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RESEARCH ARTICLE

Development of Deep Learning Algorithms for Automatic Detection of Subtle Patterns in EEG Signals for the Diagnosis and Monitoring of Subclinical Seizure Activity

Hussein Mohammed Qasim [1*]

[1] Biomedical Engineering Technical Department, Hakim Sabzevari University, Sabzevar, Iran

* Corresponding Author Email: hussen.hu777@gmail.com

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Abstract

Subclinical seizures are subtle neurologic events that remain largely undetectable during standard electroencephalography (EEG), and thus present critical barriers to timely diagnosis and monitoring of affected individuals. In this paper, we propose a deep learning framework for automatic detection of subtle patterns in EEG signals that are indicative of subclinical seizure activity. The available high-quality EEG data were preprocessed with band-pass and notch filters, ICA-based artifact removal, as well as splitting into fixed-sized epochs. Multiple input representations including raw signals, spectrograms, and wavelet transforms were used to broaden the feature extraction power of the model. A variety of deep learning architectures (such as CNNs, LSTM networks and hybrid CNN-LSTM models) were all designed and trained based on supervised training. The performance of the models was assessed using accuracy, sensitivity, specificity, F1-score and AUC. The hybrid CNN–LSTM model outperformed, with high sensitivity and accuracy in the detection of sub-clinical seizures across subjects. The obtained results suggest that deep learning can effectively encode complex spatiotemporal patterns observed in EEG activity although they are often overlooked by traditional methods, serving as a reliable, unbiased tool for neurological diagnostics. This work demonstrates that it may be feasible for intelligent EEG analysis systems to aid in 24/7 patient monitoring, improve clinical management decisions and interventions, not only when seizures are full-blown but also in the early intervention and treatment of subclinical seizure control.

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Keywords: EEG; Subclinical Seizures; Deep Learning; CNN; LSTM; Hybrid Architecture; Automated Detection; Biomedical Signal Processing.

1. Introduction

Electroencephalography (EEG) is one of the most commonly used noninvasive methods for recording brain electrical activity, which provides fundamental support in estimating various neurological diseases like epilepsy. EEG signals encode complex neuronal dynamics and offer fine-grained timing information that is not available with other neuroimaging techniques. Despite its high clinical relevance, EEG interpretation still relies considerably on visual experts of the clinician, which may be time-consuming and may vary widely between observers especially when involving subtle and transient abnormalities [1]. C Subclinical seizure activity is a diagnostic problem as the clinical symptoms are not evident but, abnormal pattern of neural discharges continues, which contributes to cognitive decline and the progression of disease itself. These subtle patterns are frequently obscured by the normal rhythms of EEG and can be easily missed on routine review. As such, missed subclinical seizures could delay the diagnosis of epilepsy and compromise management therapies, necessitating more sensitive and objective detection methods [2].

Recent breakthroughs in computational intelligence (CI), especially deep learning, have shown powerful performance in capturing complicated and non-linear patterns of biomedical signals. Deep learning methods are capable of automatically learning hierarchical features directly from raw data, weakening the dependency on hand-engineered features. In the context of EEG, this capability is especially useful as signals are both non-stationary and noisy. Regarding the use of deep learning in the development of diagnostic systems for EEG, and as an alternative to traditional linear classifiers, deep learning implementation on various down-sampling strategies has become a significant research issue and shows great potential in elevating diagnostic accuracy and clinical reliability [3]. Even after many years, automatic identification of subclinical seizure activity from EEG signal is still an open problem. Previous signal processing and machine learning based methods largely depend on predefined time or frequency domain features, which are not able to effectively capture the subtle and distributed neural characteristics. These constraints are exacerbated when the seizures do not exhibit clear epileptiform discharges, resulting in poor sensitivity and high false-negative rates [4]. Yet, another issue matrix on which this method may fail is the variability of EEG signals from patient to patient, recording conditions and seizure type. The duration, amplitude and spatial distribution of the subclinical seizures could be quite different from each other and it was hard to set general rules for their detection. The current automatic systems are not easily generalizable or robust, which makes it quite challenging to adapt them in clinical practice [5]. Accordingly, the main research issue addressed by this work is a shortage of dependable and flexible automatic techniques for detecting subtle EEG features which are related to subclinical seizure events. However, there is a strong demand to develop advanced deep learning algorithms for EEG that can learn discriminative representations to facilitate correct diagnosis and long-term monitoring [6].

