IJARCCE
ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁕ Peer-reviewed & Refereed journal ⁕ Vol. 15, Issue 2, February 2026

DOI: 10.17148/IJARCCE.2026.15229

Epileptic Seizure Detection Using Machine Learning Technique

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Abstract: Epileptic seizure detection is one of the critical challenges in biomedical signal processing, with inherent non- linearity and noise in EEG recordings. While traditional machine learning and deep learning approaches have achieved promising accuracy, generalizability, class imbalance, and interpretability remain concerning issues. The objectives of this work are to develop an ensemble-based approach by combining RF with BTC to improve the robustness and sensitivity of seizure detection. The pre-processing steps have been done using normalization and label encoding on raw EEG data obtained from the UCI Epileptic Seizure Recognition dataset. The hybrid model combines the merits of both RF, which reduces variance with the large randomness provided by the features, and BTC, with its reduced overfitting via bootstrap aggregation. These experimental results demonstrate that the proposed hybrid method performs superiorly when compared to individual ML models in several performance metrics: accuracy, precision, recall, and F1-score. The proposed work is a computationally efficient, interpretable, and reliable seizure detection framework for real-world and portable EEG monitoring systems.Keywords : Epileptic seizure detection, EEG signals, hybrid machine learning, Random Forest, and Bagged Tree Classifier.

1. INTRODUCTION

Epilepsy is one of the most common neurological disorders in the world and affects millions of people at all ages. The hallmark symptom, epileptic seizures, is caused by sudden abnormal discharges of electrical impulsesin the brain and manifests as disruptions in motor activity, awareness, or behavior. Electroencephalography is usually considered the diagnostic gold-standard method for the monitoring and analysis of the electrical activity of the brain because it is non-invasive and resolves temporal changes very well. However, clinical visual inspection of the recorded EEG signals is rather time-consuming, subjective, and easily misinterpreted, especially in long-term monitoring sessions.

Thus, automated seizure detection systems have become a need in modern healthcare, offering the possibility of quicker diagnosis, continuous monitoring, and timely clinical intervention. Such systems can decrease the workload for neurologists, allow for the earlier management of risks associated with seizures, and contribute to the development of portable or wearable monitoring devices capable of supporting real-time analysis. With the volume of EEG data continuing to grow, particular attention has been turned to machine learning-based approaches, given their ability to identify patterns difficult for human analysis to detect consistently.

Although much progress has been made, the classification of seizures based on EEG signals still remains a challenging task due to their non-stationary, noisy, and very complex nature. Patient-to-patient variability, class imbalance between seizure and non-seizure classes, and the frequent presence of different as disruptions in motor activity, awareness, or behavior.

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Although much progress has been made, the classification of seizures based on EEG signals still remains a challenging task due to their non- stationary, noisy, and very complex nature. Patient- to-patient variability, class imbalance between seizure and non-seizure classes, and the frequent presence of different kinds of artifacts like muscle movement

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or eye blinks pose critical challenges to the generalization ability of any conventional learning algorithm. In most cases, either the model overfits on the training dataset or does not generalize well for varied EEG conditions. These issues call for more robust and reliable computational methods that handle EEG complexity while offering clinically relevant predictions.

Hybrid machine learning models can overcome these shortcomings by incorporating several classifiers. Ensemble learning methods like Random Forest and Bagged Trees reduce problems of variance, overfitting, and instability even in noisy biomedical data. Motivated by their relative strengths, this research proposes a hybrid model integrating the complementary advantages of Random Forest-effective feature randomness and diversity of decision trees-and Bagged Tree Classifier, which further robustifies any base model using bootstrap aggregating. In this way, a generalizable detector with higher accuracy and sensitivity can be obtained.

