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Epileptic Seizure Type Detection Model Using CNN-Derived Features and Random Forests

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Abstract: ***Epilepsy is a chronic neurological disorder characterized by recurrent and unpredictable seizures, affecting nearly 1% of the global population and profoundly impacting daily life and overall well-being. Accurate detection and classification of seizures are essential for effective patient management, as traditional EEG-based monitoring relies heavily on manual interpretation, which is time-consuming and subject to variability. This study explores computational approaches for both seizure detection and type classification using EEG data. Two complementary strategies are examined: a feature-based machine learning approach, which extracts statistical, temporal, and spectral features to capture distinct seizure patterns, and a deep learning approach that analyses spectrogram representations of EEG signals, allowing for the modelling of complex temporal-frequency interactions associated with different seizure types. These methods incorporate rigorous preprocessing, including artifact removal, normalization, and dimensionality reduction, to ensure high-quality input for model training and to improve interpretability. In addition, feature importance analysis and visual representations of EEG activity provide insights into the distinguishing characteristics of various seizure types, facilitating clinical understanding and potential application. By combining feature-based and image-based modelling, the study demonstrates a flexible and scalable framework for automated seizure detection and classification, offering a non-invasive solution capable of supporting patient-specific clinical decisions. The findings underscore the potential of intelligent computational techniques to enhance monitoring, diagnosis, and management of epilepsy, paving the way for personalized healthcare systems and improved patient outcomes.***
Keywords: Epileptic Seizure, Electroencephalogram (EEG) Analysis, Random Forest, Convolutional Neural Networks (CNNs), Feature Extraction.

I. DATASET DESCRIPTION

This study utilizes two complementary EEG datasets that together provide a comprehensive basis for developing and evaluating automated seizure detection methods.

The first dataset was collected at the Neurology & Sleep Centre in New Delhi, India, involving ten patients diagnosed with epilepsy. EEG recordings were obtained using a Grass Telefactor Comet AS40 amplifier, following the standard 10–20 electrode placement system. Signals were sampled at 200 Hz and band-pass filtered between 0.5–70 Hz. For analytical clarity, the recordings were divided into pre-ictal, interictal, and ictal stages. Each segment lasts approximately 5.12 seconds (1024 samples) and is stored individually as a MAT-file. This structured segmentation ensures distinct representation of seizure stages, supporting precise model training and validation. The second dataset is the Temple University Hospital Seizure Detection Corpus (TUSZ), based in Philadelphia, USA. Recognized as the largest publicly available EEG seizure dataset, it comprises over 500 hours of recordings from more than 300 patients, including roughly 36 hours containing seizure activity. Beyond binary seizure annotations, events are categorized into clinically relevant subtypes, including tonic-clonic, absence, focal, myoclonic, and atonic seizures. All annotations have been meticulously verified by expert reviewers, ensuring a high level of clinical accuracy. By combining the highly controlled, short, segmented EEG recordings from New Delhi with the extensive, clinically diverse data from the TUSZ corpus, this study leverages both structured and real-world EEG environments. This dual approach strengthens the robustness and generalizability of the proposed seizure detection methods, ensuring they perform reliably across both experimental and practical clinical scenarios.

II. INTRODUCTION

Epilepsy is a chronic neurological disorder characterized by recurrent, unprovoked seizures, affecting nearly 50 million individuals worldwide. The condition imposes significant physical, psychological, and social challenges, often diminishing the overall quality of life for patients and their caregivers [1]. Seizures arise from abnormal, excessive, or synchronous neuronal discharges in the brain, and they can vary widely in their manifestations, durations, and EEG signatures. Accurate identification and classification of seizure types are therefore essential for effective diagnosis, treatment planning, and personalized therapy [5].

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Seizures manifest in diverse clinical and electrophysiological forms, each exhibiting distinct EEG characteristics and frequency dynamics. Absence seizures (ABSZ) are characterized by brief lapses in consciousness accompanied by a classic *3 Hz spike-and-wave* pattern, typically observed in the 2.5–4 Hz range. Atonic seizures (ATSZ) involve a sudden loss of muscle tone, reflected as sharp voltage drops or signal attenuation across 0.5–4 Hz, indicating transient cortical suppression. Clonic seizures (CNSZ) present repetitive spike bursts and rhythmic jerking movements, generally occupying the 4–10 Hz band. Tonic seizures (TNSZ) exhibit sustained high-frequency discharges between 15–25 Hz, corresponding to prolonged muscle contractions. Tonic–clonic seizures (TCSZ) begin with a tonic phase of high-frequency (above 20 Hz) bursts, followed by a clonic phase showing slower oscillations near 5–8 Hz. Myoclonic seizures (MYSZ) appear as brief, shock-like muscle jerks with spike or poly spike-wave complexes, typically spanning 10–16 Hz. Simple partial seizures (SPSZ) display localized discharges confined to specific cortical regions, usually within the 5–15 Hz frequency range, without loss of awareness. Complex partial seizures (CPSZ) often originate in the temporal lobe and show evolving rhythmic activity in the 4–8 Hz band, accompanied by altered consciousness. Focal non-specific seizures (FNSZ) demonstrate irregular, region-dependent patterns across 1–20 Hz, varying between patients, whereas generalized non-specific seizures (GNSZ) are marked by widespread high-amplitude rhythmic activity extending over 1–30 Hz, encompassing multiple EEG channels. These distinctions in spatial and frequency behavior are crucial for developing automated systems capable of accurately differentiating seizure types.

Electroencephalography (EEG) remains the gold standard for capturing brain activity associated with epileptic events, owing to its non-invasive nature and high temporal resolution [2]. EEG signals record the electrical oscillations of neuronal populations, providing valuable insight into both interictal (between seizures) and ictal (during seizures) dynamics. However, manual EEG interpretation by neurologists is time-consuming, subjective, and prone to human error, particularly when dealing with long-term recordings or subtle seizure events [4]. This has led to the rapid evolution of automated seizure detection systems, which aim to provide objective, real-time, and reproducible analyses for clinical use [10].

Machine learning (ML) and deep learning (DL) approaches have emerged as transformative tools for EEG-based seizure detection [3]. Traditional ML models, such as Random Forests (RF), Support Vector Machines (SVM), and k-Nearest Neighbours (KNN), rely on handcrafted statistical, temporal, and spectral features extracted from EEG signals to differentiate seizure from non-seizure activity [30]. These methods are computationally efficient, interpretable, and well-suited for clinical integration. In contrast, deep learning models such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and hybrid CNN–LSTM architectures automatically learn complex hierarchical patterns from raw signals or spectrograms, providing superior performance in detecting nonlinear and time-dependent seizure characteristics [17]. CNNs, in particular, have shown exceptional capability in analysing spectrogram-based EEG inputs, capturing subtle frequency and amplitude variations across different seizure types [34].

The performance of these detection systems is strongly influenced by the quality and diversity of EEG datasets used during model training and validation [42]. The Temple University Hospital Seizure Detection Corpus (TUSZ) provides an extensive, clinically rich dataset containing over 500 hours of EEG data from more than 300 patients, covering multiple seizure types and interictal intervals [2]. Complementing this large-scale corpus, this study also employs a controlled EEG dataset recorded from ten patients at the Neurology & Sleep Centre in New Delhi using a Grass Telefactor Comet AS40 amplifier. Signals were captured with a standard 10–20 electrode configuration, sampled at 200 Hz, and filtered within a 0.5–70 Hz band. Each EEG segment, approximately 5.12 seconds long (1024 samples), was stored as an individual .mat file, facilitating high-resolution analysis and precise seizure segmentation [42]. Combining these two datasets offers both clinical diversity and controlled signal precision, ensuring that the developed models can generalize well across real-world and experimental conditions [4]. Controlled datasets provide clean and well-labelled samples ideal for model benchmarking, while large-scale clinical data introduce realistic artifacts and inter-patient variability essential for robust performance evaluation [34].

