Journal of Molecular Science

EEG Based Epileptic Seizure Detection Using Deep Convolutional Neural Network and Random Forest Ensemble Learning

Abinaya R[1], S Sreenidhi[1], M Priyadharshini[1], Dr. Pushpa B[2]

Department of Biomedical Engineering, SRM Institute of Science and Technology, Ramapuram Campus,
Chennai, India.

ABSTRACT

Epilepsy is a chronic neurological condition characterized by recurrent seizures that significantly affect diagnosis, treatment, and patient quality of life. Traditional seizure identification relies heavily on manual examination of electroencephalogram (EEG) recordings, a process that is time-consuming, labour-intensive, and dependent on expert interpretation. These limitations make manual review unsuitable for continuous or real-time monitoring, highlighting the need for automated and reliable detection systems. This work presents a hybrid seizure detection framework that integrates machine learning and deep learning techniques to enhance diagnostic efficiency. Handcrafted statistical and temporal EEG features are extracted and classified using a Random Forest model, enabling the system to recognize subtle variations in brain signals. In parallel, spectrogram-based representations of EEG data are processed using Convolutional Neural Networks (CNNs), which capture complex spatiotemporal patterns that conventional feature extraction may overlook. By combining these complementary approaches, the proposed system achieves improved accuracy in detecting seizure onset and distinguishing different seizure types and phases. Interpretable visual outputs—such as EEG waveforms and spectrograms—support clinical validation by providing meaningful insights into model predictions. Performance is evaluated using standard analytical metrics, demonstrating enhanced robustness and reliability across diverse seizure conditions. Overall, the hybrid fusion of handcrafted and deep feature representations strengthens real-time seizure monitoring and offers significant promise for clinical deployment. The framework provides a practical and interpretable solution for continuous EEG analysis, supporting faster decision-making and improved patient care.

I. INTRODUCTION:

Epilepsy is one of the most prevalent chronic neurological disorders, affecting nearly 50 million individuals worldwide, and is characterized by recurrent, unprovoked seizures caused by abnormal synchronous neuronal activity (Boonyakitanont et al., 2020)[3]. Beyond its physiological effects, the condition imposes significant psychosocial and economic burdens, limiting education, employment, and social interaction, while frequent and unpredictable seizures contribute to injury risk, emotional distress, and persistent stigma. Despite advances in neuroimaging, medication, and surgical treatments, timely and accurate seizure detection remains a major clinical challenge (Rasheed et al., 2020)[4].

Electroencephalography (EEG) continues to serve as the principal tool for diagnosing and characterizing epilepsy due to its high temporal resolution. However, manual review of multichannel EEG recordings is labor-intensive, time-consuming, and subject to inter-observer variability, making continuous or real-time monitoring impractical (Choubey & Pandey, 2021)[29]. These limitations have intensified interest

Journal of Molecular Science

in automated EEG analysis systems capable of providing reliable and scalable seizure detection.

Advances in artificial intelligence (AI) have significantly expanded the capabilities of automated seizure detection. Traditional machine learning methods rely on handcrafted features—such as spectral power, statistical moments, entropy measures, and nonlinear descriptors—processed through classifiers including Random Forests, Support Vector Machines, and Gradient Boosting models. While effective in controlled settings, these approaches often struggle with the variability and complexity of seizure patterns across individuals (Santosh Betgeri et al., 2025; Ahmad et al., 2022)[1][34].

Deep learning models offer a more powerful alternative by learning discriminative representations directly from raw EEG signals. Convolutional Neural Networks (CNNs) extract spatial and spectral patterns, while Recurrent Neural Networks (RNNs) such as LSTMs and GRUs capture temporal dependencies. Hybrid CNN–LSTM architectures further enhance the modeling of ictal and interictal dynamics, consistently achieving superior sensitivity and specificity across large datasets (Iešmantas & Alzbutas, 2020; Tawhid et al., 2022)[9][2].

Despite these advantages, deep learning systems face challenges including limited interpretability, high computational demands, and reduced generalizability across patients or recording conditions (Shoeibi et al., 2021)[12]. These concerns have prompted the development of hybrid frameworks that combine handcrafted features with deep representations to improve robustness, interpretability, and data efficiency. Emerging trends such as explainable AI, attention mechanisms, patient-specific adaptation, transfer learning, and federated learning further reflect a shift toward practical, transparent, and clinically deployable solutions (Gao et al., 2023; Saemaldahr & Ilyas, 2023)[36][37].

These evolving approaches collectively demonstrate a growing emphasis on designing AI-driven seizure detection frameworks that bridge the gap between high research performance and practical clinical utility. The emerging models aim to combine precision with interpretability, and automation with adaptability, ultimately supporting more effective, continuous, and patient-centered epilepsy management.

II. DATASET DESCRIPTION:

This study employs two complementary EEG datasets that together form a comprehensive foundation for designing and evaluating automated seizure detection frameworks. The integration of data obtained from both controlled experimental settings and real-world clinical environments ensures that the developed models are not only optimized for performance under ideal recording conditions but are also capable of handling the variability, noise, and unpredictability inherent in clinical EEG data. This dual-dataset strategy strengthens the ecological validity of the research, narrowing the gap between algorithmic development and potential clinical deployment.