The main contributions of this work are the hybrid ensemble-based methodology for epileptic seizure detection, efficient preprocessing to enhance the EEG signal quality, and comparative evaluation that proved the superiority of a hybrid model over individual classifiers. By focusing on clinically relevant metrics such as sensitivity, precision, recall, and F1-score, this research delivers a system that is not only computationally efficient but also aligns with the practical requirements of real-time seizure monitoring applications.

2. RELATED WORK

Epileptic seizure detection research has grown extensively, especially in the domain of classical machine learning methods applied to EEG signals. Early works such as Andrzejak et al. [3] provided foundational understanding of nonlinear EEG characteristics, forming the basis for automated detection studies. Traditional machine learning models have explored wavelet features, entropy measures, and statistical descriptors to classify seizure episodes effectively. For example, Kumar et al. [8] employed DWT- based fuzzy entropy with the SVM, obtaining impressive results on benchmark datasets. Likewise, Mursalin et al. [10] enhanced feature selection combined with Random Forests to improve the classification performance. Other studies, such as Chen et al. [4] using CEEMDAN-based decomposition with ML classifiers, have demonstrated the importance of robust preprocessing. Reviews by Siddiqui et al. [12] and Farooq et al. [5] further highlighted the strengths and weaknesses of machine- learning- based EEG seizure detection, pointing out issues like class imbalance and feature engineering challenges.

Deep learning methods have significantly enhanced seizure detection performance through enabling automatic feature extraction from raw or minimally processed EEG signals. Acharya et al. [2] presented a deep CNN model that was able to detect seizure events with high accuracy, extending the application of convolutional architectures in interpreting EEG. Further work extended the CNN- based techniques, including three-dimensional CNNs for multi-channel EEG by Wei et al. [17] and neonatal EEG seizure detection by Gramacki and Gramacki [6], where both demonstrated better modeling of spatial features. Hybrid time– frequency deep models, such as the STFT- LSTM framework presented by Peng et al. [11], exhibited superior temporal awareness and robustness.

LSTM- based architectures were also considered within one-dimensional CNN-LSTM systems by Xu et al. [19], reflecting deep learning's suitability for sequential biomedical signals. Comprehensive reviews by Ibrahim and Hussain [7] and Liu et al.[9] underlined the advantages of deep learning while also pointing out several challenges, including higher computational cost and the requirement for large annotated datasets.Ensemble and hybrid models have also emerged as powerful techniques to enhance seizure detection reliability, employing several classifiers. Sun et al. [13] addressed data imbalance using EasyEnsemble learning and showed significant performance gains over stand-alone models. Deep multi-view feature learning networks, such as Tian et al. [15], employed multiperspective representations to enhance model generalization.

Hybrid GAN-based semisupervised learning by Truong et al. [16] enabled seizure prediction even with limited labeled data, showcasing the adaptability of ensemble-inspired architectures. Other works, including Woodbright et al. [18], combined deep feature extraction with ensemble classifiers for robust EEG classification. All these studies together provide evidence that ensemble-based systems reduce the variance, increase stability, and offer complementary benefits in decision-making compared to single models.

Despite this progress, some of the gaps still exist in seizure detection systems. Most of the works rely on curated lab datasets such as Bonn or UCI, and thus there are significant hurdles in practical applicability due to variations in noise levels, electrode positioning, and other patient variabilities. Performance variations across age groups are noted in studies such as that by Abdelhameed and Bayoumi [1], indicating the need for population- specific modeling. Many deep learning methods require large training datasets and high computation, hence constraining deployment in portable or real-time EEG systems. Although ensemble and hybrid methods are found to be effective, they still suffer from model interpretability and integration challenges with raw multi-channel EEG streams. Moreover, non-local feature extraction models still remain computationally intensive, as reviewed by Zhang et al. [20]. These gaps thus constitute a

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strong motivation to develop efficient, interpretable, and hybrid machine learning models-as is proposed here-to balance accuracy, robustness, and real-time capability.