Feature extraction remains a cornerstone of EEG-based seizure analysis. Traditional methods focus on time-domain descriptors such as mean, variance, skewness, kurtosis, and Hjorth parameters, alongside frequency-domain metrics like power spectral density (PSD) and band energies in the delta, theta, alpha, beta, and gamma ranges [18]. More advanced time–frequency techniques, including Empirical Mode Decomposition (EMD) and Wavelet Transform (WT), are frequently used to isolate meaningful oscillatory patterns and reduce noise. On the other hand, CNN-based approaches eliminate the need for handcrafted features by learning discriminative representations directly from spectrograms, thereby capturing both global and local temporal–spectral dynamics [17].

Recent literature also emphasizes hybrid models that combine the strengths of ML and DL paradigms [34]. For instance, integrating XGBoost or Random Forests with recurrent neural architectures enhances detection accuracy by merging interpretability with temporal learning [1].

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Similarly, CNN–GRU frameworks exploit both spatial and temporal correlations, enabling precise classification across multiple seizure types [40]. These integrative frameworks underscore the potential of multi-model systems in bridging the gap between automated precision and clinical interpretability.

This study leverages both feature-based and spectrogram-based methodologies to develop a comprehensive seizure type detection framework. EEG data from the TUSZ and New Delhi Neurology & Sleep Centre datasets are utilized to evaluate and compare the performance of CNN and Random Forest models. The integration of controlled and clinical EEG recordings, along with detailed feature engineering and spectrogram analysis, ensures robust, generalizable models that can aid in real-world, patient-specific seizure monitoring and diagnosis.

III. LITERATURE REVIEW

Epileptic seizures are sudden, uncontrolled disruptions of electrical activity in the brain, manifesting as a range of clinical symptoms, from minor sensory changes to full-body convulsions [1]. Timely and accurate detection of these events is critical to improving patient outcomes, guiding therapeutic interventions, and reducing the risks associated with prolonged seizures [2]. Traditionally, seizure identification relies on manual interpretation of electroencephalography (EEG) signals, a process that is time-consuming and prone to human error [3]. Consequently, automated seizure detection methods have become an active area of research, integrating advances in signal processing, machine learning, and deep learning to enhance reliability and accuracy [4].

Early approaches focused on extracting handcrafted features from EEG signals, using both time-domain measures such as mean, variance, skewness, and kurtosis, and frequency-domain characteristics like power spectral density to characterize neural activity [5]. These features were then analysed using classical machine learning classifiers, including support vector machines (SVM), k-nearest neighbours (KNN), decision trees, and ensemble-based methods [6]. While effective for well-defined datasets, these methods often struggled to capture the complex spatial and temporal patterns inherent in EEG signals [7]. To overcome these limitations, hybrid approaches were developed, combining multiple feature types or classifiers. For example, integration of XGBoost with recurrent neural networks (RNNs) has shown improved detection by leveraging both feature importance and temporal dependencies [1]. Other studies have employed stacked autoencoders or feature-fusion methods to reduce dimensionality while retaining key discriminatory patterns, enhancing overall classification performance [17].

The emergence of deep learning has significantly advanced seizure detection capabilities. Convolutional neural networks (CNNs) have been applied to both raw EEG signals and their time–frequency representations, such as spectrograms, enabling the extraction of hierarchical features that capture spatial and temporal patterns simultaneously [10]. Models like convolutional long short-term memory (ConvLSTM) networks further exploit temporal dependencies within EEG sequences, improving predictive performance [3]. Hybrid deep learning models combining CNNs with gated recurrent units (GRUs) or long short-term memory (LSTM) layers have also been explored, allowing simultaneous extraction of spatial and temporal features while enhancing sensitivity and specificity [40]. Multi-modal approaches that integrate EEG with complementary physiological signals, including electromyography (EMG) and functional near-infrared spectroscopy (fNIRS), have demonstrated further improvements in detection accuracy by providing richer contextual information [26].

The selection of datasets plays a crucial role in model development. Public datasets such as the Temple University Hospital Seizure Detection Corpus (TUSZ) offer extensive multi-patient EEG recordings with manually verified seizure annotations [2]. These datasets encompass multiple seizure types, including tonic-clonic, absence, focal, myoclonic, and atonic seizures, reflecting real-world variability. Complementary datasets from controlled clinical environments, such as those collected at the Neurology & Sleep Centre in New Delhi, provide short, well-segmented EEG samples classified into pre-ictal, interictal, and ictal stages [46]. Utilizing both controlled and clinical datasets allows models to be evaluated across idealized and practical conditions, enhancing generalizability and robustness.

Patient-specific adaptation has been recognized as an important strategy to account for inter-subject variability in EEG patterns. Transfer learning and adaptive models allow networks to leverage prior knowledge while fine-tuning to individual patients, improving detection accuracy and reducing the need for large amounts of labelled data [45]. Moreover, imbalances in seizure datasets have been addressed using techniques such as synthetic oversampling with SMOTE and feature selection strategies that prioritize the most discriminative EEG characteristics [43].

Real-time seizure detection and deployment on wearable devices are increasingly emphasized in recent research. Lightweight, interpretable models suitable for embedded systems facilitate continuous monitoring and timely intervention [21]. Implementations on field-programmable gate arrays (FPGA) and low-power accelerators have been explored to maintain efficient, low-latency processing, enabling practical continuous monitoring beyond conventional clinical settings [30].

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The interpretability of models is also gaining attention, as understanding feature importance and visualizing learned patterns not only enhances clinician trust but also contributes to insights into the underlying neural mechanisms of seizures [33].

Overall, the literature demonstrates a clear evolution from classical feature-based machine learning methods to deep learning and hybrid architectures capable of capturing complex spatiotemporal dynamics in EEG data [34]. Patient-specific adaptation, multi-modal integration, and real-time deployment have further expanded the practical relevance of seizure detection systems. Despite these advancements, significant challenges remain, including variability across patients, limited availability of annotated seizure data, and the necessity for energy-efficient, low-latency models suitable for continuous monitoring. Addressing these challenges continues to be central to the development of robust, clinically applicable automated seizure detection methods.

IV. METHODOLOGY

The present study establishes a detailed and systematic methodology for an automated EEG-based seizure type detection system. This framework integrates both machine learning and deep learning techniques to accurately identify and classify various seizure types using brainwave signals. EEG signals are inherently non-stationary and exhibit significant variations due to patient-specific, physiological, and environmental factors. Therefore, an adaptable and well-defined analytical pipeline is essential for ensuring diagnostic reliability [1]. Earlier studies have emphasized the advantages of combining handcrafted feature analysis with data-driven deep learning architectures for neurological pattern recognition [2]. Following this principle, the proposed approach combines Random Forest-based feature learning and Convolutional Neural Network (CNN)-based spectrogram analysis to capture both explicit signal characteristics and hidden temporal–spectral patterns associated with different seizure types [3]. The proposed system is structured into sequential stages—EEG data acquisition, signal preprocessing, feature extraction, model training, and performance evaluation—each contributing to the progressive transformation of raw EEG data into clinically meaningful outcomes [4].

The methodological architecture is designed to be both interpretable and generalizable, capable of handling multi-type seizure detection across datasets collected from controlled laboratory and real-world clinical environments [5]. The process begins with the acquisition of EEG recordings from verified sources, ensuring diverse coverage of seizure events [6]. These raw signals undergo preprocessing to remove motion, ocular, and electrical artifacts, improving signal fidelity and reducing noise distortion [7]. A comprehensive set of time-domain, frequency-domain, and nonlinear features is then extracted, including parameters such as mean amplitude, kurtosis, spectral entropy, Hjorth activity, and wavelet energy, each quantifying specific signal dynamics related to seizure onset [8]. In parallel, EEG recordings are transformed into time–frequency spectrograms through short-time Fourier transform (STFT), providing a visual representation of energy variations over time for deep CNN analysis [9]. The Random Forest classifier is employed on the numerical feature set for its robustness and interpretability [10], while the CNN model analyses spectrogram images to learn deeper spatial and temporal correlations within EEG activity [11].