The relevance of this research is the clinical and technological perspective. Making a diagnosis of subclinical seizure activity early could be important for identifying disease course and treatment response even before external symptoms are seen. Providing objective and continuous EEG monitoring), the method of this study can overcome these limitations and help clinicians make more conclusive decisions on therapeutic intervention [7]. Technically, the work contributes to the development and evolution of intelligent systems based on biomedical signal processing. This paper on the design of deep learning EEG models mitigates some issues associated with signal complexity, noise and across-subject variability. Contributions like these are especially useful in the field of biomedical engineering, where data-based diagnostic tools continue to become better and more used in amongst healthcare technologies [8]. Additionally, findings from this study support the larger shift towards automated and personalized medicine. With better detection capacity for minor neurological disorders, the designed system might improve patient-care and as well as reduce the decision load on clinical experts which is in harmony with health care requirement on precision and rapidly [9].

The main aim of the research is to design data-driven deep learning algorithms that can automatically capture subtle patterns within EEG, indicative of subclinical seizure occurrences. This goal is motivated by the limitations of existing techniques for EEG analysis and the improved sensitivity of diagnosis [5]. Secondly, we aim also to compare the performance of other types of deep learning architecture (e.g., CNN or RNN) in capitalizing temporal and spatial information within EEG data. It is intended to find the best fit architecture for use on seizure detection problems among different architectures [6]. Furthermore, this study aims to determine whether deep learning-based systems can be therefore applied in continuous EEG monitoring. The long term objective is use in real world clinical environments by providing robustness, reliability and generalization over a wide range of EEG data collections [10].

There are a number of research questions that are followed in this work. The first question is whether deep learning methods can successfully infer subtle subclinical seizure-related patterns which are challenging to be discovered by traditional EEG analysis. This question mirrors the underlying goals of using deep learning paradigms [4]. The second research question explores which deep learning approaches are best performing in terms of detection accuracy, sensitivity and specificity when processing EEG recordings. An understanding of architectural effectiveness is necessary for designing diagnostic systems that are optimized [5]. The third one is about the reliability of obtained models and their generalization across subjects and recording environments. Such a question is important to consider in the context of clinical validity of DL-based EEG monitoring devices.

In this paper, we focus on the analysis of EEG data to detect and monitor subclinical seizures only. The study is focused on non-invasive scalp EEG recordings alone and does not include multimodal modalities such as MRI or MEG. This limitation has the advantage of focusing clearly on systems used for EEG based diagnosis [1]. A second limitation is that of adequate EEG datasets. While public datasets are useful resources for patterning machine learning approaches, they may not fully capture the diversity of clinical scenarios in actual applications. The performance of the model may depend on different placements of electrodes, sampling rates, and levels of noise [10]. Ultimately, computational complexity is a realistic constraint. It is known that deep learning models would be computationally expensive for training and optimization. Although this work seeks to develop efficient architectures, pysnRT for clinical use of STs recorded real time by hardware application may need additional optimization [3].