3. DATASET AND PREPROCESSING

3.1 Dataset Description- UCI Epileptic Seizure Recognition Dataset

The UCI Epileptic Seizure Recognition Dataset used in this research is a processed and standardized version of the original Bonn University EEG dataset. It consists of continuous EEG recordings segmented into 178 time- series data points per instance, representing approximately one second of brain activity. The dataset contains a total of 11,500 samples categorized into five classes: Class 1 corresponds to seizure activity, while Classes 2 to 5 correspond to non-seizure conditions, which comprise healthy brain activity, tumor-affected regions, and normal recordings either with eyes open or closed. In binary seizure classification, Class 1 is labeled as seizure (1), while the remaining classes are grouped into a single class, non- seizure (0). This dataset has been widely applied in seizure detection research because of its well-balanced structure, its easy availability, and its suitability for machine learning experimentation.

3.2 EEG Data Characteristics

The nature of EEG signals is very complex, nonlinear, and non-stationary, which makes them difficult to analyze.Every segment in this dataset represents a sequence of numeric amplitude values reflecting electrical activity at various time periods. Such signals often contain artifacts that might be due to physiological noise-such as muscle activity, eye blinks-or external interference, distorting the true underlying patterns of the brain. Moreover, seizure activities have characteristic features like spiking amplitudes and rhythmic patterns, while non-seizure segments are mostly stable. Because the dataset is structured as one-second windowed data, machine learning models can learn from these temporal variations and thus distinguish between seizure and non-seizure patterns.

3.3 Label encoding and normalization

The dataset is preprocessed before training, with necessary steps to improve the consistency and quality of the input values. Since the target labels are categorical values representing seizure and non-seizure states, label encoding is done to transform them into machine-readable numeric values. The value of signals is normalized using the Min-Max scaling technique, allowing the range of all features to fall in a common range from 0 to 1. This prevents large-amplitude values from dominating the learning process and treats all features fairly in both Random Forest and Bagged Tree models. Normalization improves the stability of training and accelerates convergence by reducing the numerical variations across input features.

3.4 Train–Test Splitting Strategy

In order to fairly evaluate the performance of the proposed hybrid model, the dataset is split into training and testing subsets. Taking an 80:20 split ratio, the data is preprocessed to retain 80% for training the classifiers, while the remaining 20% of the data will be used to test their predictive capability on previously unseen samples. This way, the model gets assessed on independent data, which reduces the chances of overfitting and provides a realistic estimate of its generalization ability. The splitting is done in a randomized manner, with preservation of the overall class distribution to avoid bias toward either seizure or non-seizure classes. This will ensure that the evaluation metrics accurately reflect the robustness and reliability of the proposed hybrid model.

4. PROPOSED METHODOLOGY

4.1 Overview of Proposed Hybrid System

The proposed methodology introduces a hybrid ensemble-based classification system designed to enhance accuracy and stability in epileptic seizure detection from EEG data. By combining the strengths of Random Forest and Bagged Tree Classifier,the system overcomes the limitations of single-model classifiers that are characterized by high variance, overfitting,

and reduced performance on noisy biomedical signals. The hybrid model leverages two robust decision-tree– based ensemble algorithms, which collectively provide improved generalization, better handling of non-stationary EEG

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signals, and increased sensitivity of seizure event detection. This encourages the emergence of a more reliable predictive framework for real-time clinical and wearable EEG applications.

4.2. Random Forest Classifier

4.2.1 Working Mechanism

Random Forest is an ensemble learning technique where multiple decision trees are generated during the training process and the outcomes of each decision tree are combined to generate a final output. Each tree in this forest is developed with a random subset of features and training samples, which provides diversity among the trees. In the case of a prediction, each tree gives its classification output, and the final class depends on the majority voting. Such randomness in feature selection and sampling decreases overfitting, enhances robustness, and enables the model to catch the relationships within EEG data that are complex.