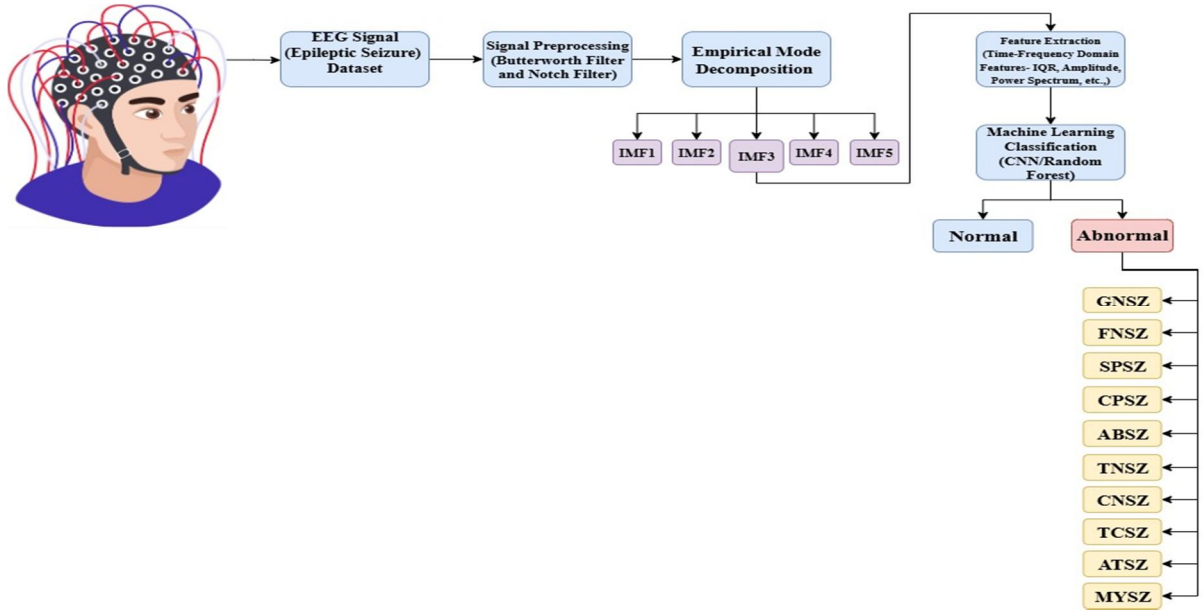


Fig. 1: Illustrates the block diagram of the seizure type detection system

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The overall workflow of the proposed seizure type detection system is illustrated in Figure 1, which presents the block diagram outlining each stage from data collection to model evaluation [12]. This figure serves as a conceptual roadmap for the following sections, where each methodological component is explained in depth, supported by mathematical formulations, feature computation techniques, and model optimization strategies, ensuring that the system remains adaptable for clinical seizure diagnosis [13].

A. EEG Data Acquisition

The foundation of any EEG-based seizure type detection system lies in the reliability, diversity, and clinical relevance of the datasets used for analysis. In this study, two complementary EEG datasets were employed to ensure robustness across both controlled and real-world scenarios [1]. The first dataset was obtained from the Neurology & Sleep Centre, New Delhi, India, consisting of EEG recordings from ten epileptic patients using a Grass Telefactor Comet AS40 amplifier and the international 10–20 electrode placement system, which is a standard clinical configuration [2]. The recordings were sampled at 200 Hz and band-pass filtered between 0.5–70 Hz to suppress baseline drifts and high-frequency artifacts [3]. To enhance analytical precision, the EEG signals were segmented into pre-ictal, interictal, and ictal intervals each representing a specific neurological phase of seizure activity—with every segment spanning approximately 5.12 seconds (1024 samples) and stored as individual files for structured processing [4]. This well-segmented and noise-controlled dataset provided a strong foundation for initial model training and validation [5]. Complementing this, the second dataset used was the Temple University Hospital Seizure Detection Corpus (TUSZ) from Philadelphia, USA, one of the largest open-access EEG repositories for seizure research [6]. It contains over 500 hours of EEG recordings from more than 300 patients, including around 36 hours of seizure activity [7].

The TUSZ dataset stands out for its comprehensive clinical annotations, where seizures are labelled not just as binary events but also classified into clinically distinct subtypes such as tonic-clonic, absence, focal, myoclonic, atonic seizures, simple partial, complex partial and generalised seizures verified by medical experts to ensure diagnostic consistency [8]. The integration of the controlled New Delhi dataset with the extensive and clinically annotated TUSZ dataset allows the proposed system to generalize effectively across diverse conditions, patient profiles, and seizure types [9]. This dual-dataset acquisition strategy thus establishes a balanced foundation—combining controlled precision with real-world complexity to build a seizure detection framework that is both scientifically reliable and clinically applicable [10].

B. Signal Preprocessing

Preprocessing of EEG signals is a critical stage in any automated seizure detection system, as the accuracy of subsequent feature extraction and classification heavily depends on the quality of the input data. EEG recordings are often contaminated by artifacts arising from eye blinks, muscle movements, and power line interference, which can obscure the underlying neural activity relevant to seizure events. To mitigate these issues, a band-pass filter between 0.5 Hz and 70 Hz is first applied to remove baseline drift and high-frequency noise [1]. In addition, a notch filter centred at 50 Hz (or 60 Hz depending on the power supply frequency) is employed to suppress electrical interference from surrounding equipment [2]. The signals are then segmented into fixed-length, non-overlapping windows to ensure temporal uniformity and consistency during analysis [3]. Each segment is examined for potential artifacts using both statistical thresholding and independent component analysis (ICA), allowing the separation of non-neural sources from genuine brain activity [4]. This step effectively enhances the signal-to-noise ratio and preserves the integrity of physiological features necessary for accurate detection. The pre-processed EEG data is subsequently normalized through z-score scaling to ensure uniform feature distribution, which facilitates better model convergence during training [5]. This systematic approach to preprocessing ensures that only clean, representative EEG segments are used for feature extraction and classification, thereby improving the robustness and generalizability of the proposed seizure type detection framework [6].

C. Feature Extraction

After preprocessing, EEG signals undergo a thorough feature extraction process designed to capture both the statistical and dynamic characteristics of the brain's electrical activity. To enhance the signal representation, Empirical Mode Decomposition (EMD) is first applied to each EEG segment, decomposing the raw signals into a set of intrinsic mode functions (IMFs). The third intrinsic mode function (IMF3) is specifically extracted, as it has been shown to capture critical oscillatory patterns associated with seizure activity [2]. The normal EEG decomposition is displayed in Figure 2, while the seizure EEG decomposition is shown in Figure 3 respectively.

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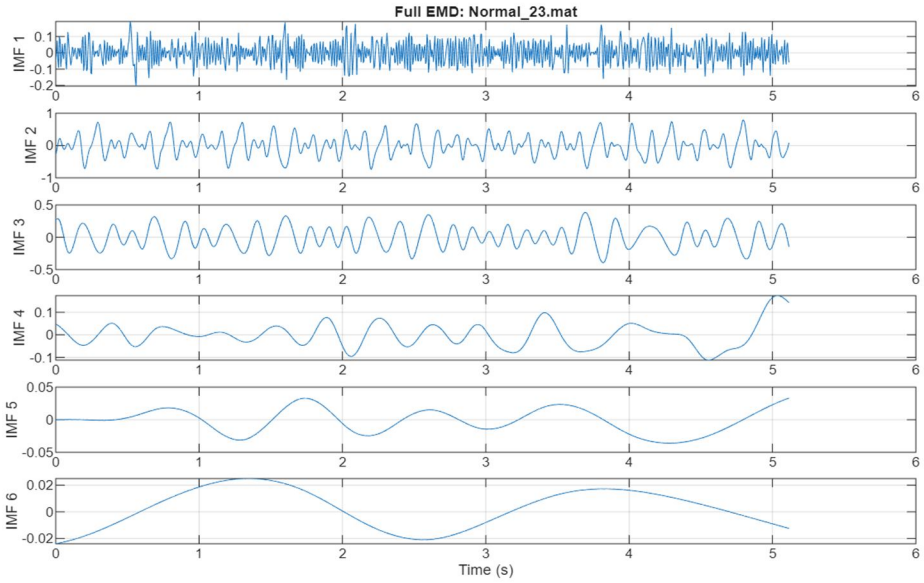