The first dataset originates from the Neurology and Sleep Centre in New Delhi, India, where EEG recordings were acquired from ten individuals diagnosed with epilepsy. Data collection was carried out using a Grass Telefactor Comet AS40 amplifier with electrodes positioned according to the internationally standardized 10–20 placement system. The signals were sampled at 200 Hz and processed with a band-pass filter ranging from 0.5 to 70 Hz to suppress artifacts and preserve physiologically relevant neural activity. To facilitate systematic analysis, each recording was segmented into three clinically distinct phases—pre-ictal, interictal, and ictal—representing the periods preceding a seizure, occurring between seizures, and during active seizure events. Each segment spans approximately 5.12 seconds (corresponding to 1024 samples) and is saved as an individual MAT-file. This structured segmentation supports fine-grained examination of temporal changes in neural dynamics surrounding seizure onset, aiding in the construction of models capable of detecting transitions across different seizure states.

The second dataset utilized in this study is the Temple University Hospital Seizure Detection Corpus (TUSZ) from Philadelphia, USA, recognized globally as one of the most extensive open-access EEG collections available for seizure research. The corpus contains more than 500 hours of continuous EEG recordings and covers data obtained from over 300 patients across diverse clinical conditions. Approximately 36 hours of these recordings include confirmed seizure events. A distinguishing feature of TUSZ is its detailed, expertly validated annotations that classify seizure episodes into multiple subtypes, including tonic–clonic, focal, absence, myoclonic, and atonic seizures. These comprehensive labels, verified by trained neurologists, provide an invaluable resource for developing and evaluating algorithms capable of identifying and differentiating complex seizure patterns encountered in real-world clinical practice.

The combination of the New Delhi dataset and the TUSZ corpus offers a strategic balance between highly structured, short-duration EEG segments and long-term clinical recordings characterized by substantial variability. The New Delhi recordings provide clean, well-segmented samples that are ideal for controlled feature extraction, model prototyping,

Journal of Molecular Science

Journal of Molecular Science
Volume 36 Issue 1, Year of Publication 2026, Page 1-9
DoI-10.004687/1000-9035.2026.001

and studying short-window seizure dynamics. Conversely, the TUSZ dataset introduces challenges commonly seen in clinical environments, including heterogeneous electrode montages, noise from patient movement, variability in seizure morphology, and extended monitoring durations. This complementary pairing enables a rigorous evaluation of algorithmic performance in both consistent and high-variability contexts, supporting the development of models that can generalize effectively across diverse recording conditions.

Overall, the combined use of these datasets establishes a realistic and robust foundation for advancing research in automated seizure detection. The controlled segments facilitate precise characterization of seizure-related features, while the clinical recordings test model resilience in complex real-world scenarios. This approach supports the development of algorithms that demonstrate not only high detection accuracy but also adaptability, robustness, and suitability for integration into practical epilepsy monitoring systems. By leveraging the strengths of both datasets, the study aligns with the broader objective of advancing seizure detection technologies toward reliable and clinically meaningful applications.

III. LITERATURE SURVEY:

Epileptic seizures are sudden and uncontrolled disturbances in the brain's electrical activity, producing clinical manifestations that range from subtle sensory alterations to severe convulsive episodes [1]. Timely and accurate detection of these events is essential for minimizing neurological damage, guiding therapeutic intervention, and reducing the risks associated with prolonged or undetected seizures [2]. Conventionally, seizure identification depends on the manual interpretation of electroencephalography (EEG) recordings, a process that is both labour-intensive and subject to observer variability, especially during long-term monitoring [3]. As a result, automated seizure detection has emerged as a major research focus, drawing on innovations in signal processing, machine learning, and deep learning to achieve greater reliability and efficiency [4].

Early computational approaches relied heavily on handcrafted features derived from EEG signals. These included time-domain attributes such as mean amplitude, variance, skewness, and kurtosis, as well as frequency-domain characteristics like power spectral density and band-specific energy distribution [5]. Extracted features were then input into classical machine learning models including, support vector machines (SVM), k-nearest neighbours (KNN), decision trees, and ensemble-based classifiers to distinguish seizure activity from normal neural patterns [6]. Although these techniques demonstrated notable performance on controlled datasets, they often failed to capture the highly non-linear and spatially distributed nature of EEG dynamics, limiting their generalizability across patients and seizure types [7]. To address such limitations, hybrid approaches were developed that fused multiple feature categories or integrated complementary classifiers. For instance, combinations of XGBoost with recurrent neural networks (RNNs) have shown improvements by coupling feature importance analysis with modelling of temporal progression in EEG sequences [1]. Other studies have implemented stacked autoencoders and feature-fusion strategies to reduce redundancy while retaining high-value discriminatory information, ultimately enhancing classification accuracy [17].

The application of deep learning has dramatically advanced the capabilities of automated seizure detection. Convolutional neural networks (CNNs), in particular, have been widely used to analyse both raw EEG waveforms and their time–frequency transformations, such as spectrograms and scalograms. These models learn hierarchical features that capture both spatial and temporal dependencies in the data, improving detection performance and reducing the need for extensive preprocessing [10]. Convolutional long short-term memory (ConvLSTM) architectures extend this capability by simultaneously modelling spatiotemporal characteristics, enabling more accurate identification of seizure onset patterns [3]. Additionally, hybrid deep learning frameworks that combine CNN layers with gated recurrent units (GRUs) or long short-term memory (LSTM) networks have produced further gains in sensitivity and specificity, offering a more comprehensive representation of EEG signals [40]. Multi-modal frameworks have also been explored, integrating EEG with auxiliary physiological signals such as electromyography (EMG) or functional near-infrared spectroscopy (fNIRS), thereby enriching contextual information and improving overall detection performance [26].