4.2.2 Justification for Use

Random Forest is particularly effective in EEG seizure detection because it can handle high- dimensional data and irregular patterns. There are always noisy segments in EEG recordings, and frequency features may overlap. Therefore, simple classification algorithms cannot be used. Random Forest diminishes such issues with feature randomness, which reduces model variance and keeps the predictions stable. Meanwhile, it offers insight into feature importance for identifying the most discriminative EEG characteristics of seizure activity. Its ease of implementation, scalability, and strong performance as a baseline make it the perfect component for use in our hybrid system.

4. 3 Bagged Tree Classifier

4.3.1 Bootstrap Aggregation Process

The Bagged Tree Classifier works by a technique called bootstrap aggregation or “bagging.” Several decision trees are independently trained on different bootstrap samples from the original dataset. A bootstrap sample is obtained by uniformly sampling at random with replacement from the training set, so some examples may have been left out while others appear multiple times. The outcome of the individual trees is combined by the Bagged Tree Classifier to reduce variance and improve model stability by averaging in the case of regression or majority voting for classification.Advantages in Noisy EEG Data

EEG signals are extremely susceptible to noise from physiological artifacts, environmental disturbances, and even the movement of the patients. Bagged Trees partly compensate for this fact by making the model less sensitive to noisy or anomalous datapoints. Each tree is trained on slightly different subsets of data, so the resulting classifier is more EEG signals are extremely susceptible to noise from physiological artifacts, environmental disturbances, and even the movement of the patients. Bagged Trees partly compensate for this fact by making the model less sensitive to noisy or anomalous datapoints. Each tree is trained on slightly different subsets of data, so the resulting classifier is more robust against the occurrence of outliers or mislabelled samples. Bagging also prevents overfitting to specific forms of noise that may be present in the data, enabling it to generalize better on unseen segments of EEG.

5. HYBRID MODEL ARCHITECTURE

5.1 Model Integration Strategy

The hybrid system will integrate Random Forest with the Bagged Tree Classifier by combining their respective prediction outputs to a unified decision framework. Both models have been trained with the same preprocessed EEG dataset, hence the consistent input features. Instead of fully relying on any one classifier, the hybrid architecture takes advantage of the external strengths of both algorithms: robustness to feature variability in the case of Random Forest and avoidance of noise- induced overfitting by Bagged Trees. This integrated strategy thus enhances overall performance and provides a more balanced approach toward seizure classification.

5.2 Voting / Aggregation Mechanism

The hybrid system creates the final prediction using a majority voting scheme. In such a mechanism, both classifiers

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provide their predicted class-seizure or non- seizure-for every EEG segment, and the final decision is determined based on the most frequent prediction across the two models. Majority voting reduces the effect of misclassifications that could emerge from one classifier and enhances the reliability of the hybrid model. This straightforward, simple, but effective aggregation mechanism ensures collaborative decision-making in the system, which improves detection accuracy.