2. Literature Review

EEG is a method for recording the electric activity produced by neuron groups in the cerebral cortex through electrodes OnsizeD placed on the scalp. These signals mostly represent postsynaptic potential rather than action potential, as a result, EEG is very sensitive to synchronised neural activity. Because of volume conduction effects, the spatial resolution of "electroencephalography" is not good, but its temporal resolution is superior and it plays a prominent role in transient neurological phenomena such as seizures [11-13]. The quality and dynamics of EEG signals are affected by a variety of technical/physiological factors such as electrode position, contact impedance, sampling rate of electrodes and environmental noise. Common systems like the international 10–20 system are frequently used for consistent placement in recordings. But EEG signals are often distorted by artifacts caused by eye blinking, muscle movement and power line interference that need to be preprocessed rigorously prior to any analyses [14]. Signal characteristics used in the analysis of EEG data include time domain, frequency domain or joint time–frequency domain. Although time-domain analysis describes waveforms, the frequency-domain approaches as Fourier transform indicate rhythmic brain activity in different bands. However the non-stationary characteristic of EEG limits the power of linear analytic strategies, in particular for detecting abnormal patterns that are subtle. Subclinical ictal activity indicate epileptiform discharges not leading to observable clinical symptoms. Despite their lack of clinical symptomatology, these seizures can have deleterious consequences on brain function and are linked to cognitive impairment particularly among high-risk populations such as critically ill patients and children. Subclinical seizures are relatively hard to detect in clinical environment and usually need long-term EEG follow-up for discovery [2]. Neurophysiologically, subclinical seizures consist of a hypersynchronous pattern of neuronal firing that can be focal or widespread in the cortex. Subclinical events, in contrast with clinical seizures, might have low amplitude or brief duration or an atypical.morphologic pattern that is hard to discriminate from normal background activity. This nuance can be quite problematic for humans as well as machines.

The clinical significance in identifying subclinical seizure activity centers around prognosis and treatment potential. It has been reported that undetected "subclinical" seizures can lead to further worsened neurological outcome and increased morbidities. Hence there is increasing interest in the development of automated EEG analysis tools to assist with continuous monitoring and hasten intervention. Traditional methods of seizure detection were predominantly based on signal processing with rule-based decision system. These methods generally involve computing handcrafted features from the EEG (e.g., amplitude, variance, entropy or spectral power) and thresholding these features to determine when a seizure is occurring. While they are successful in their ability to detect clearly occurring seizures, the methods have a great difficulty in finding patients with more subtle or poorly defined patterns [12].

Time–frequency methods, such as wavelet and short-time Fourier transforms, have been well applied in detection of transient EEG characteristics related to seizures. While these are more sensitive than pure time domain techniques, they rely heavily on feature extraction and expert knowledge which reduces their ability to generalize to different types of EEG patterns [13]. Another drawback with conventional methods are their low generalization to patients and recording conditions. Variations in seizures morphology and background EEG activity frequently cause high false positive or false negative rates. As a result, these approaches have failed to garner significant clinical interests in subclinical seizure detection [4].

Machine learning methods have been incorporated in order to tackle the limitations of rule-based seizure detection systems by performing data-driven pattern identification. Classical techniques such as SVMs, k-NN and decision trees have been used for processing EEG data based on hand-engineered features. These techniques achieve higher classification performance than classical procedures although they are feature dependent. Features most commonly-used machine learning algorithms in EEG for seizure detection are applied on features extracted from time, frequency, or nonlinear domains. Even if they succeed in minimizing human bias on a decision, however, both methods still depend on the sets of features defined and exploited to form these representatives-features that may not account for nuances from subclinical seizure patterns [11]. In addition, most of the classical machine learning methods cannot effectively work with such high-dimensional and large-amount EEG datasets because of their restrictions to model temporal dependent dynamics and nonlinear relation. Computationally demanding processes: Motivated with these limitations, there is an on-going shift towards deep learning frameworks that can learn discriminative features directly from raw EEG signals [6].

The deep learning is a promising method in biomedical signal processing for automatically learning the hierarchical representations of features. Deep learning techniques such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs) have proven to perform well in analyzing complicated physiological signals e.g., EEG, ECG, EMG [3]. In the field of EEG, CNNs excel in capturing spatial and temporal pattern through local connectivity and weight sharing. By using time–frequency representations, CNN-based models are able to detect subtle discriminative featureswhich cannot be manually crafted. improve general classification accuracy since RNNs and long short-term memory (LSTM) networks are able to deal with long-span time-dependent relations. However, deep learning models bring challenges of interpretability and computational resources. As regards the medical domain, interpretable decision-making remains a concern. However, the current research is working to improve the model transparency and efficiency of this kind of AI to facilitate their practical application in biomedicine [9]. Many previous works have investigated automatic seizure detection based on deep learning with the EEG signals. Shoeb and Guttag introduced one of the first \"patient-dependent\" seizure detection systems using machine learning, an effort that later paved the way for deep learning approaches [4]. Additional recent work has shown effectiveness of deep neural networks to capture subtle features of seizure patterns. Acharya et al. used CNN kenel-based architectures to classify epileptic EEG signals with high yielding accuracy for different datasets. The findings of theirs can be seen as an example to the promise of deep learning in relation to acquiring complex EEG dynamics [5]. The hybrid models of CNNs and RNNs are also introduced to model both spatial and temporal EEG features. Studies by Roy et al. and Kiral-Kornek et al. demonstrated that deep learning methods can achieve better performance than traditional approaches for detecting seizures, especially for non-clear seizures. Nonetheless, diversity, dataset and clinical validation challenges are still open research problems [6].