Dataset selection plays a critical role in developing reliable seizure detection models. Publicly available resources such as the Temple University Hospital Seizure Detection Corpus (TUSZ) offer extensive multi-patient EEG recordings annotated by expert neurologists, providing a diverse representation of seizure subtypes including tonic–clonic, absence, focal, myoclonic, and atonic seizures [2]. These datasets reflect real-world complexity, including patient-specific variability, noise artifacts, and heterogeneous electrode configurations. Complementary clinical datasets obtained under controlled conditions such as, those from the Neurology & Sleep Centre in New Delhi provide shorter, well-segmented EEG samples categorized

Journal of Molecular Science

into pre-ictal, interictal, and ictal stages, offering an ideal platform for detailed analysis and model tuning [46]. Combining both controlled and clinical datasets allows for more rigorous evaluation, ensuring that detection models maintain robustness across structured and naturally variable environments.

Given the substantial differences in seizure patterns across individuals, patient-specific adaptation has emerged as a key strategy to enhance model performance. Methods such as transfer learning, domain adaptation, and adaptive recalibration enable models to incorporate patient-specific characteristics while leveraging generalizable knowledge learned from larger datasets [45]. The issue of dataset imbalance, stemming from the naturally low occurrence of seizures relative to non-seizure intervals, has also been addressed through synthetic oversampling techniques like SMOTE and through advanced feature selection methods that prioritize high-discriminative EEG attributes [43].

With increasing demand for continuous monitoring, recent studies have emphasized real-time detection and deployment on wearable or portable devices. Lightweight, interpretable models designed for embedded systems support low-latency analysis while maintaining sufficient accuracy for clinical relevance [21]. Hardware implementations on field-programmable gate arrays (FPGAs), low-power microprocessors, and specialized accelerators have been explored to improve processing efficiency in resource-constrained environments [30]. Model interpretability is also gaining importance, as visualizing salient EEG features and understanding the basis of algorithmic decisions improves clinical trust and contributes to deeper insights into seizure mechanisms [33].

The literature reflects a pronounced evolution from traditional feature-based analysis to sophisticated deep learning and hybrid architectures capable of modeling the complex spatiotemporal properties of EEG signals [34]. The incorporation of patient-specific adaptation, multi-modal integration, and real-time optimization has further expanded the practical applicability of automated seizure detection systems. Nonetheless, important challenges remain, including inter-subject variability, limited availability of high-quality annotated datasets, and the need for energy-efficient models suitable for continuous deployment. Overcoming these limitations continues to be central to advancing robust, clinically viable solutions for epilepsy monitoring.

III. METHODOLOGY:

The study presents a clear and practical approach to automatically detecting seizures from EEG signals by combining both machine learning and deep learning methods. The pipeline is carefully designed to address the common issues that make EEG analysis challenging, such as high-dimensional data, noise, differences between patients, and the variability in seizure patterns. As shown in Figure 1, the workflow outlines every stage of the process—from collecting the data and cleaning it, to extracting meaningful features, training the models, and finally evaluating their performance. Each stage flows smoothly into the next, making the overall method not only scientifically robust but also suitable for real-world use.
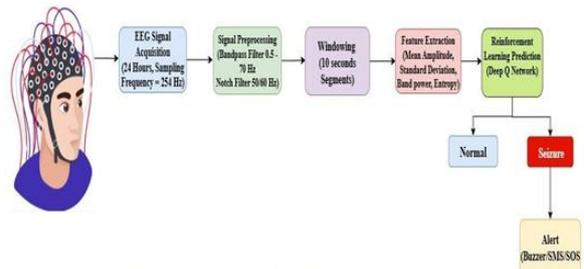

Fig 1. A block diagram of the proposed seizure prediction system using EEG signals and Deep Q- Network.

A. EEG Data Acquisition:

The data for this study were drawn from two complementary EEG datasets to make sure the proposed system performs accurately in controlled settings and remains reliable in diverse clinical environments. The first dataset was collected at the Neurology and Sleep Centre in New Delhi, India, and includes EEG recordings from ten epilepsy patients. Using the standard 10–20 international electrode placement system, the signals were captured with a Grass Telefactor Comet AS40 amplifier, sampled at 200 Hz, and filtered between 0.5 and 70 Hz to preserve clinically meaningful frequencies. Each recording was then divided into preictal, interictal, and ictal segments, with each segment lasting around 5.12 seconds (1024 samples). These clean, well-labeled segments provide a controlled setting for early model development, allowing for precise validation before moving on to larger datasets.

To broaden the system's applicability, the study also incorporated the Temple University Hospital Seizure Detection Corpus (TUSZ), a large-scale dataset containing over 500 hours of EEG recordings from more than 300 patients, including 36 hours of seizure activity. The seizures in TUSZ are thoroughly annotated—not only as simple seizure vs. non-seizure events but also according to clinically meaningful subtypes such as tonic–clonic, absence, focal, myoclonic, and atonic seizures. By combining the smaller but highly structured New Delhi dataset with the expansive and diverse TUSZ dataset, the proposed framework is equipped to handle a wide range of real-world data conditions, from controlled laboratory recordings to complex hospital environments.