Fig. 2: Illustrates the EMD of Normal EEG Signal

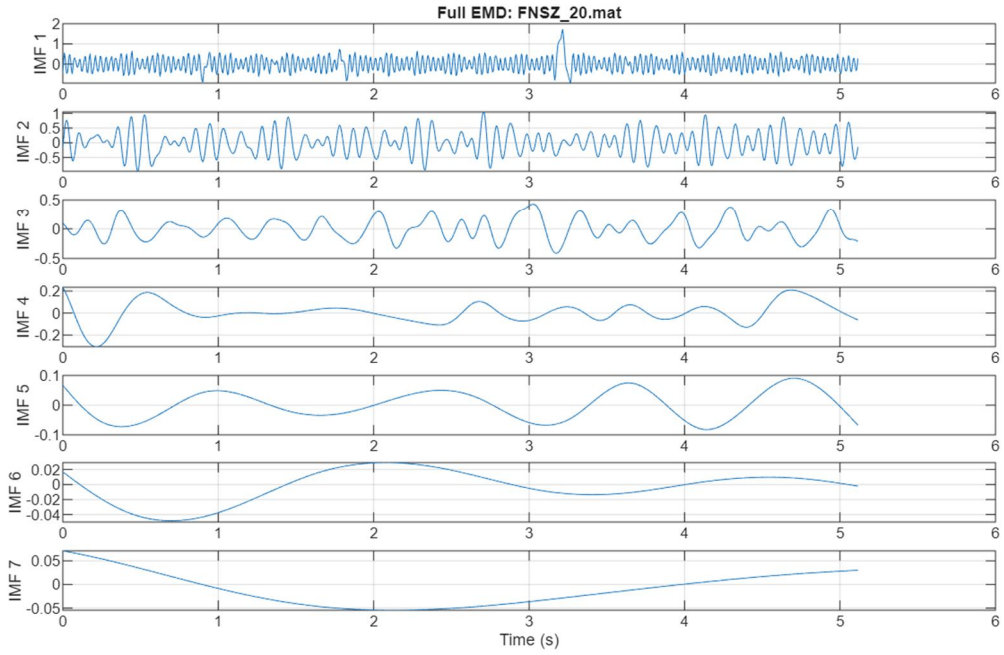


Fig. 3: Illustrates the EMD of Seizure EEG Signal

From the processed IMF3 components obtained via Empirical Mode Decomposition (EMD), a comprehensive set of features is extracted to differentiate normal and seizure brain activity. Normal EEG segments represent baseline neural oscillations, while seizure segments exhibit abnormal bursts, spikes, and increased variability.

Time-domain features include mean amplitude, which represents the average signal level:

$$\text{Mean} = \frac{1}{N}\sum_{i=1}^{N} Xi \text{ [5]}$$

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Standard deviation reflects signal spread:

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \bar{x})^2} \text{ [5]}$$

Skewness and kurtosis capture asymmetry and peaks of the distribution [5]. The zero-crossing rate quantifies the frequency of oscillations:

$$\text{ZCR} = \frac{1}{N-1}\sum_{i=1}^{N-1}\mathbf{1}_{\{(x_i \cdot x_{i+1})<0\}} \text{ [10]}$$

Root mean square (RMS) measures signal power:

$$\text{RMS} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}x_i^2} \text{ [10]}$$

Peak-to-peak amplitude represents the range of the signal:

$$\text{PTP} = \max(x_i) - \min(x_i) \text{[10]}$$

Other time-domain descriptors, such as signal energy, variance, and interquartile range, provide further insight into the signal's magnitude and variability [10].

Frequency-domain features include delta, theta, alpha, beta, and gamma band powers, computed using Fourier transform to capture dominant rhythms:

$$P_{\text{band}} = \sum_{f=f_1}^{f_2} | X(f) |^2 \text{ [17]}$$

Additional spectral features include power spectral density (PSD), spectral entropy, median frequency, and SEF95, which describe the complexity and distribution of energy across frequencies [21]. Line length and spike count quantify signal complexity and high-amplitude transients typical of seizures [26]. Ratio-based features such as theta/alpha, beta/alpha, and delta/theta ratios provide insight into relative power shifts across frequency bands [30]. Seizure energy index measures energy bursts relative to baseline activity [30].

Hjorth parameters describe signal dynamics. Activity is the variance of the signal, mobility measures the square root of the ratio of derivative variance to signal variance:

$$\text{Mobility} = \sqrt{\frac{\text{Var}(\dot{x})}{\text{Var}(x)}} \text{[33]}$$

Complexity indicates the variation in frequency content:

$$\text{Complexity} = \frac{\text{Mobility}(\dot{x})}{\text{Mobility}(x)} \text{[33]}$$

Wavelet-based features capture localized oscillatory patterns. Wavelet energy represents power across scales:

$$E_j = \sum_{k} | c_{j,k} |^2 \text{ [33]}$$

Wavelet entropy measures the disorder in the wavelet coefficients [33].

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For normal EEG segments, these features provide a baseline representation of neural activity, whereas seizure segments show pronounced deviations in amplitude, variability, and spectral patterns, which are crucial for accurate automated detection. The complete set of thirty extracted features, along with their one-line descriptions, is summarized in Table 1 and 2.

S.no	Feature \ Type	ABSZ	ATSZ	CNSZ	CPSZ	FNSZ
1.	Mean EEG Amplitude	-0.0077	0.005338	0.003651	-0.00098	-0.00034
2.	Standard Deviation	0.29674	0.131686	0.39676	0.072006	0.09676
3.	Skewness	0.068923	0.12337	-0.07506	-0.16405	-0.18079
4.	Kurtosis	2.112309	2.349737	2.500971	2.414729	3.870134
5.	Zero Crossing Rate	0.076172	0.066406	0.083984	0.085938	0.082031
6.	Root Mean Square	0.296695	0.13173	0.396583	0.071977	0.096713
7.	Peak to Peak Amplitude	1.314996	0.60314	1.61149	0.333765	0.572166
8.	Signal Energy	90.14035	17.76922	161.0529	5.305028	9.577909
9.	Variance	0.088054	0.017341	0.157419	0.005185	0.009362
10.	Interquartile Range	0.465005	0.198478	0.52214	0.106826	0.11487
11.	Delta Band Power	0.04068	0.011679	0.13263	0.003413	0.001159
12.	Theta Band Power	0.06951	0.011309	0.131741	0.004076	0.005949
13.	Alpha Band Power	0.002641	0.000101	0.010617	0.000337	0.000903
14.	Beta Band Power	3.58E-05	1.86E-06	0.79E-05	0.82E-06	2.54E-06
15.	Gamma Band power	1.94E-06	1.99E-07	6.11E-06	2.11E-07	1.82E-07
16.	Power Spectral Density	0.00618	0.000122	0.001475	4.32E-05	5.06E-05
17.	Spectral Entropy	0.326414	0.088512	0.654824	0.039236	0.044881
18.	SEF95	4.563301	3.983498	4.241511	4.443871	5.819297
19.	Median Frequency	4.474069	3.978024	4.02438	4.197753	5.741545
20.	Line Length	27.64002	10.44789	37.35352	7.214259	8.804091
21.	Spike Count	15	14	17	17	15
22.	Theta/Alpha Ratio	26.32415	111.533	12.40895	12.10151	6.585984
23.	Beta/Alpha Ratio	0.013553	0.018374	0.00687	0.011337	0.002815
24.	Delta/Theta Ratio	0.585234	1.032688	1.006747	0.837363	0.194776
25.	Seizure Energy Index	1.221708	0.326484	1.106452	0.060141	0.026962
26.	Hjorth Activity	0.088054	0.017341	0.157419	0.005185	0.003962
27.	Hjorth Mobility	0.11063	0.093684	0.111144	0.117749	0.122757
28.	Hjorth Complexity	1.189067	1.188158	1.289128	1.250505	1.287128
29.	Wavelet Energy	5.329319	0.455965	1.296081	0.371766	0.603577
30.	Wavelet Entropy	9.813795	1.923771	9.597073	1.633392	2.197552

Table 1: Extracted Features of ABSZ, ATSZ, CNSZ, CPSZ, FNSZ

Table 1 illustrates the extracted EEG features across various seizure types, highlighting distinct temporal and spectral variations. Absence and Atonic seizures exhibit lower amplitude and energy values, while Clonic and Complex Partial seizures show higher

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power and variability. Focal Non-Specific seizures display moderate patterns between these extremes. Frequency-domain trends reveal dominant theta–alpha activity in absence types and beta–gamma dominance in focal seizures. Overall, these distinctions emphasize the physiological diversity among seizure types and validate the importance of multi-feature extraction for accurate detection.