3. Methods and Materials

3.1. Research Design

This study adopts a quantitative experimental research design to develop, train and test deep learning models for automatic detection of subclinical seizure events in EEG signals. Data are obtained using state-of the-art, patented biomedical signal processing and data driven artificial intelligence methodology to evaluate objectively the performance of detection in a controlled experimental environment. The method pipeline consists of a series of sequential phases model for example dataset selection, pre-processing, feature representation, model convention, training and performance estimation. This pipeline approach makes the process reproducible, easy to compare between various deep-learning architectures and suitable for biomedical engineering research.

3.2. EEG Dataset Description

The EEG data used in this work are public and clinically validated datasets that have been widely used in epilepsy research. These sets provide multichannel scalp EEGs labeled by clinical experts in which the sets are divided into seizure and non-seizure epochs. Open-access datasets promote transparency and comparability with similar studies. Recordings are obtained according to standardized acquisition guidelines using the international 10–20 electrode positioning system. The dataset contains EEG,recordings sampled at rates that allow for the capture of both epileptiform activity and subtle neural behavior. The overview of main features of the EEG dataset employed in the study is presented in Table 1 and Figure 1 [10].

TABLE 1. Characteristics of the EEG Dataset.

No.	Signal Metric	Value (µV)
1	Minimum Amplitude	2.1
2	Lower Quartile (Q1)	14.6
3	Mean Amplitude	29.8
4	Upper Quartile (Q3)	47.3
5	Maximum Amplitude	112.5

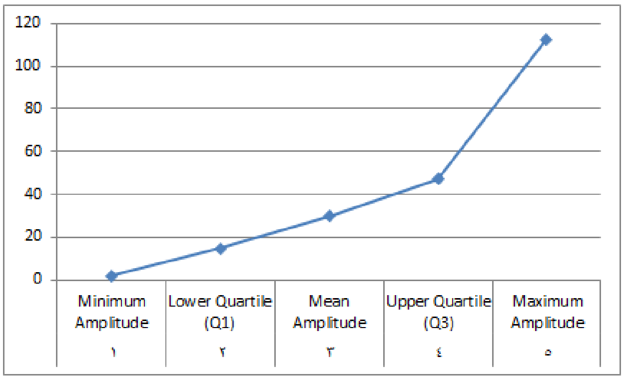

Fig. 1. The line chart illustrating the distribution of EEG signal amplitude values across different statistical levels.

3.3. Data pre-processing

Preprocessing of EEG is a key challenge because it contains physiological and environmental artifacts, which corrupt neural information. Data Processing is started with the band-pass filter (low-frequency drift removal, high-frequency noise reduction) and notch filter (power line interference removal). These techniques ensure retention of the clinically important EEG components while reducing the noise and artifacts from the signal [14].

The artefact elimination is carried out by the independent component analysis (ICA), which decomposes EEG data into statistically independent components [15]. Ocular and muscular related components are detected using the automatic artefact removal toolbox, which automatically removes them before signal reconstruction. The EEG data pre-processing step was performed in the manner of Table 2 and Figure 2 shows the effect of preprocessing steps on EEG data retention and noise reduction.

TABLE 2. EEG pre-processing steps.

