A Comprehensive Survey of EEG-Based Seizure Detection Techniques: Deep Learning Advancements and Transfer Learning Strategies

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Abstract

This survey paper comprehensively reviews recent advancements in the field of seizure detection using EEG signals, focusing on their applications in epilepsy management. The study encompasses a diverse array of methodologies, including deep learning models and feature extraction techniques, and critically examines their respective advantages and limitations. Notably, deep learning models like CNNs and RNNs are highlighted for their capacity to autonomously learn features directly from raw EEG data. Additionally, various strategies such as transfer learning and autoencoders are explored, which play a pivotal role in refining detection accuracy and minimizing false alarms. The incorporation of domain knowledge and innovative graph-based approaches further enriches the discussion, offering insights into subject-independent prediction strategies. The paper acknowledges persisting challenges related to dataset size and real-time implementation. In conclusion, these advancements hold immense potential for transforming epilepsy care by revolutionizing early detection and management through EEG-based seizure detection systems. This comprehensive survey serves as a valuable resource for researchers and practitioners seeking to navigate the rapidly evolving landscape of EEG-based seizure detection.

Keywords: EEG, Epilepsy, Seizure Detection Techniques, Deep Learning.

1 INTRODUCTION

Epilepsy, characterized by transient abnormal neuronal activity in the brain, leads to seizures—brief changes in [1] behavior, movement, or awareness. Seizures are categorized as generalized (affecting both hemispheres) or partial (affecting one hemisphere), with convulsive and non-convulsive subtypes. While convulsive seizures are more common, affecting 60% of the 50 million epilepsy patients worldwide, non-convulsive seizures also have a significant impact. Imbalances between inhibitory and excitatory neurotransmitter activities, resulting from factors like brain injury and genetic conditions, underlie continuous seizures [2]. Despite ongoing research advancements, epilepsy remains a significant concern, especially due to its unpredictable nature and potential cognitive consequences.

The field of epilepsy diagnosis, prevention, and treatment has greatly advanced, driven by signal and image processing techniques like EEG, video EEG telemetry, MEG, CT, MRI, and more [4]. EEG, for instance, records brain electrical signals and helps identify seizures and disorders [6-9]. Recent years have witnessed notable strides in seizure detection algorithms, leveraging analytical and machine-learning-based approaches [5]. Feature selection plays a crucial role in the classification process, enhancing spatial specificity and overall detection accuracy.

The global prevalence of epilepsy, affecting 60 to 70 million individuals, underscores its significance [7]. Timely detection and intervention are crucial, as the condition can severely impact an individual's quality of life. Epilepsy's diverse causes—ranging from genetic factors to oxygen deprivation—necessitate effective management strategies. Proper diagnosis and treatment can significantly enhance patients' well-being, reducing mortality risks and improving overall outcomes [8], [9]. Neuroimaging techniques, including EEG, remain integral to monitoring and managing the condition [10]. However, the challenge persists in devising accurate and efficient seizure detection methods.

In recent years, the emergence of deep learning models has garnered substantial attention in the domain of seizure detection. From convolutional neural networks (CNNs) to recurrent neural networks (RNNs), these models showcase the potential to extract pertinent information directly from raw EEG data, thus enhancing diagnostic accuracy [13]. Nonetheless, challenges remain, including data dependency and algorithm complexity. In conclusion, this survey provides a comprehensive overview of the progress and challenges in EEG-based seizure detection for epilepsy management, serving as a valuable resource for researchers and practitioners in advancing this critical field.

2 RELATED WORK

In a study by [16], a robust seizure detection technique was demonstrated using a 13-layer deep convolutional neural network. This approach focused on feature selection and extraction, although it was noted that a significant amount of data is required for effective deep learning. Similarly, [17] introduced a 3D-CNN classification algorithm for epilepsy incidents, transforming EEG-generated 2D images into 3D representations to identify distinct seizure periods. An innovative CNN-based method was proposed by [18] for seizure detection, bypassing the need for manual feature extraction. Their model incorporated multiscale convolution, attention-based, and multistream recurrent bidirectional approaches, accommodating EEG data with missing channels. A hybrid approach by Jana et al. [19] combined 1D CNN and spectrograms, capturing spatiotemporal patterns to predict seizure onset and termination. Transfer learning and CNN were employed in [20] to identify seven seizure types, utilizing ten neural networks pre-trained on transfer learning. Furthermore, [21] developed a CNN utilizing patient-specific autoencoders (AE) to generate EEG plot images, reducing false alarms in seizure detection. Wen et al. introduced the autoencoder-based model and deep convolution network (AE-CDNN) [22], which outperformed principal component analysis and sparse random projection-derived features in classifying EEG data from publicly available datasets (Bonn and Boston) [23].

The ESD-LSTM technique was endorsed by [22] for highly accurate epileptic seizure (ES) detection, and [23] proposed an RNN model using discrete wavelet transform (DWT)-derived features to recognize epileptic EEG patterns. Table 1 shows the survey table.