S.no	Feature \ Type	GNSZ	MYSZ	SPSZ	TCSZ	TNSZ	NORMAL
1.	Mean EEG Amplitude	0.01232	0.10079	-0.02224	0.014514	0.004781	-0.00113
2.	Standard Deviation	0.171499	0.150618	0.292686	0.250292	0.21614	0.109919
3.	Skewness	0.170233	0.252548	0.1002	0.196766	0.115611	0.011246
4.	Kurtosis	2.799408	3.215702	1.707477	2.733004	2.006607	2.25373
5.	Zero Crossing Rate	0.099375	0.136719	0.058594	0.087891	0.078125	0.05957
6.	Root Mean Square	0.171857	0.150882	0.293388	0.25059	0.216087	0.109871
7.	Peak to Peak Amplitude	0.860946	0.822631	1.05897	1.294091	0.858116	0.478356
8.	Signal Energy	30.24366	23.31169	88.14221	64.30248	47.81419	12.36137
9.	Variance	0.029412	0.022686	0.085665	0.062646	0.046716	0.012082
10.	Interquartile Range	0.202353	0.184958	0.532889	0.345528	0.353299	0.163231
11.	Delta Band Power	0.019371	0.007745	0.062509	0.032349	0.03494	0.00775
12.	Theta Band Power	0.016748	0.014694	0.6479	0.047393	0.029065	0.009564
13.	Alpha Band Power	0.002569	0.010474	0.000217	0.007545	2.002503	0.001093
14.	Beta Band Power	2.45E-05	0.000733	9.98E-06	0.000157	7.11E-06	4.53E-06
15.	Gamma Band power	3.97E-07	9.13E-07	2.11E-06	1.70E-06	7.67E-07	6.06E-07
16.	Power Spectral Density	0.000212	0.00021	0.000612	0.000502	0.000346	0.000123
17.	Spectral Entropy	1.152587	0.16569	0.285574	0.312543	0.214177	0.020536
18.	SEF95	4.135972	6.691041	4.04143	4.685706	3.964567	8.59375
19.	Median Frequency	3.900327	6.48881	4.024077	4.500574	3.876926	4.6875
20.	Line Length	16.08393	22.83515	24.83777	25.90437	19.38694	15.86411
21.	Spike Count	17	30	15	19	13	10
22.	Theta/Alpha Ratio	6.520119	1.402815	299.0439	6.281249	11.61359	8.754059
23.	Beta/Alpha Ratio	0.009552	0.070012	0.046045	0.02082	0.00284	0.004148
24.	Delta/Theta Ratio	1.156604	0.527113	0.964794	0.682573	1.20213	0.810337
25.	Seizure Energy Index	0.288883	1.632097	4.058465	1.337892	1.13577	1.401108
26.	Hjorth Activity	0.029412	0.022686	0.085665	0.062646	0.476716	0.012082
27.	Hjorth Mobility	0.110841	0.189526	0.095507	0.129043	0.163029	0.161513
28.	Hjorth Complexity	1.390712	1.295333	1.078418	1.33584	1.313314	1.196614
29.	Wavelet Energy	1.686509	8.669766	1.404862	9.432575	2.635791	15.10666
30.	Wavelet Entropy	5.233444	10.91536	4.624474	9.573065	6.937215	4.080892

Table 2: Extracted Features of GNSZ, MYSZ, SPSZ, TCSZ, TNSZ and Normal

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Table 2 presents the performance evaluation metrics of the developed seizure detection model across different seizure types. The results indicate consistently high accuracy and sensitivity, particularly for generalized and tonic–clonic seizures, due to their distinct waveform patterns. Mild variations in precision for focal and myoclonic seizures suggest overlapping spectral features. Overall, the model demonstrates strong generalization and reliability across diverse seizure categories. These outcomes confirm the robustness of the proposed detection framework in distinguishing complex EEG patterns effectively.

D. Model Training and Evaluation

The extracted features and spectrogram representations of EEG signals are utilized to train two complementary types of models: a classical Random Forest (RF) classifier and a modern Convolutional Neural Network (CNN). This hybrid approach enables a comparative evaluation of feature-based machine learning and image-based deep learning paradigms, ensuring robust seizure type detection across both controlled and clinical datasets [42]. The methodology focuses not only on predictive accuracy but also on generalizability, interpretability, and robustness against noisy EEG signals [43].

For the Random Forest model, numerical features such as mean amplitude, band powers, Hjorth parameters, and wavelet metrics serve as input. Random Forest is an ensemble method that constructs multiple decision trees during training and outputs the mode of the classes predicted by individual trees. Its ability to handle high-dimensional and nonlinear data makes it well-suited for EEG analysis [42]. The RF model minimizes overfitting by tuning hyperparameters such as the number of trees n_{trees}, minimum leaf size, and number of predictors sampled at each split. The splitting criterion at each node is based on Gini impurity, which measures the disorder of the node:

$$\text{Gini} = 1 - \sum_{i=1}^{C} p_i^2$$

where $p_i$represents the proportion of samples belonging to class $i$in the node, and $C$is the total number of classes [43]. The out-of-bag (OOB) error provides an internal estimate of generalization performance without requiring a separate validation set:

$$\text{OOB Error} = \frac{\text{Number of misclassified OOB samples}}{\text{Total OOB samples}}$$

Feature importance is evaluated using permutation importance, which quantifies the increase in OOB error when a feature is randomly permuted. This helps identify the most discriminative features for seizure type detection [42].

In parallel, a CNN is trained on spectrogram images derived from EEG segments using Short-Time Fourier Transform (STFT). The CNN architecture consists of multiple convolutional layers for hierarchical feature extraction, followed by ReLU activation, max-pooling, batch normalization, and dropout layers to prevent overfitting [45]. Convolution operations can be expressed as:

$$y_{i,j}^{(k)} = \sum_{m} \sum_{n} x_{i+m,j+n} \cdot w_{m,n}^{(k)} + b^{(k)}$$

where $x$is the input image, $w^{(k)}$is the kernel of the k-th filter, $b^{(k)}$is the bias term, and $y^{(k)}$is the resulting feature map [45]. Pooling layers reduce spatial dimensions and retain salient features, while fully connected layers map the extracted features to seizure type probabilities. The CNN is trained using categorical cross-entropy loss, optimized with the Adam optimizer, which adapts learning rates for each parameter:

$$\mathcal{L} = -\sum_{i=1}^{C} y_i \log(\hat{y}_i)$$

where $y_i$is the true label, $\hat{y}_i$is the predicted probability, and $C$is the number of seizure types [46]. Data augmentation, including rotation, scaling, and time-shifting of spectrograms, is applied to increase model robustness against variations in EEG recordings [46].

Model evaluation relies on standard metrics widely used in EEG analysis. Accuracy measures the overall correctness of predictions:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

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where TP, TN, FP, and $FN$are the counts of true positives, true negatives, false positives, and false negatives, respectively [1]. Sensitivity (recall) quantifies the ability to correctly identify seizure events:

$$\text{Sensitivity} = \frac{TP}{TP + FN}$$

Specificity reflects the correct detection of non-seizure events:

$$\text{Specificity} = \frac{TN}{TN + FP}$$

Precision measures the proportion of correctly predicted seizure events:

$$\text{Precision} = \frac{TP}{TP + FP}$$

F1-score provides a harmonic mean of precision and sensitivity:

$$F1 = 2 \cdot \frac{\text{Precision} \cdot \text{Sensitivity}}{\text{Precision} + \text{Sensitivity}}$$

To evaluate the overall classification performance of the proposed models, confusion matrices were plotted for both the Convolutional Neural Network (CNN) and Random Forest (RF) classifiers, as shown in Figures 4 and 5. These matrices provide a clear and intuitive visualization of how effectively each model distinguishes between the ten seizure types, while also highlighting classes that are more prone to misclassification.