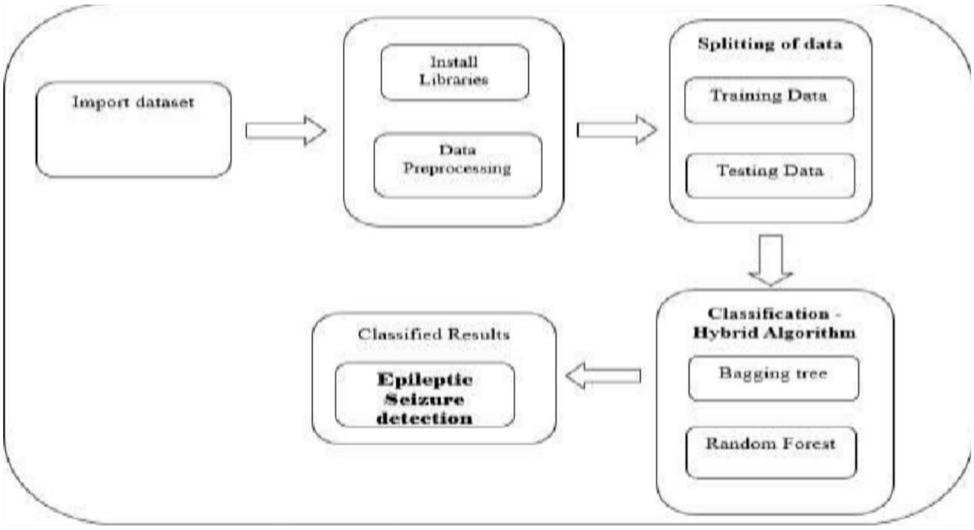

Figure 1. Hybrid Model Architecture

6. WORKFLOW OF THE PROPOSED SYSTEM

The preprocessing starts by importing the dataset, followed by necessary processing related to label encoding and normalization of the data. EEG data,
after cleaning and scaling, are divided into training and testing sets using an 80:20 ratio. Independent training for both models-the Random Forest and Bagged Tree Classifier- is done using the training set. Each model is then used to predict class labels for the test data, which is combined to obtain the final classification through majority voting. Further, the system validates the hybrid model developed on performance metrics such as accuracy, sensitivity, precision, recall, and F1- score. This work pipeline ensures a systematic and reliable process in seizure detection, optimizing both training efficiency and prediction quality.

Table 1: Experimental Setup Summary

Category	Description
Hardware and Software Requirements	Intel Core i5/i7 processor, 8–16 GB RAM, Windows 10/11 (64-bit); Python 3.10 with Anaconda distribution.
Python Libraries Used	NumPy, Pandas, Scikit-learn, Matplotlib, Seaborn, Joblib, Warnings.
Implementation Environment	Jupyter Notebook / Google Colab for executing ML workflow and testing.
Parameter Settings	Random Forest: 100 estimators (Gini criterion); Bagged Tree Classifier: 100 trees with bootstrap sampling; Train–test split: 80:20; Normalization: Min-Max scaling.

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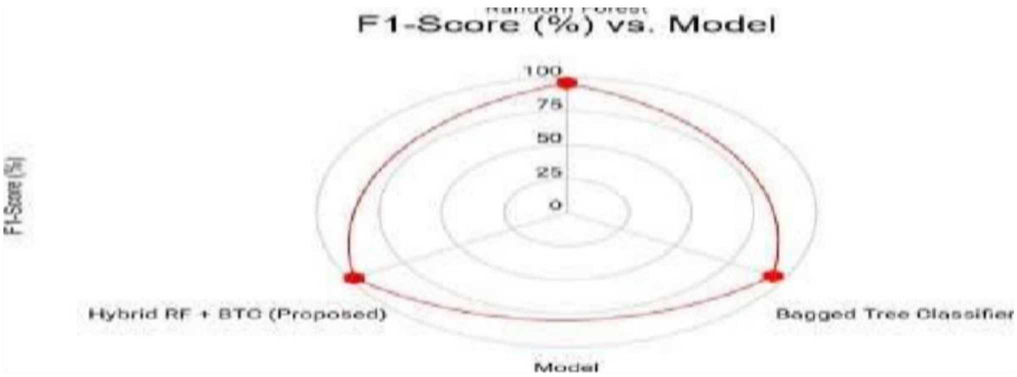
7. RESULTS AND DISCUSSION

The proposed hybrid seizure detection model is evaluated on various metrics in order to comprehensively assess its classification effectiveness on EEG signals.