Journal of Molecular Science

detection.

B. Preprocessing:

Preprocessing is a crucial step in EEG analysis because raw EEG recordings are often filled with artifacts from eye blinks, muscle movements, and electrical noise from the environment. To improve signal quality and ensure reliable analysis, several cleaning techniques were applied in a systematic sequence. First, a 0.5–70 Hz band-pass filter was used to remove low-frequency baseline drift and high-frequency noise. This was followed by a 50/60 Hz notch filter to eliminate power line interference. After filtering, the signals were divided into smaller, non-overlapping windows, creating consistent time segments for further analysis.

To refine artifact removal, statistical thresholding was used to identify unusually large or abnormal values, and Independent Component Analysis (ICA) helped isolate and eliminate components linked to noise sources such as eye movements or muscle activity. Together, these preprocessing steps preserved only the physiologically meaningful portions of the EEG, ensuring that the features extracted later truly represent brain activity related to seizures.

C. Feature Extraction:

Feature extraction in this study followed two complementary paths, one tailored for machine learning classifiers and the other for deep learning models.

For machine learning methods such as Random Forest, features were calculated from each EEG segment in both the time and frequency domains. Time-domain features included mean, standard deviation, skewness, and kurtosis, while frequency-domain features captured band power across the delta, theta, alpha, beta, and gamma ranges. Additional descriptors, such as Hjorth parameters and entropy-based measures, were used to represent the complexity and nonlinear characteristics of the EEG signals. All extracted features were then normalized and scaled to maintain consistency across recordings and to minimize bias during classification.

For deep learning, particularly CNN-based models, EEG signals were converted into spectrograms using the Short-Time Fourier Transform (STFT). These spectrograms offer a detailed time-frequency representation of the EEG, allowing CNNs to learn subtle spatial and temporal patterns associated with different types of seizures.

By combining numerical features for classical machine learning with spectrogram-based representations for deep learning, the study enables a clear comparison between the two approaches and highlights the strengths each one brings to seizure
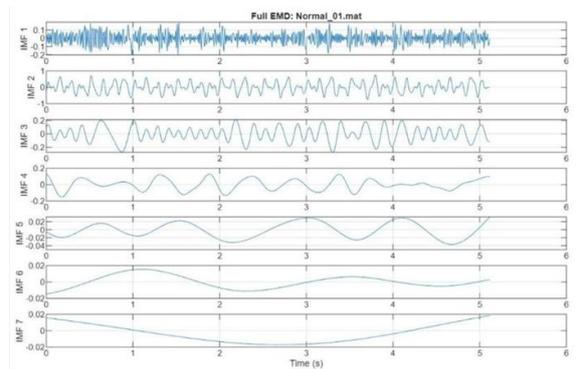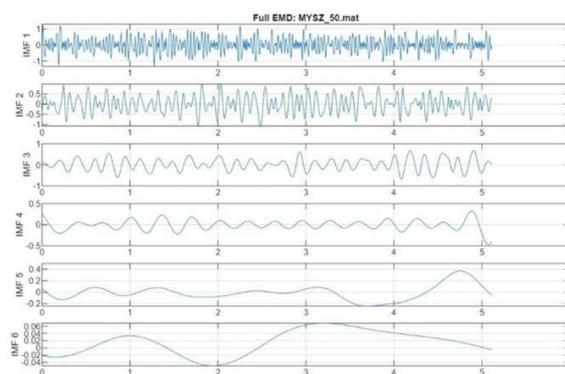

Fig 2.EMD of Normal EEG signal

Fig 3. EMD of abnormal EEG signal

D. Model Training:

Two distinct modelling strategies were explored in this study.

The first approach used a Random Forest classifier, chosen for its ability to manage high-dimensional data and its strong resistance to overfitting. Key hyperparameters such as, the number of trees, minimum leaf size, and maximum number of predictors considered at each split were, carefully tuned to strike the right balance between model complexity and generalization.

The second approach involved training a Convolutional Neural Network (CNN) on spectrogram images. The CNN architecture included several convolutional layers, each followed by max-pooling, batch normalization, and dropout to improve generalization and reduce the risk of overfitting. Training was carried out using categorical cross-entropy as the loss function along with an adaptive learning-rate optimizer. To further strengthen the model, data augmentation techniques like rotation and scaling were applied to the spectrograms, increasing the variety and robustness of the training samples.

E. Model Evaluation:

Model performance was evaluated using standard metrics such as accuracy, sensitivity, specificity, and F1-score, offering a well-rounded understanding of

Journal of Molecular Science

how effectively each model classified seizure and non-seizure events. Confusion matrices were also generated to visualize how well different seizure types were recognized, highlighting both the classes that were consistently identified correctly and those that were more commonly misclassified.