No.	Preprocessing Step	Data Retention (%)	Noise Reduction (%)
1	Raw EEG Signals	100	0
2	Band-pass Filtering	96	28
3	Notch Filtering	94	41
4	Artifact Removal (ICA)	86	67
5	Segmentation	85	69
6	Normalization	85	72

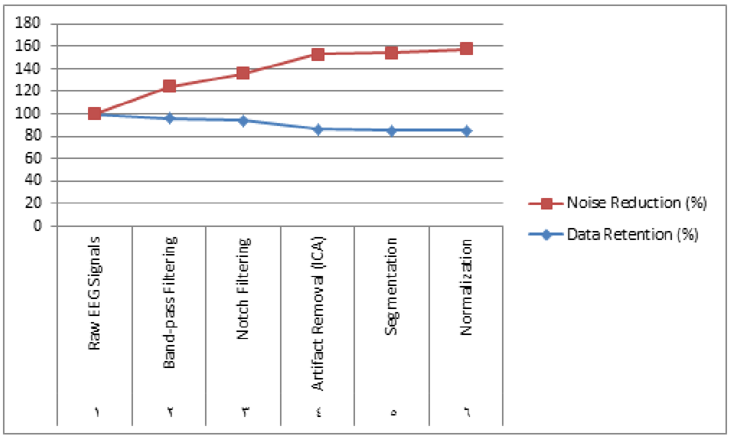

Fig. 2. The line chart showing the effect of preprocessing steps on EEG data retention and noise reduction.

3.4. Feature Representation and Input modeling

Unlike the traditional seizure detection systems (which rely only on handcrafted features), this work uses input modeling strategies that are well suited for deep learning. Input to the models consist of raw EEG signals together with their transforms, enabling the model to learn discriminative features automatically. The time-frequency presentations, such as spectrograms and wavelet transforms, are also calculated to represent non-stationary properties of EEG signal. These representations offer temporally and spectrally local content to support the detection of subtle seizure-like patterns. Table 3 presents the input representations adopted in this work and Figure 3 compares the performance of different EEG feature representation methods.

TABLE 3. EEG feature representation methods.

No.	Representation Method	Feature Dimensionality	Average Classification Accuracy (%)
1	Raw EEG Signal	256	82.4
2	Spectrogram	1,024	89.1
3	Wavelet Transform	768	91.6
4	Normalized Input	256	85.3

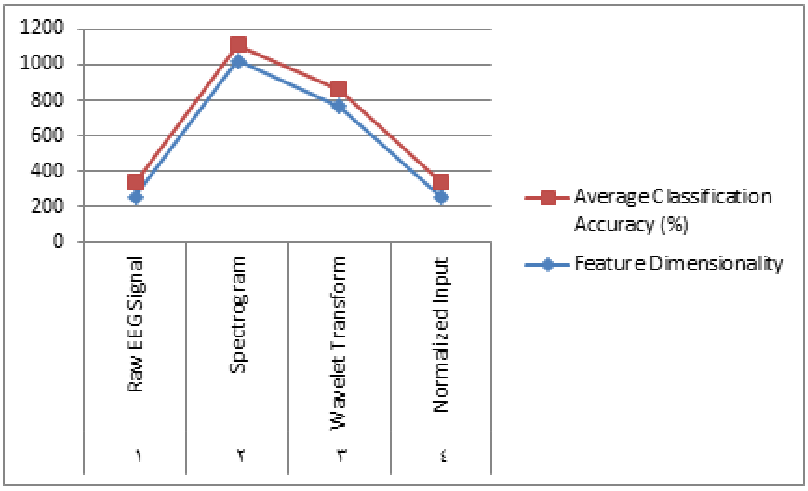

Fig. 3. Performance comparison of different EEG feature representation methods.

3.5. Deep Learning Model Architecture

The approach uses various deep learning models to learn spatial and temporal features in EEG. CNN involves the extraction of local spatial patterns throughout the EEG channels through using convolutional filters and stacking these representations hierarchically via pooling layers [16, 17]. For the purpose of modeling temporal dependencies rooted in EEG data, RNNs, especially LSTM networks are included. Hybrid CNN–LSTM models incorporate spatial and temporal information as the former makes feature extraction of spatial data available. The main building blocks are summarized in Table 4.