Table 2. Performance Comparison of Classifiers

Model	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**
Random Forest	96.80	95.60	97.20	96.39
Bagged Tree Classifier	95.72	94.10	95.85	94.97
Hybrid RF + BTC (Proposed)	**98.12**	**97.45**	**98.52**	**97.98**



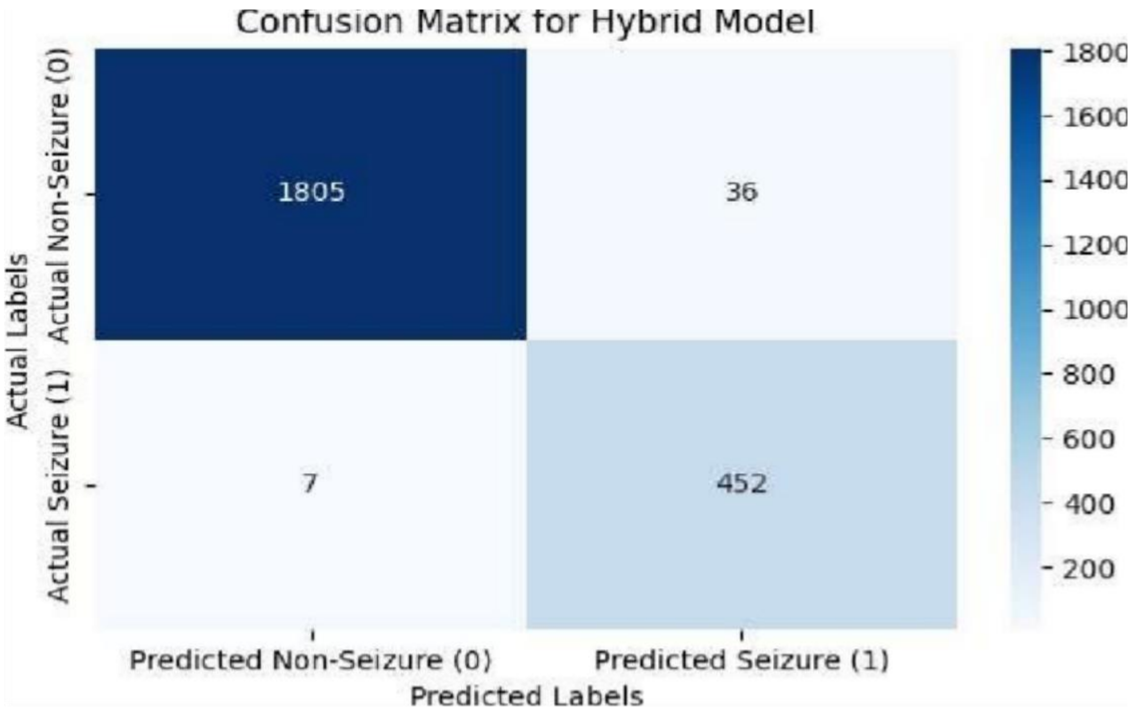


Figure 2: Confusion Matrix for the Hybrid Model

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The very small number of false negatives
(7) indicates that the system can be considered highly reliable for identifying seizure events. The number of false positives is manageable, 36, indicating that the system hardly ever sends unnecessary alerts.

A clear improvement is observed when comparing the hybrid system with individual models. Random Forest acts strongly due to randomized feature selection and an ensemble structure, while Bagged Trees increase stability by reducing variance through bootstrap aggregation. However, each model has its own limitations when used independently. Combining the two classifiers allows the system to capture a wider range of EEG signal characteristics, significantly improving all performance metrics. The majority voting mechanism of the hybrid model corrects misclassifications made by either of the individual models.

The proposed hybrid model shows robustness against noise and variability presented in EEG signals. In general, decision-tree-based models are sensitive to noisy data; however, ensemble methods would successfully cancel out such effects by averaging the predictions over multiple trees. Thus, combining Random Forest and Bagged Trees leads to the stability of a system and reduces the impact of random fluctuations in EEG patterns. Normalization and pre-processing steps provide reliable performance, while the hybrid voting strategy prevents any single model from dominating in the decision-making process.