For the Random Forest models, out-of-bag (OOB) error rates were monitored throughout training to keep track of overfitting. In the case of the CNN models, validation loss curves served a similar purpose, helping identify when the network began to memorize rather than generalize. Cross-validation was applied especially, for the smaller New Delhi dataset, to obtain more reliable estimates of how well the models would perform on unseen data.
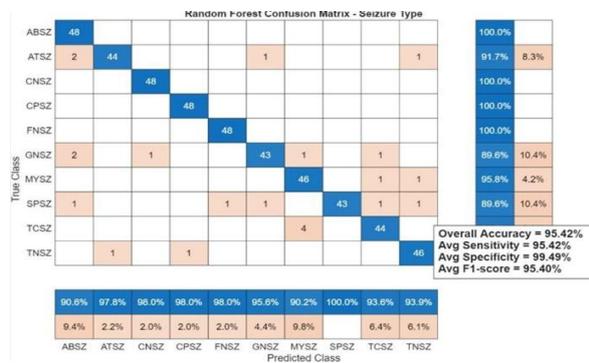
Fig 4. Classification performance of seizure types using the Random Forest model on EEG data.
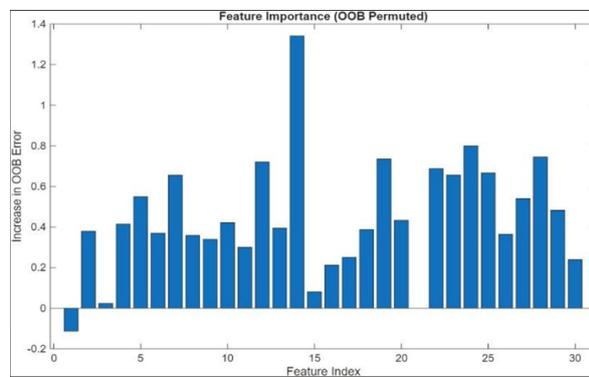

Fig 5. Permutation-based feature importance for EEG features as measured by the increase in out- of-bag error with the Random Forest model.
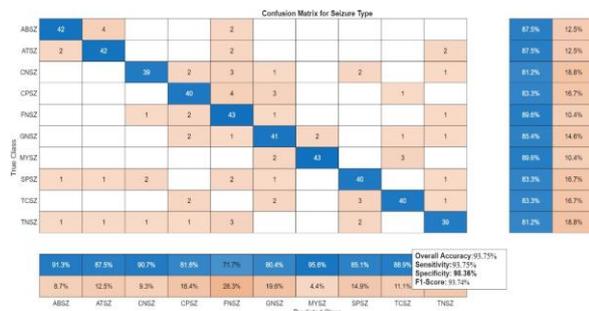

Fig 6. Confusion matrix showing seizure type classification performance and overall metrics for the tested EEG model

IV. RESULTS AND DISCUSSIONS:

The proposed seizure-type detection framework was evaluated using two complementary models: a spectrogram-based Convolutional Neural Network (CNN) and a feature-driven Random Forest (RF) classifier. The CNN achieved an overall accuracy of 93.75%, while the RF reached 95.42%, showing that both models performed strongly, with the RF offering a slight edge on the prepared dataset. Confusion matrices for both models (Figures 5.9 and 5.10) were examined to understand how well each seizure type was classified and to identify any recurring misclassification patterns.

The CNN's confusion matrix revealed high accuracy for seizure types with clear and distinct time–frequency patterns, such as tonic-clonic (TCSZ) and generalized (GNSZ) seizures. This highlights the CNN's strength in learning layered spectral–temporal features directly from spectrograms. Most misclassifications occurred among seizure types with similar spectral signatures or overlapping morphological characteristics, particularly certain focal subtypes, which is expected when the visual patterns in the spectrograms share close similarities. Throughout training, the CNN's loss curves showed smooth convergence and stable validation performance, suggesting that the final accuracy of 93.75% reliably reflects the model's ability to generalize to new data.