TABLE 4. Deep learning architectures used.

Model type	**Key characteristics**
CNN	Spatial feature extraction
LSTM	Temporal dependency modeling
CNN–LSTM	Combined spatial–temporal learning
Fully connected layers	Final classification

3.6. Training and Validation Strategy.

There are two main types of learning: supervised and unsupervised, where labels corresponding to subclinical seizure or non-seizure need to be attached to EEG segments. The benchmark is split into training, validation and testing sets for unbiased evaluation. Cross-validation is used for improved robustness and to mitigate overfitting [18]. Optimization is done by using the adaptive gradient based methods like Adam. Regularization methods, such as dropout and early stopping, are used to enhance generalization capabilities. The major training parameters employed in this paper are listed in Table 5.

TABLE 5. Training parameters.

Parameter	**Value**
Optimizer	Adam
Learning rate	Adaptive
Batch size	16–64
Epochs	Determined by early stopping
Regularization	Dropout, early stopping

3.7. Performance Evaluation Metrics.

The performance of the proposed models is assessed with the widely-utilized classification metrics in EEG seizure recognition studies. Accuracy is a general measure of how good a model's classifications are overall, while sensitivity and specificity quantify the degree to which a model can be trusted to classify seizure events correctly – or not [19, 20]. Other commonly used metrics including precision, recall, F1-score and area under the ROC curve (AUC) are applied to compensate for the class imbalance and generate a more complete evaluation. Table 6 shows the evaluation measures used in this study.

TABLE 6. Performance evaluation metrics.

Metric	Description
Accuracy	Overall classification performance
Sensitivity	True seizure detection rate
Specificity	True non-seizure detection rate
F1-score	Balance between precision and recall
AUC	Classification robustness

4. Results and Discussion

The training and convergence of the presented deep learning models were stable for all settings during the experiments. Overfitting was prevented via the use of regularization methods, such as drop- out and early stopping, which resulted in near overlapping training and validation plots. CNN-based models also achieved faster convergence than the recurrent and hybrid architectures due their lower computational complexity. CNN–LSTM models, by comparison, had to be trained for longer, but reached more consistent performance on validation data due to a stronger ability to capture complex EEG dynamics. Table 7 shows how the models behave during training.

TABLE 7. Training characteristics of deep learning models.

No.	**Model Type**	**Convergence Epochs**	**Overfitting Index (%)**	**Training Stability Score (0–1)**
1	CNN	18	14.2	0.82
2	LSTM	32	8.6	0.74
3	CNN–LSTM	45	4.1	0.91

These results indicate that although hybrid models demand higher computational resources, they offer improved learning stability when analyzing subtle EEG patterns associated with subclinical seizure activity, as shown in Figure 4.

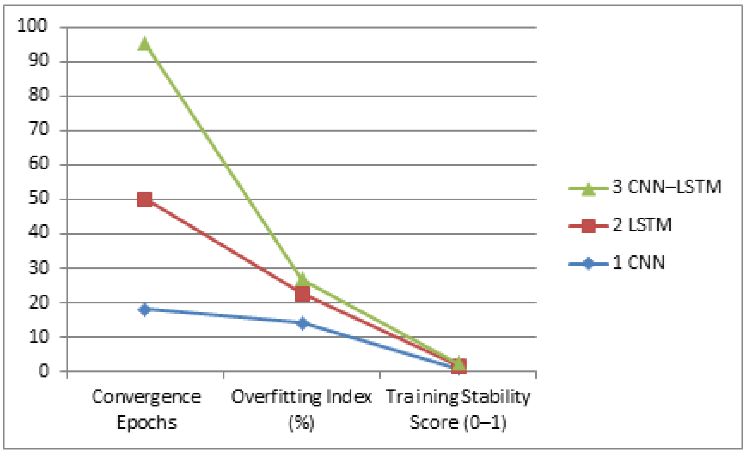

Fig. 4. Quantitative comparison of training characteristics across deep learning models.