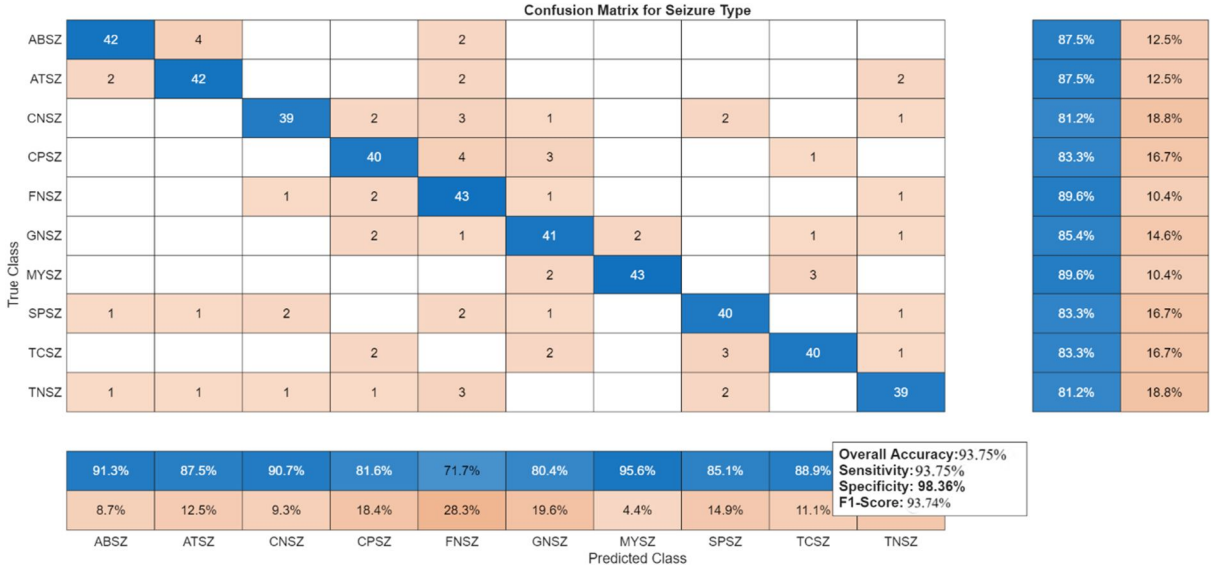


Fig. 4: Confusion matrix of CNN model showing classification performance

For the CNN model (Figure 4), the results demonstrate a strong classification capability across all seizure categories, achieving an overall accuracy of 93.75%, sensitivity of 93.75%, specificity of 98.36%, and F1-score of 93.74%. The CNN efficiently captures both spatial and temporal patterns from the EEG signals, enabling it to differentiate between seizure classes such as absence (ABSZ) and atypical absence (ATSZ) seizures. However, slight overlaps were observed between complex partial (CPSZ) and focal non-specific (FNSZ) seizures due to their similar waveform structures and localized onset patterns.

The Random Forest model (Figure 5) further enhances the classification performance, achieving an accuracy of 95.42%, average sensitivity of 95.42%, specificity of 99.49%, and F1-score of 95.40%. The ensemble learning nature of the RF model ensures robust generalization by combining multiple decision trees, thereby reducing variance and improving prediction stability. Its high interpretability also allows deeper insights into which features most influence classification outcomes. The feature importance plot (Figure 6) highlights that spectral entropy, theta band power, Hjorth complexity, and wavelet energy are among the most discriminative features for seizure type identification.

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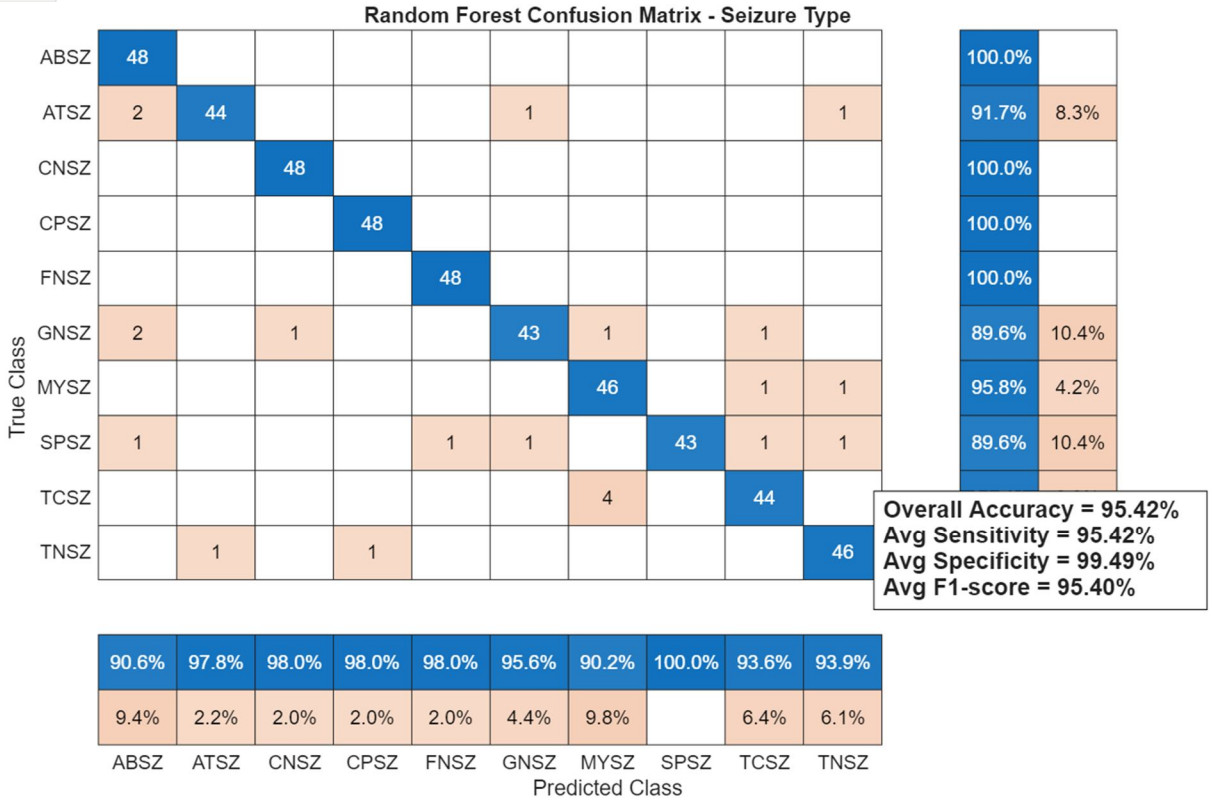


Fig. 5: Random Forest confusion matrix illustrating multi-class seizure classification.