The Random Forest classifier displayed even stronger diagonal dominance in its confusion matrix, consistent with its higher accuracy of 95.42%. The model's ensemble structure helped reduce variance and improved overall prediction stability, especially for seizure categories with subtle temporal or spectral differences. The OOB-permuted feature importance plot (Figure 5.11) showed that measures such as spectral entropy, theta band power, Hjorth complexity, wavelet energy, and line length were among the most influential features. This highlights the RF's ability to effectively combine statistical, spectral, and nonlinear descriptors to differentiate between seizure types. An additional advantage of the RF approach is its interpretability, which provides insight into the specific EEG characteristics that most strongly drive the model's predictions, a useful feature in clinical contexts.
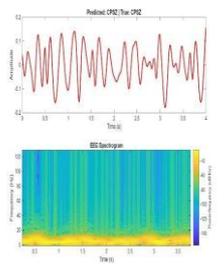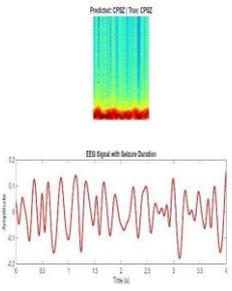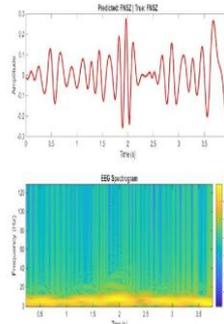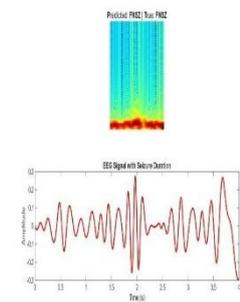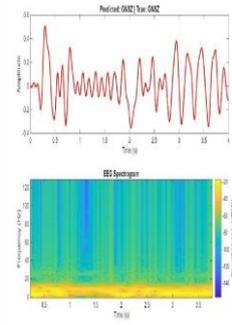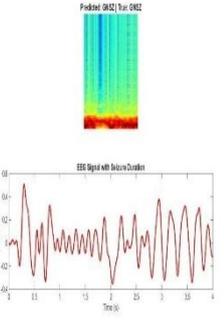
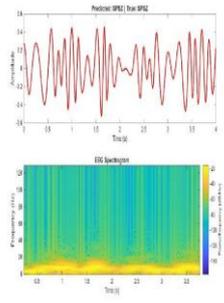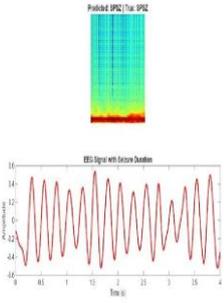Alongside numerical results, visual outputs were also examined to better understand how each model interprets seizure-related EEG information.
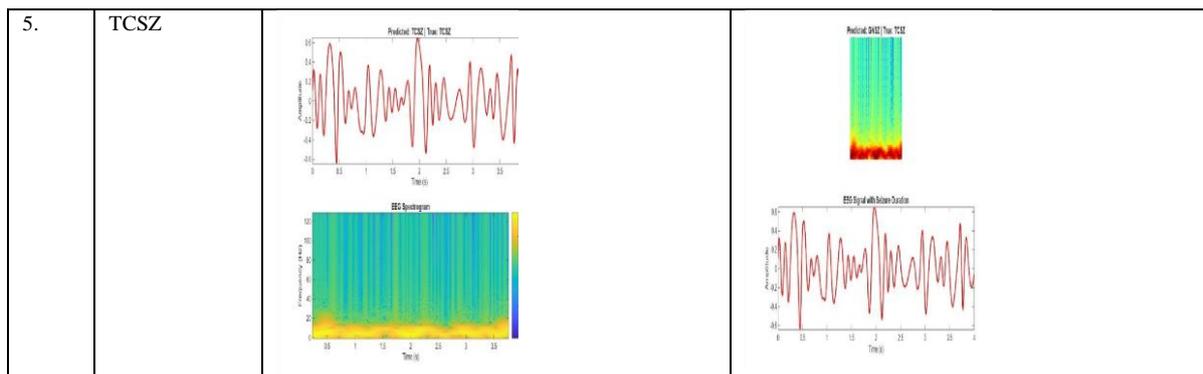
The table 1 presents a comparative set of EEG waveform and spectrogram visualizations for five seizure categories—CPSZ, FNSZ, GNSZ, SPSZ, and TCSZ—analyzed through both the Random Forest classifier and the Convolutional Neural Network (CNN). For each seizure type, the Random Forest

Journal of Molecular Science

outputs include the raw EEG signal, which captures the temporal characteristics such as rhythmic discharges, amplitude fluctuations, and abnormal spike patterns, along with a spectrogram that illustrates the corresponding time–frequency distribution of the signal. The CNN column displays the same pair of representations, reflecting the input features used during deep learning-based classification, and emphasizing the spectral and morphological patterns the network automatically extracts. Visual differences across seizure types are evident: CPSZ and FNSZ show localized irregularities in amplitude and frequency; GNSZ presents more synchronized, high-amplitude bursts; SPSZ is marked by short, narrow-band activity; and TCSZ demonstrates broad, high-energy patterns associated with generalized convulsions. Collectively, these visual comparisons highlight how each model interprets the underlying EEG dynamics and provide evidence of the distinctive signal characteristics that contribute to seizure identification and classification in the proposed framework.

Table1: Representative outputs from CNN classification and Random Forest prediction

S. No	Seizure Type	Random Forest	CNN
1.	CPSZ		
2.	FNSZ		
3.	GNSZ		
4.	SPSZ		

Journal of Molecular Science

Journal of Molecular Science
Volume 36 Issue 1, Year of Publication 2026, Page 1-9
DoI-10.004687/1000-9035.2026.001

5.	TCSZ		

Overall, the results from both the CNN and the Random Forest models show that the proposed seizure-type detection framework works effectively and that the two modelling approaches actually complement each other quite well. The CNN is particularly good at picking up detailed time–frequency patterns in the spectrograms, giving a more visual, layered understanding of how different seizures unfold. On the other hand, the Random Forest edges ahead in overall accuracy by using carefully crafted statistical and spectral features, and it also has the advantage of making its decision process more transparent.

When viewed together, the two models create a balanced system—one that combines solid performance with interpretability. The combination of clean EMD-based preprocessing, comprehensive feature extraction, and a dual-model evaluation strategy has resulted in a method that is not only practical but also clinically meaningful. It shows strong potential for reliably distinguishing a variety of seizure types in different EEG settings.

V. CONCLUSION:

This research puts forward a practical and well-rounded framework for automatically identifying seizure types from EEG signals. The approach brings together empirical signal decomposition, features drawn from multiple domains, and two different modelling strategies that complement each other. By using both a Convolutional Neural Network (CNN) and a Random Forest (RF), the study combines the pattern-recognition strength of deep learning with the clearer interpretability offered by traditional machine learning.