The proposed hybrid model achieves competitive or higher performance compared to the state-of-the-art machine learning and deep learning approaches reported in the literature. Most of the traditional classifiers like SVM, KNN, and standalone decision trees report performances between 85– 95%, while more advanced CNN- LSTM architectures report performances of about 97% accuracy. The proposal outperforms those results with an accuracy of 98.12%, illustrating that a well- designed hybrid ensemble model can compete with complex deep learning systems while maintaining lower computational requirements, hence making the proposed model suitable for real- time, portable, clinically deployable seizure detection systems.

CONCLUSIONS AND FUTURE WORK

A hybrid machine learning model based on Random Forest and a Bagged Tree Classifier showed considerable enhancement in detectingepileptic seizures using EEG signals. The findings of the study revealed that the proposed hybrid model fairly outperformed stand-alone classifiers in terms of accuracy, precision, recall, and F1- score, reflecting its capability to handle complexity and noise in EEG signals. The improved performance of the system validates that the judicious integration of ensemble methods improves robustness and reliability, hence making it a promising solution for clinical and real-time monitoring applications. The study also contributes a structured preprocessing pipeline, a performance evaluation framework, and a hybrid methodology that offers a balanced and computationally efficient alternative to deep learning models with higher complexities. Nevertheless, it is worth mentioning that the study has some limitations: first, it is conducted on a preprocessed and structured dataset instead of raw multi-channel clinical EEG recordings; second, the model has not been tested on real-time or patient-specific environments yet, which may introduce additional challenges related to signal variability and noise. The following extensions could further enhance the applicability and performance of this system: deep learning architectures like CNNs, LSTMs, or hybrid CNN- LSTM models might be able to better extract relevant features from the raw EEG signals and hence enable end-to-end learning. The model would also be clinically useful, ensuring continuous seizure prediction with timely intervention if it were implemented in real-time environments such as wearable EEG devices or bedside monitoring systems. Further, the use of multi- channel raw EEG data could capture richer spatial information and lead to better detection performance in different brain regions. Explainable AI would not only help clinicians better understand what features drive seizure predictions but also increase trust and facilitate a more transparent deployment of this system.

REFERENCES

[1] 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. doi: 10.3389/fncom.2021.650050.

[2] U. R. Acharya, S. L. Oh, Y. Hagiwara, J. H. Tan, and H. Adeli, "Deep convolutional neural network for the automated detection and diagnosis of seizure using EEG signals," Computers in Biology and Medicine, vol. 100, pp. 270–278, 2018. doi: 10.1016/j.compbiomed.2017.09.017.

[3] R. G. Andrzejak, K. Lehnertz, F. Mormann, C. Rieke, P. David, and C. E. Elger, "Indications of nonlinear deterministic and finite-dimensional structures in time series of brain electrical activity: Dependence on recording

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

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region and brain state," Physical Review E, vol. 64, no. 6, p. 061907, 2001. doi: 10.1103/PhysRevE.64.061907.

[4] X. Chen, Z. Rao, and J. Wang, "Automatic epileptic seizure detection using complete ensemble empirical mode decomposition with adaptive noise (CEEMDAN) and machine learning," Biomedical Signal Processing and Control, vol. 10, pp. 1–10, 2014. doi: 10.1016/j.bspc.2013.11.010.

[5] M. S. Farooq, A. Zulfiqar, and S. Riaz, "Epileptic seizure detection using deep learning techniques," Diagnostics, vol. 13, no. 6, p. 1058, 2023. doi: 10.3390/diagnostics13061058.

[6] A. Gramacki and J. Gramacki, "A deep learning framework for epileptic seizure detection based on neonatal EEG signals," Scientific Reports, vol. 12, p. 13010, 2022. doi: 10.1038/s41598-022-15830-2.

[7] F. E. Ibrahim and A. Hussain, "Deep-learning-based seizure detection and prediction: A comprehensive review and perspectives," Computational Methods in Applied Mechanics and Engineering, vol. 392, p. 114612, 2022. doi: 10.1016/j.cma.2021.114612.