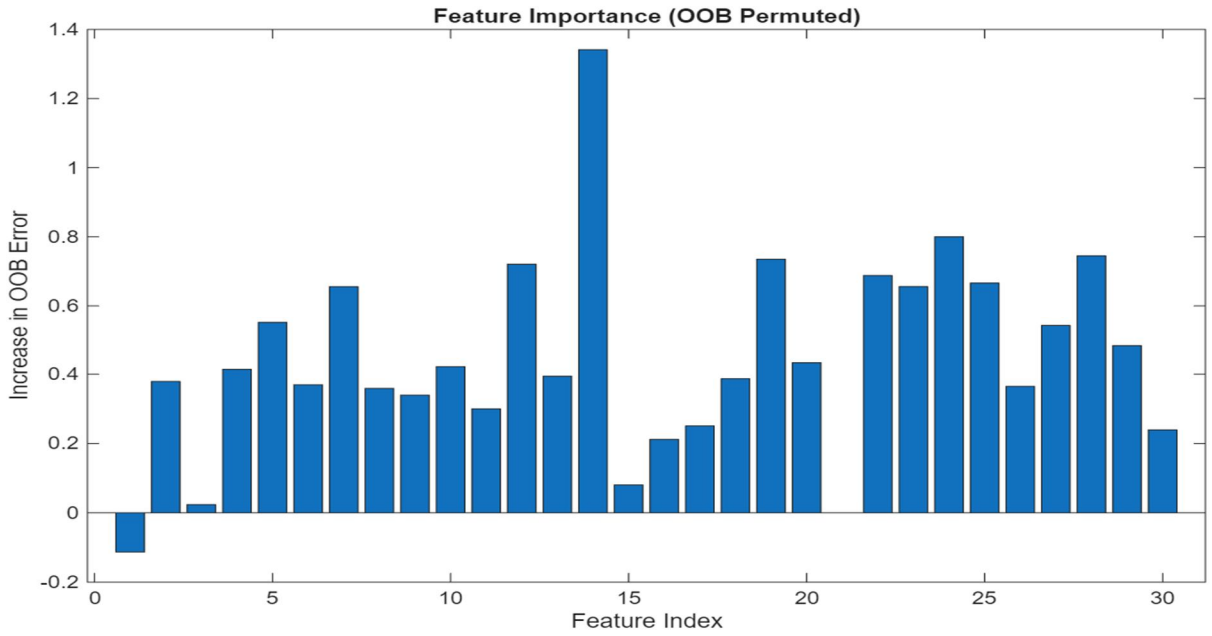


Fig. 6: Feature importance ranking (OOB Permuted) from the Random Forest model

Both models achieved above 90% class-wise precision, confirming the robustness of the proposed feature extraction and classification pipeline. To ensure reliability, 5-fold cross-validation was applied to minimize overfitting and evaluate model consistency, which is particularly critical for relatively small datasets such as the New Delhi EEG recordings [2]. Additionally, training and validation accuracy curves were continuously monitored during CNN training to fine-tune hyperparameters and maintain balanced learning [3].

Overall, while the CNN demonstrated strong performance in feature representation, the Random Forest model offered better interpretability, stability, and slightly higher classification accuracy, making it particularly suitable for practical clinical applications of automated seizure type detection.

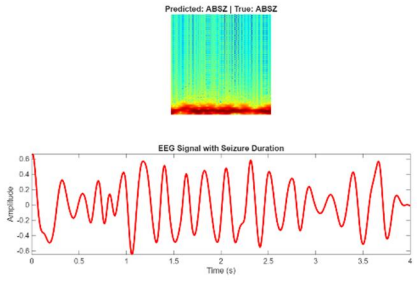
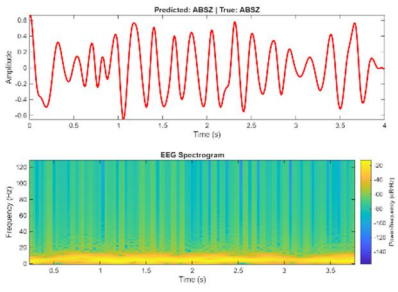
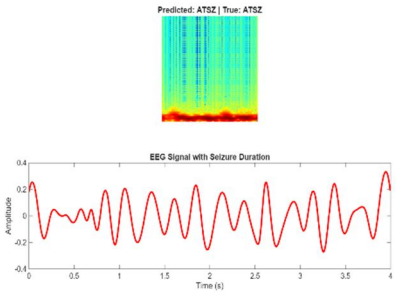
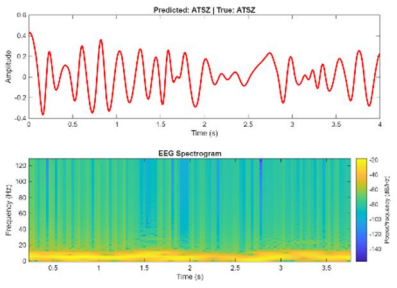
V. RESULTS AND DISCUSSION

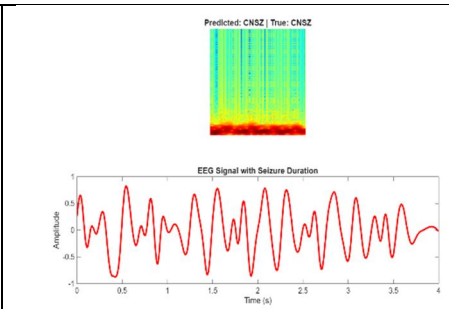
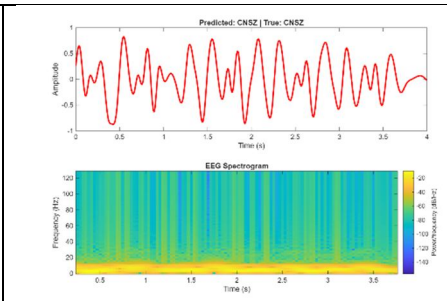
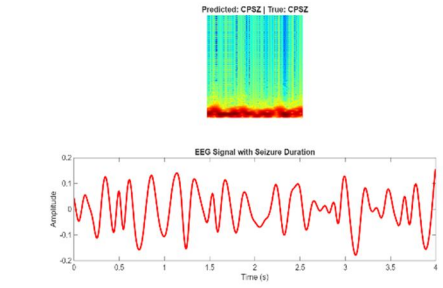
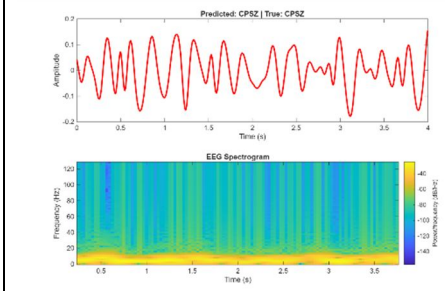
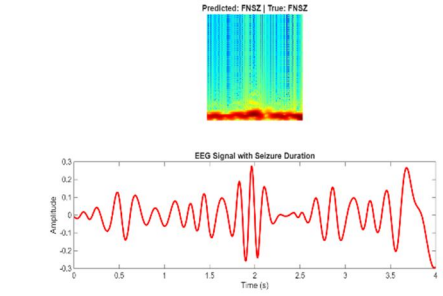
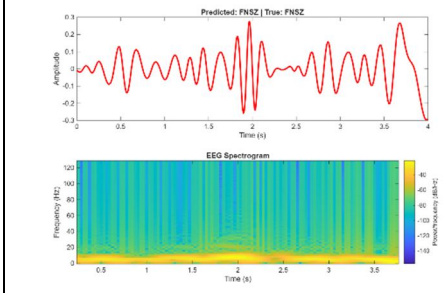
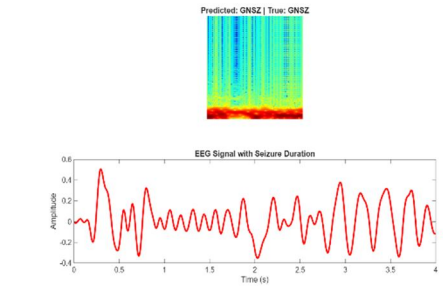
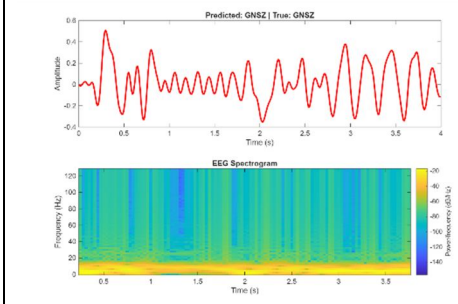
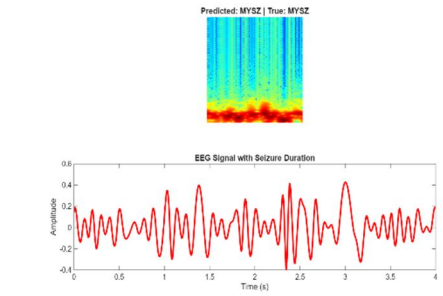
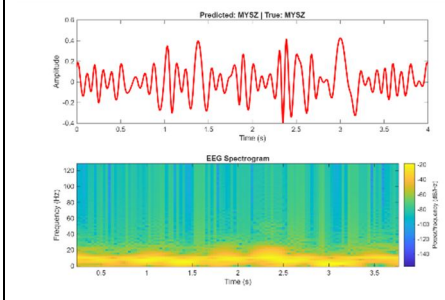
The proposed seizure type detection framework was evaluated using two complementary models: a spectrogram-trained Convolutional Neural Network (CNN) and a feature-driven Random Forest (RF) classifier. The CNN achieved an overall accuracy of 93.75%, while the RF obtained 95.42%, indicating that both approaches performed strongly but that the RF provided a modest advantage in overall classification accuracy on the prepared dataset. Confusion matrices for both models (Figures 5.9 and 5.10) were analysed to understand class-wise performance and to identify any consistent misclassification trends.