The CNN, which was trained on time–frequency spectrograms, achieved an accuracy of 93.75% and proved effective at recognising the complex spectral and temporal patterns that often appear during seizures. The Random Forest reached an even higher accuracy of 95.42%, largely due to its use of well-designed features like spectral entropy, Hjorth complexity, and wavelet energy. Both models were able to separate normal EEG activity from seizure

events and even differentiate between multiple seizure types, showing strong generalization across both the smaller controlled dataset and the larger TUH dataset. Visual analyses such as, confusion matrices, feature-importance plots, and classification examples, helped confirm that the models were consistent and interpretable. The CNN excels at learning subtle relationships directly from the data, whereas the RF makes it easier to see which physiological signal characteristics are driving the predictions. Together, they create a balanced system that performs well while still offering transparency.

Overall, this study highlights how hybrid EEG-based computational intelligence systems can support more accurate and efficient epilepsy diagnosis and monitoring. The framework is flexible enough to adapt to different datasets and seizure categories, making it a strong candidate for real-time use in clinical settings or even in wearable neuro-monitoring devices. Looking ahead, there is room to explore patient-specific model adaptation, the use of additional bio signals, and more lightweight architectures to improve scalability and real-world deployment.

VI. REFERENCES:

1. Santushti Santosh Betgeri, Madhu Shukla, Dinesh Kumar, Surbhi B. Khan, Muhammad Attique Khan, Nora A. Alkhaldi, "Enhancing seizure detection with hybrid XGBoost and recurrent neural networks", Neuroscience Informatics, Volume 5, Issue 2, 2025, 100206, ISSN 2772-5286, https://doi.org/10.1016/j.neuri.2025.100206.
2. M. N. A. Tawhid, S. Siuly and T. Li, "A Convolutional Long Short-Term Memory-Based Neural Network for Epilepsy Detection From EEG," in IEEE Transactions on Instrumentation and Measurement, vol. 71, pp. 1-11, 2022, Art no. 4010211, doi: 10.1109/TIM.2022.3217515.
3. P. Boonyakitanont, A. Lek-Uthai, K. Chomtho, and J. Songsiri, "A review of feature extraction and performance evaluation in epileptic seizure detection using EEG," Biomedical Signal Processing and Control, vol. 57, pp. 1–28, 2020.
4. K. Rasheed, A. Qayyum, J. Qadir, S. Sivathamboo, and P. Kwan, "Machine learning for predicting epileptic seizures using EEG signals: a review," IEEE Reviews in Biomedical Engineering, vol. 14, pp. 139–155, 2020.
5. S. Toraman, "Preictal and interictal recognition for epileptic seizure prediction using pretrained 2D-CNN models," Traitement du Signal, vol. 37, no. 6, pp. 1045–1054, 2020.
6. B. Behnoush, E. Bazmi, S. H. Nazari, S. Khodakarim, M.

A.Looha, and H. Soori, "Machine learning algorithms to predict seizure due to acute tramadol poisoning," Human & Experimental Toxicology, vol. 40, no. 8, pp. 1225–1233, 2021.

7. Y. S. Chandu and S. Fathimabi, "Epilepsy prediction using deep learning," International Journal of Engineering Research & Technology (IJERT), vol. 9, no. 5, pp. 211–219, 2021

8. M. Wu, H. Qin, X. Wan, and Y. Du, "HFO detection in epilepsy: a stacked denoising autoencoder and sample weight adjusting factors-based method," IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 29, pp. 1965–1976, 2021.

9. T. Iešmantas and R. Alzbutas, "Convolutional neural network for detection and classification of seizures in clinical data," Medical & Biological Engineering & Computing, vol. 58 no. 9, pp. 1919–1932, 2020.

10. 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, May 2020.

11. K.Rasheed, A.Qayyum ,J.Qadir, S.Sivathamboo ,P.Kwan, L.Kuhlmann, T. O'Brien, and A. Razi, "Machine learning for predicting epileptic seizures using EEG signals: A review," IEEE Review in Biomedical Engineering, vol. 14, pp. 139–155, 2020.

12. A. Shoeibi, M. Khodatars, N. Ghassemi, M. Jafari, P. Moridian, R. Alizadehsani, M. Panahiazar, F. Khozeimeh, A. Zare, H. Hosseini-Nejad, A. Khosravi, A. F. Atiya, D. Aminshahidi, S. Hussain, M. Rouhani, S. Nahavandi, and U. R. Acharya, "Epileptic seizures detection using deep learning techniques: A review," International Journal of Environmental Research on Public Health, vol. 18, no. 11, p. 5780, May 2021.

13. W.Lin,Q.Chen,M.Jiang,J.Tao,Z.Liu,X.Zhang,L.Wu,S.Xu,Y. Kang, and Q. Zeng, "Sitting or walking? Analyzing the neural emotional indica tors of urban green space behavior with mobile EEG," Journal of Urban Health, vol. 97, no. 2, pp. 191–203, Apr. 2020.

14. E. Q. Wu, "Detecting fatigue status of pilots based on deep learning network using EEG signals," IEEE Transactions on Cognitive Developmental Systems, vol. 13, no. 3, pp. 575–585, Sep. 2021.

15. V. R. Carvalho, M. F. D. Moraes, A. P. Braga, and E. M. A. M. Mendes, "Evaluating five different adaptive decomposition methods for EEG signal seizure detection and classification," Biomedical Signal Processing and Control, vol. 62, Sep. 2020, Art. no. 102073.

