019.

[53] N. J. Stevenson, K. Tapani, L. Lauronen, and S. Vanhatalo, "A dataset of neonatal eeg recordings with seizure annotations," *Scientific data*, vol. 6, no. 1, pp. 1–8, 2019.

[54] P. Swami, B. Panigrahi, S. Nara, M. Bhatia, and T. Gandhi, "Eeg epilepsy datasets," *DOI: https://doi.org/10.13140/RG*, vol. 2, no. 14280.32006, 2016.

[55] A. H. Shoeb, *Application of machine learning to epileptic seizure onset detection and treatment*. PhD thesis, Massachusetts Institute of Technology, 2009.

[56] R. G. Andrzejak, K. Schindler, and C. Rummel, "Nonrandomness, nonlinear dependence, and nonstationarity of electroencephalographic recordings from epilepsy patients," *Physical Review E*, vol. 86, no. 4, p. 046206, 2012.