[8] Y. Kumar, M. L. Dewal, and R. S. Anand, "Epileptic seizure detection using DWT based fuzzy approximate entropy and support vector machine," Neurocomputing, vol. 133, pp. 271–279, 2014. doi: 10.1016/j.neucom.2013.11.009.

[9] G. Liu, X. Li, and S. Zhang, "Minireview of epilepsy detection techniques based on electroencephalogram and magnetoencephalogram," Frontiers in Systems Neuroscience, vol. 15, p. 685387, 2021. doi: 10.3389/fnsys.2021.685387.

[10] M. Mursalin, Y. Zhang, and N. V. Chawla, "Automated epileptic seizure detection using improved correlation-based feature selection with random forest classifier," Neurocomputing, vol. 228, pp. 83–95, 2017. doi: 10.1016/j.neucom.2017.02.053.

[11] P. Peng, Y. Zheng, Z. Qin, and Z. Zhang, "Seizure prediction in EEG signals using STFT and LSTM: A robust deep learning method," Frontiers in Neuroscience, vol. 15, p. 825434, 2021. doi: 10.3389/fnins.2021.825434.

[12] M. K. Siddiqui, R. Morales-Menendez, X. Huang, and N. Hussain, "A review of epileptic seizure detection using machine learning classifiers," Brain Informatics, vol. 7, no. 1, p. 5, 2020. doi: 10.1186/s40708-020-00105-1.

[13] C. Sun, H. Cui, W. Zhou, W. Nie, X. Wang, and Q. Yuan, "Epileptic seizure detection with EEG textural features and imbalanced classification based on EasyEnsemble learning," International Journal of Neural Systems, vol. 29, no. 10, p. 1950021, 2019. doi: 10.1142/S0129065719500217.

[14] M. N. A. Tawhid, S. Siuly, and T. Li, "A convolutional long short-term memory-based neural network for epilepsy detection from EEG," IEEE Transactions on Instrumentation and Measurement, vol. 71, pp. 1–11, 2022. doi: 10.1109/TIM.2022.3217515.

[15] X. Tian, B. Zhang, Y. Zhang, C. Zhou, and T. Ye, "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. doi: 10.1109/TNSRE.2019.2940480.

[16] N. D. Truong, L. Kuhlmann, M. R. Bonyadi, and O. Kavehei, "Semi-supervised seizure prediction with generative adversarial networks," IEEE Transactions on Neural Networks and Learning Systems, vol. 29, no. 1, pp. 115–124, 2018. doi: 10.1109/TNNLS.2017.2760745.

[17] X. Wei, L. Zhou, Z. Chen, L. Zhang, and Y. Zhou, "Automatic seizure detection using three-dimensional convolutional neural network based on multi-channel EEG," BMC Medical Informatics and Decision Making, vol. 18, Suppl. 5, p. 111, 2018. doi: 10.1186/s12911-018-0693-8.

[18] M. Woodbright, B. Verma, and A. Haidar, "Autonomous deep feature extraction based method for epileptic EEG brain seizure classification," Neurocomputing, vol. 444, pp. 91–103, 2021. doi: 10.1016/j.neucom.2021.02.052.

[19] G. Xu, T. Ren, Y. Chen, and W. Che, "A one-dimensional CNN-LSTM model for epileptic seizure recognition

DOI: 10.17148/IJARCCE.2026.15229

using EEG signal analysis," Frontiers in Neuroscience, vol. 14, p. 578126, 2020. doi: 10.3389/fnins.2020.578126.

[20] G. Zhang, L. Yang, B. Li, Y. Lu, Q. Liu, W. Zhao, T. Ren, J. Zhou, S.-H. Wang, and W. Che, "MNL-Network: A multi-scale non-local network for epilepsy detection from EEG signals," Frontiers in Neuroscience, vol. 14, p. 870, 2020. doi: 10.3389/fnins.2020.00870.