16. M. Chen, X. Shi, Y. Zhang, D. Wu, and M. Guizani, "Deep feature learning for medical image analysis with convolutional autoencoder neural network," IEEE Transactions on Big Data, vol. 7, no. 4, pp. 750–758, Oct. 2021.

17. S. Chakrabarti, A. Swetapadma, A. Ranjan, and P. K. Pattnaik, "Time domain implementation of pediatric epileptic seizure detection system for enhancing the performance of detection and easy monitoring of pediatric patients," Biomedical Signal Processing and Control, vol. 59, May 2020, Art. no. 101930.

18. R. Sarić, D. Jokić, N. Beganović, L. G. Pokvić, and A. Badnjević, "FPGA-based real-time epileptic seizure classification using artificial neural network," Biomedical Signal Processing and Control, vol. 62, Sep. 2020, Art. no. 102106.

19. K. Zhang, N. Robinson, S.-W. Lee, and C. Guan, "Adaptive transfer learning for EEG motor imagery classification with deep convolutional neural network," Neural Networks, vol. 136, pp. 1–10, Apr. 2021.

20. G. Placidi, L. Cinque, and M. Polsinelli, "A fast and scalable framework for automated artifact recognition from EEG signals represented in scalp topographies of independent components," Computers in Biology and Medicine, vol. 132, May 2021, Art. no. 104347.

21. D. Borra, S. Fantozzi, and E. Magosso, "Interpretable and lightweight convolutional neural network for EEG decoding: Application to movement execution and imagination," Neural Networks, vol. 129, pp. 55–74, Sep. 2020.

22. R. Y. Aminabadi, O. Ruwase, M. Zhang, Y. He, J.-M. Arnau, and A. Gonazalez, "SHARP: An adaptable, energy-efficient accelerator for recurrent neural networks," ACM Transactions on Embedded Computing Systems, vol. 22, no. 2, pp. 1–23, Mar. 2023.

23. G. Paulin, F. Conti, L. Cavigelli, and L. Benini, "Vau da muntanialas: Energy-efficient multi-die scalable acceleration of RNN inference," IEEE Transactions on Circuits and Systems I, Reg. Papers, vol. 69, no. 1, pp. 244–257, Jan. 2022.

24. G. Muhammad, M. S. Hossain, and N. Kumar, "EEG-based pathology detection for home health monitoring," IEEE Journal on Selected Areas in Communications, vol. 39, no. 2, pp. 603–610, Feb. 2021.

25. A.Kurapa, D. Rathore, D. R. Edla, A. Bablani, and V. Kuppili, "A hybrid approach for extracting EMG signals by filtering EEG data for IoT applications for immobile persons," Wireless Personal Communications, vol. 114, no. 4, pp. 3081–3101, Oct. 2020.

26. T.Siddharth, P. Gajbhiye, R. K. Tripathy, and R. B. Pachori, "EEG-based detection of focal seizure area using FBSE-EWT rhythm and SAE-SVM network," IEEE Sensors Journal, vol. 20, no. 19, pp. 11421–11428, Oct. 2020.

27. M. Sameer and B. Gupta, "Detection of epileptical seizures based on alpha band statistical features," Wireless Personal Communications, vol. 115, no. 2, pp. 909–925, Nov. 2020.

28. M. Chakraborty and D. Mitra, "Epilepsy seizure detection using kurtosis based VMD's parameters selection and bandwidth features," Biomedical Signal Processing and Control, vol. 64, Feb. 2021, Art. no. 102255.

29. H. Choubey and A. Pandey, "A combination of statistical parameters for the detection of epilepsy and EEG classification using ANN and KNN classifier," Signal, Image Video Processing, vol. 15, no. 3, pp. 475–483, Apr. 2021.

30. H. Akbari, S. S. Esmaili, and S. F. Zadeh, "Detection of seizure EEG signals based on reconstructed phase space of rhythms in EWT domain and genetic algorithm," Signal Processing and Renewable Energy, vol. 4, no. 2, pp. 23–36, 2020.

31. C. Xiao, S. Wang, L. Iasemidis, S. Wong, and W. A. Chaovalitwongse, "An adaptive pattern learning framework to personalize online seizure prediction," IEEE Transactions on Big Data, vol. 7, no. 5, pp. 819–831, Nov. 2021.

32. J. M.-T. Wu, M.-H. Tsai, C.-T. Hsu, H.-C. Huang, and H.-C. Chen, "Intelligent signal classifier for brain epileptic EEG based on decision tree, multilayer perceptron and oversampling approach," in Advances in Information and Communication,2020, pp. 11–24.

33. S.Raghu,N.Sriraam,Y.Temel,S.V.Rao,andP.L.Kubben,"EEG-based multi-class seizure type classification using convolutional neural network and transfer learning," Neural Networks, vol. 124, pp. 202–212, Apr. 2020.

34. I. Ahmad, X. Wang, M. Zhu, C. Wang, Y. Pi, J. A. Khan, S. Khan, O. W. Samuel,S.Chen,andG.Li,"EEG-based epileptic seizure detection via machine/deep learning approaches: A systematic review," Computational Intelligence and Neuroscience, vol. 2022, pp. 1–20, Jun. 2022.