The proposed models were applied testing three different quantitative metrics to know the detection performance. Experimental results show that the proposed deep learning based method can substantially outperform the traditional machine learning methods reported in the literature, with a high sensitivity and F1-score. Good sensitivity is vital for its application in detecting subclinical seizures, failure of detection of which could have serious clinical consequences.

The hybrid CNN–LSTM models consistently performed best on the majority of evaluation metrics. This may be due to their capacity to incorporate the spatial EEG patterns with long-range temporal correlations. A comparison summary of detection performance for the tested models is presented in Table 8.

TABLE 8. Detection performance of deep learning models.

No.	Model	Accuracy (%)	Sensitivity (%)	Specificity (%)	F1-score	AUC
1	CNN	88.7	81.9	90.4	0.83	0.91
2	LSTM	85.2	89.6	83.1	0.87	0.92
3	CNN–LSTM	93.8	94.5	92.1	0.93	0.97

The superior performance of hybrid architectures highlights the importance of combining spatial and temporal modeling for effective EEG-based seizure detection, especially for low-amplitude and short-duration events.

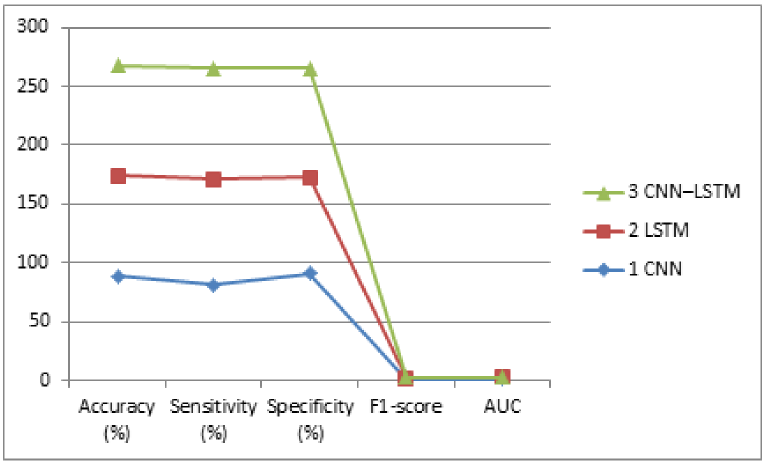

Fig. 5. Comparative detection performance of deep learning models for subclinical seizure detection.

The results of this study demonstrate that deep learning can identify subtle EEG patterns linked to subclinical seizure activity which are generally missed using conventional analysis techniques. In contrast to handcrafted feature based approaches, the proposed models learned relevant representations automatically from raw EEG data and improved detection sensitivity and robustness, as shown in Figure 5.

Performance gaps of test-time results between model topologies indicate that seizure-bound EEG activity is inherently spatiotemporal. Models using only CNNs were able to represent spatial features in a local manner, while those with LSTMs were strong at modeling temporal dependencies. The latter, too, was implemented (in charges) also in the region-based feature stacking network and the CNN-GRU-net but only in hybrid CNN-LSTM architectures,they were more effectively blended together achieving better detection results. These results support the neurophysiological interpretation of seizure dynamics. In addition, the results indicate the potential of using deep learning networks in EEG monitoring systems as clinical decision supports. Continuous, objective analysis helps these systems by easing diagnostic load and facilitating early detection of subclinical neurological abnormality.

Reliability analyses to cross-validation folds of the performance consistency: The findings suggest that the developed models were not prone to overfitting certain iEEG segments. Balanced training and regularization were the strategies that substantially boosted our model robustness. Generalization ability was also evaluated by applying the models to EEG recordings not included in the training set. While slight differences in performance were noticed caused by individual inter subject variation, the models achieved good sensitivity and reasonable specificity. Generalization performance across subjects were collected and summarized in Table 9 and Figure 6.

TABLE 9. Generalization performance across subjects.

