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Epileptic Seizure Detection Using a Transfer Entropy-based Causal Deep Learning Model

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Introduction

Epilepsy is a chronic neurological disorder characterized by recurrent, unpredictable seizures caused by abnormal electrical activity in the brain. Affecting over 50 million individuals globally, it imposes a significant burden on patients, caregivers, and healthcare systems. Accurate and timely detection of epileptic seizures is essential for diagnosis, treatment optimization, and patient safety. Traditionally, seizure detection has relied on manual interpretation of Electroencephalogram (EEG) recordings by trained neurologists. However, this method is labour-intensive, time-consuming, and subject to inter-rater variability. As such, there is an urgent need for automated, real-time, and highly accurate seizure detection systems. In recent years, the integration of Artificial Intelligence (AI) and particularly deep learning techniques has revolutionized biomedical signal processing, offering novel approaches for modelling complex, nonlinear patterns in EEG data. One of the emerging frontiers in this domain involves the fusion of deep learning with causality-based frameworks particularly those using transfer entropy to improve seizure detection accuracy and interpretability. This paper explores a modern approach for epileptic seizure detection using a transfer entropy-based causal deep learning model that leverages spatio-temporal features to extract meaningful patterns of brain connectivity during ictal and interictal states [1].

Description

Deep learning architectures such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and transformer-based models have demonstrated significant success in seizure detection due to their ability to automatically learn hierarchical features from raw EEG data. However, most of these models treat EEG signals primarily as spatial or temporal sequences without explicitly considering the causal relationships between different brain regions. Yet, in neuroscience, understanding the directionality and influence of neuronal interactions especially during the transition into a seizure is crucial. This is where Transfer Entropy (TE) becomes particularly valuable. Transfer entropy is a model-free, information-theoretic measure of directed (causal) information flow between time series. Unlike linear measures such as Granger causality, TE captures nonlinear, dynamic dependencies, making it well-suited for analyzing brain signals where interactions are often non-linear and time-varying. The proposed approach integrates causal inference using transfer entropy into a spatio-temporal deep learning pipeline. In this framework, multichannel EEG signals are first preprocessed (e.g., artifact removal, band-pass filtering) and then transformed into a causal connectivity matrix using pairwise or multivariate TE [2].

This matrix, which represents the directional flow of information between different EEG channels (brain regions), captures the topological and functional reorganization of the brain during seizures. These causal graphs can be treated as dynamic sequences or image-like representations, which are then fed into deep learning models such as a hybrid CNN-LSTM or Graph Neural Network (GNN) to classify seizure and non-seizure states. This architecture offers several advantages over traditional deep learning models. First, by incorporating causal structure, the model is able to better distinguish between functionally connected regions and mere statistical correlations, reducing noise and improving generalization. Second, the use of spatio-temporal modelling allows the system to capture both the spatial layout of brain interactions and their evolution over time, critical for identifying pre-ictal warning signs or sudden seizure onsets. Third, integrating TE improves the explain ability of the model. Unlike black-box approaches, the derived TE matrices can be visualized and interpreted by clinicians as functional brain networks, offering insights into which regions are initiating and propagating seizure activity [3].

In terms of performance, studies have shown that TE-based features enhance classification accuracy, sensitivity, and specificity in seizure detection tasks. Benchmark datasets such as the CHB-MIT Scalp EEG Database and Freiburg Intracranial EEG data are often used to evaluate these models. When tested on such datasets, the proposed models typically outperform baseline architectures that use raw EEG or simple statistical features. Furthermore, the use of transfer learning where pretrained models are fine-tuned on patient-specific data can further boost performance, addressing the challenge of inter-patient variability. Beyond seizure detection, this model architecture has implications for real-time monitoring systems, such as wearable or implantable devices, where early seizure detection can trigger therapeutic interventions (e.g., responsive neuro stimulation, medication delivery). The efficiency of TE computation has also improved thanks to parallelization techniques and GPU acceleration, making it feasible to deploy such causal deep learning models in near-real-time applications. However, challenges remain. TE estimation can be sensitive to parameter choices such as embedding dimension and time delay. Also, high-dimensional TE computations may be computationally expensive, especially with long EEG recordings or high-density electrode arrays [4].

To address this, researchers have proposed dimensionality reduction techniques (e.g., PCA, ICA), adaptive TE estimators, and sparsity-based models that focus on the most informative channel pairs. There is also growing interest in combining TE with attention mechanisms, allowing models to learn which causal interactions are most relevant for seizure detection. The clinical translation of this approach depends on robust validation, generalizability across diverse datasets, and the ability to integrate with EEG acquisition systems. Interdisciplinary collaboration between data scientists, neurologists, and engineers will be essential for refining these models and establishing their practical utility in real-world settings. Furthermore, spatio-temporal architectures provide a comprehensive view of brain network behaviour over time, making them particularly well-suited for detecting subtle precursors to seizures and enabling early intervention. While challenges in computation, generalization, and integration remain, the trajectory of research points strongly toward the adoption of causality-aware, AI-driven systems in the next generation of neuro diagnostic tools [5].

Conclusion

The integration of transfer entropy with deep learning represents a powerful paradigm shift in the field of epileptic seizure detection. By capturing the causal, spatio-temporal dynamics of brain activity, these models move beyond traditional pattern recognition, offering more robust, interpretable, and biologically meaningful insights into the onset and propagation of seizures. The use of transfer entropy as a core feature extractor enables deep learning

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models to distinguish true neural connectivity from statistical noise, improving both performance and clinical relevance. As these technologies mature, they hold the promise of transforming epilepsy care enhancing diagnostic precision, enabling personalized monitoring, and ultimately improving quality of life for millions of patients worldwide.

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Conflict of Interest

There are no conflicts of interest by author.

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