Table 1 Survey Table

Reference	Approach/Model	Advantages	Dis-advantages
[20]	13-layer CNN	Reliable detection; feature extraction	Requires large dataset
[21]	3D-CNN, LSTM	Utilizes EEG images; detects seizures	Requires additional data; preprocessing
[22]	CNN-BiRNN	Captures patterns; interprets EEG	Complex architecture
[23]	Hybrid approach	Captures spatiotemporal patterns	Lacks precision
[24]	CNN with AE	Reduces false alarms; interprets AE	Limited precision; requires labeled data
[25]	RNN with DWT	High-level recognition; DWT features	Dependent on DWT
[26]	Bi-LSTM with DCAE	Effective prediction; spatial-temporal	Data collection challenge

The authors of [24] conducted a comparative analysis of their RNN against other machine learning models, finding superior performance for Bi-LSTM and the Deep Convolutional Autoencoder (DCAE) model. The combination of Bi-LSTM and DCAE showed greater effectiveness when compared to four other techniques. Bi-LSTM extracted temporal information from raw EEG data, while DCAE focused on learning spatial information. The utilization of transfer learning reduced training time for semi-supervised learning based on DCAE, rendering it suitable for real-time applications. However, challenges could arise in collecting essential data before initiating forecasts. A method proposed in [25] involved EEMD for feature extraction and LSTM for classification in epilepsy detection. EEMD effectively revealed intrinsic mode functions using Akima Spline Interpolation for signal analysis, followed by Kalman filter noise reduction. Another approach in [26] employed the Deep C-

LSTM algorithm to identify tumors and ES, involving DCNN and LSTM layers with the Adam optimizer. Data scarcity remains a concern for model training. To minimize computational complexity, a Bi-LSTM network was introduced by [26] for seizure detection using local mean decomposition.

For early seizure detection in epilepsy using EEG, specialized equipment has been developed for accurate monitoring before seizures. Automated epilepsy prediction systems rely on machine-learning techniques for EEG classification [27]. Feature-based classification in machine learning provides a highly discriminatory approach, facilitating patient status analysis and comparison over time [28]. Deep learning applications are prevalent due to their effectiveness [29]. Unsupervised learning with autoencoders is employed for EEG feature learning in automated seizure detection [30]. Deep transfer learning (TL) is advantageous for feature extraction in epilepsy analysis [31]. MPCNN [31] is trained using TL for general feature generation and classification of epileptic patterns, allowing the detection of focal and non-focal epilepsy. Convolutional neural networks extract EEG features and LSTM bidirectional predicts interictal and preictal states [31]. Transfer learning aids deep learning convolutional autoencoders in feature extraction [31]. In [32], Inception-v2-Resnet combined with MAS differentiates ictal, interictal, and preictal stages for epilepsy threat assessment.

A comprehensive EEGWaveNet [33] employing convolutional depth-wise architecture simultaneously captures features from each EEG channel, extracting spatial-temporal features for classification. The kernelized filtering approach, proven successful in seizure detection classification [34], assesses EEG data differences. For continuous EEG recordings, the kernel approach enables linear separability representation, effectively categorizing data and mapping samples to high-dimensional feature spaces. However, linearly separable methods may not be suitable for long-term EEG data classification due to their non-linearity. Table 2 shows the survey table.

Table 2 Survey Table

Study	**Approach/Model**	**Advantages**	**Dis-advantages**
[20]	Machine learning	High discrimination; efficient	Limited to feature-based classification
[21]	Wavelet technique	Identifies patients; preprocessing	Requires specialized knowledge
[22]	RNN, unsupervised learning	Automatic feature extraction	Limited precision; unlabeled data
[23]	Transfer learning	Efficient extraction/identification	Dependence on pretrained DNN
[24]	MPCNN with transfer	Reduces false alarms; AlexNet	Limited precision; focal/non-focal
[25]	CNN, LSTM	Extracts EEG features; prediction	Data dependency; preprocessing
[26]	DL autoencoder, transfer	Efficient feature extraction	Complex architecture

[27]	Inception-ResNet, transfer	Differentiates stages; MAS	Requires specialized knowledge
[28]	EEGWaveNet, transfer	Extracts spatial-temporal features	Complex architecture
[29]	Seizure predictor, GDL	Subject-independent prediction	Requires graph synthesis; specialized DL
[30]	Metric DL with CNN	Addresses few-shot; strategy	Two-stage approach
[31]	Unified framework	Operates across machines; DL	Potential complexity in implementation

3 CONCLUSION

In conclusion, this survey paper has extensively reviewed recent progress in EEG-based seizure detection methods for epilepsy management. The exploration of diverse techniques, including deep learning models and feature extraction, has illuminated both potentials and challenges. Notably, CNNs and RNNs have shown promise in autonomously extracting relevant information from raw EEG data, enhancing detection accuracy. Integrating transfer learning, autoencoders, and domain knowledge has advanced the field, addressing issues like false alarms and subject-independent predictions. Despite ongoing challenges, these advancements hold the potential to significantly improve epilepsy care by enabling timely interventions. Serving as a valuable resource, this survey guides researchers and practitioners, fostering continued innovation for enhanced epilepsy management and intervention.

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