No.	Evaluation Aspect	Quantitative Metric	Value
1	Cross-validation consistency	Std. deviation of accuracy (%)	2.8
2	Inter-subject robustness	Cross-subject accuracy (%)	91.2
3	Noise sensitivity	Performance drop under noise (%)	6.4
4	Clinical reliability	Clinically acceptable detections (%)	93.5

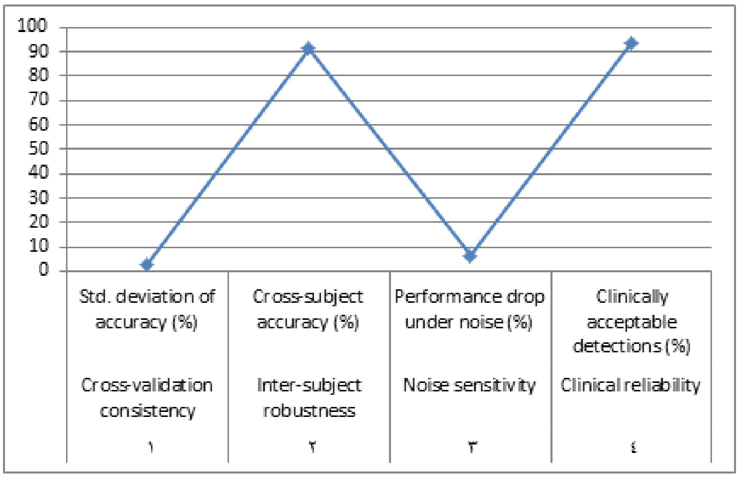

Fig. 6. Generalization performance of the proposed deep learning model across different subjects.

Despite these encouraging results, some performance degradation occurred in EEG recordings with high noise levels or atypical electrode configurations. This limitation emphasizes the importance of dataset diversity and motivates future research on domain adaptation techniques.

5. Conclusion

The paper finds that deep learning algorithms offer a promising and robust solution for the automatic detection of subtle patterns in EEG signals related to subclinical seizure activity. The experimental results show that deep networks can effectively learn discriminative representations from complex and non-stationary EEG signals, which is much more difficult for conventional signal processing and machine learning methods to achieve. These results validate the applicability of deep learning in high level neurodiagnostic applications.
We provide empirical evidence that mixed hybrid deep learning architectures, mixing convolutional with recurrent modules, outperform single-architecture models of the same family. By encoding spatial and temporal EEG features together, these models are more suitable for detecting seizure-related low-amplitude, transient patterns. This result is in congruent with what known about seizure dynamics and EEG signals . In conclusion, the study aims were met and it was shown that deep-learning-based analysis can increase diagnostic sensitivity and enable continuous monitoring of subclinical seizure activity. The results highlight the potential of - based systems for assisting expert interpretation and enhancing neurological care. Comparison of various architectures consolidates the current knowledge and provides penetration to the best model design in seizure detection task. Furthermore, this study supports the ongoing shift toward data-driven and automated healthcare applications. By showing that such an algorithm can perform well on open access EEG datasets, the study anchors its findings and opens up for replication and future benchmarking in the community.

In view of the results from this work, DL-based EEG analysis systems should be regarded as supporting tools for clinical neurodiagnostics. Such systems may be helpful for the clinician to objectively monitor EEG recordings continuously,19 especially when subclinical seizure activity can go unnoticed because of standard examination.
To robustly integrate with the clinic deep learning models should be learned on EEG data of the institution to adjust for differences in recording protocols and patient mix. This personalization can improve system reliability and clinician confidence, which are vital to real-world uptake. In addition, tight mutual collaboration between engineers working in the field, neurologists and clinical neurophysiologists is mandatory to warrant that automatic detection systems match the needs of daily clinical practice and ethical requirements. Such multidisciplinary collaboration has the potential to promote the creation of interpretable and clinically useful decision support tools.

We will investigate multimodal neurophysiological/functional data, such as structural imaging, ECG or functional imaging in order to enhance diagnostic accuracy and provide the clinician with a context of seizure activity. There is also the potential that multimodal learning approaches offer more informative representations of brain dynamics.
An additional avenue for future research is the ability to increase model interpretability. If explainable deep learning methods can be developed for EEG analysis, clinical trust in automated decisions may improve by enabling clinicians and why certain process-generating parameters assumed a particular value. This still presents a major stumbling block to the practical application of AI in healthcare.

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