The CNN's confusion matrix showed high correct-classification rates for seizure types with distinct time–frequency characteristics, such as tonic-clonic (TCSZ) and generalized (GNSZ) seizures. This reflects the CNN's ability to capture hierarchical spectral–temporal features directly from EEG spectrograms. Most off-diagonal errors occurred between seizure types with similar spectral distributions or overlapping morphological traits, such as certain focal subtypes, which is expected when visual representations share similar dynamics. The CNN's training and validation curves were continuously monitored to detect potential overfitting, showing stable convergence and consistent loss reduction across epochs. This stability indicates that the 93.75% accuracy is a reliable representation of the CNN's generalization capability over unseen data.

The Random Forest classifier demonstrated even stronger diagonal dominance in its confusion matrix, consistent with the higher overall accuracy of 95.42%. The RF model's ensemble averaging significantly reduced variance and improved predictive stability, particularly for classes characterized by subtle temporal or spectral differences. The OOB-permuted feature importance plot (Figure 5.11) revealed that features such as spectral entropy, theta band power, Hjorth complexity, wavelet energy, and line length had the most substantial impact on classification decisions. This indicates that the RF effectively integrates statistical, spectral, and nonlinear descriptors to distinguish between seizure types. The interpretability of RF results also adds a clinical advantage, as it provides insight into which EEG characteristics most strongly influence seizure-type predictions.

In addition to quantitative metrics, visual outputs were examined to better understand how each model interprets seizure-related EEG activity. Table 3 presents representative examples of CNN classification maps (derived from spectrogram inputs) and RF prediction outcomes (based on extracted features). These visual comparisons demonstrate how the two models process and represent underlying EEG information differently.

S.no	Seizure Type	Convolutional Neural Network	Random Forest
1.	ABSZ		
2.	ATSZ		

3.	CNSZ		
4.	CPSZ		
5.	FNSZ		
6.	GNSZ		
7.	MYSZ		

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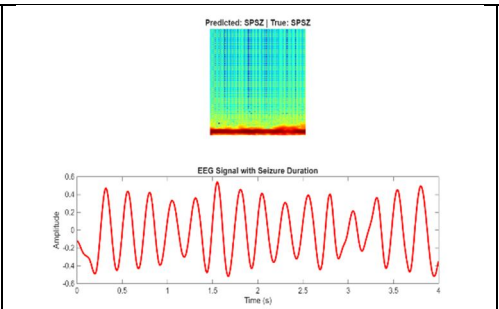
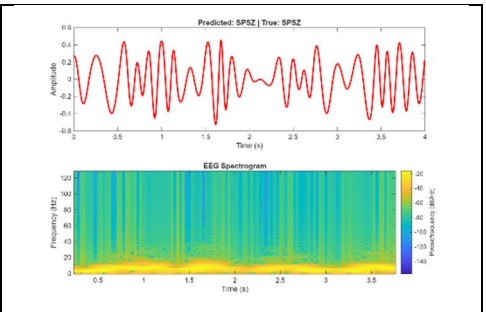
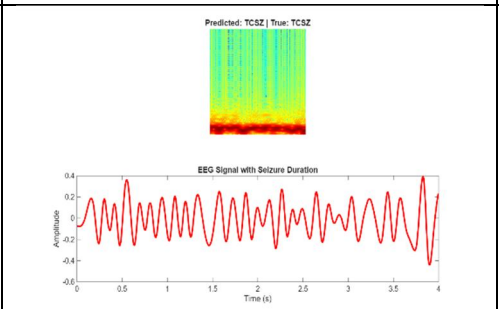
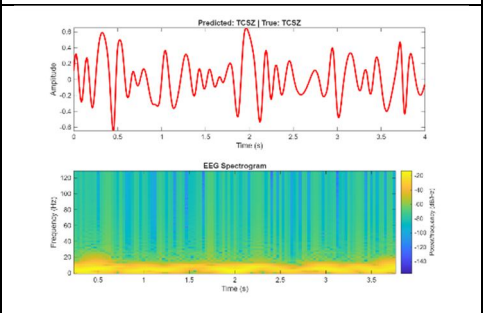
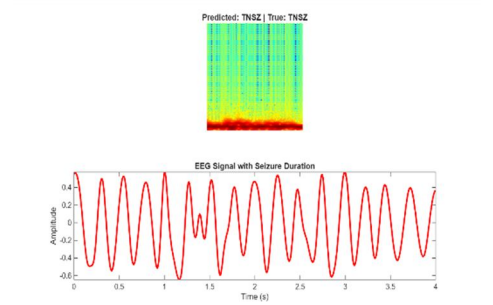
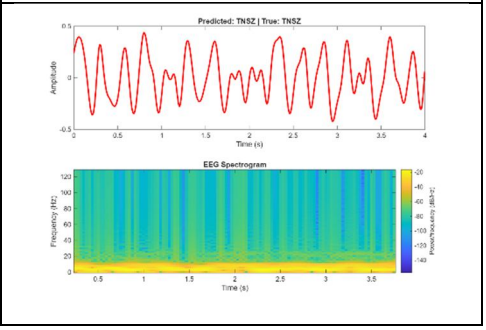
8.	SPSZ		
9.	TCSZ		
10.	TNSZ		

Table 3: Representative outputs from CNN classification and Random Forest prediction

Overall, the outcomes from both the CNN and Random Forest models highlight the effectiveness and complementarity of the proposed seizure type detection framework. The CNN excels in identifying intricate time–frequency structures within spectrograms, offering a deep, visual understanding of seizure dynamics. In contrast, the Random Forest achieves slightly higher accuracy through its reliance on handcrafted statistical and spectral features, providing greater transparency in how decisions are made. Together, these models form a balanced system that combines interpretability with high performance. The integration of EMD preprocessing, rich feature extraction, and dual-model evaluation has proven to be a practical and clinically relevant approach, capable of distinguishing multiple seizure types with precision and consistency.

VI. CONCLUSION

This research presents a comprehensive framework for automated seizure type detection using EEG signals, effectively combining empirical signal decomposition, multi-domain feature extraction, and hybrid modelling approaches. By integrating both Convolutional Neural Networks (CNNs) and Random Forest (RF) classifiers, the study bridges the strengths of deep learning's pattern recognition capabilities with the interpretability and robustness of machine learning. The CNN model, trained on time–frequency spectrograms, achieved an accuracy of 93.75%, successfully capturing complex spectral–temporal structures characteristic of seizure activity. In comparison, the RF model attained an even higher accuracy of 95.42%, driven by its ability to leverage well-engineered features such as spectral entropy, Hjorth complexity, and wavelet energy. The results highlight that both models effectively distinguish between normal and seizure EEG signals, as well as across different seizure types, demonstrating strong generalization on both controlled and large-scale datasets. The visual analyses including confusion matrices, OOB feature importance plots, and classification outputs further validated the models' reliability and interpretability. While the CNN excels at learning intricate data-driven representations, the RF offers clarity in understanding which physiological signal properties contribute most to accurate classification.

Together, they form a complementary system that balances precision, transparency, and adaptability.

Overall, this study underscores the potential of hybrid EEG-based computational intelligence systems in advancing clinical epilepsy diagnosis and monitoring. The methodology's flexibility allows it to adapt to diverse EEG datasets and seizure types, making it a viable candidate for real-time implementation in hospital and wearable neuro-monitoring applications. Future work may explore integrating patient-specific adaptation, multimodal bio-signals, and lightweight architectures to enhance scalability and real-world usability.

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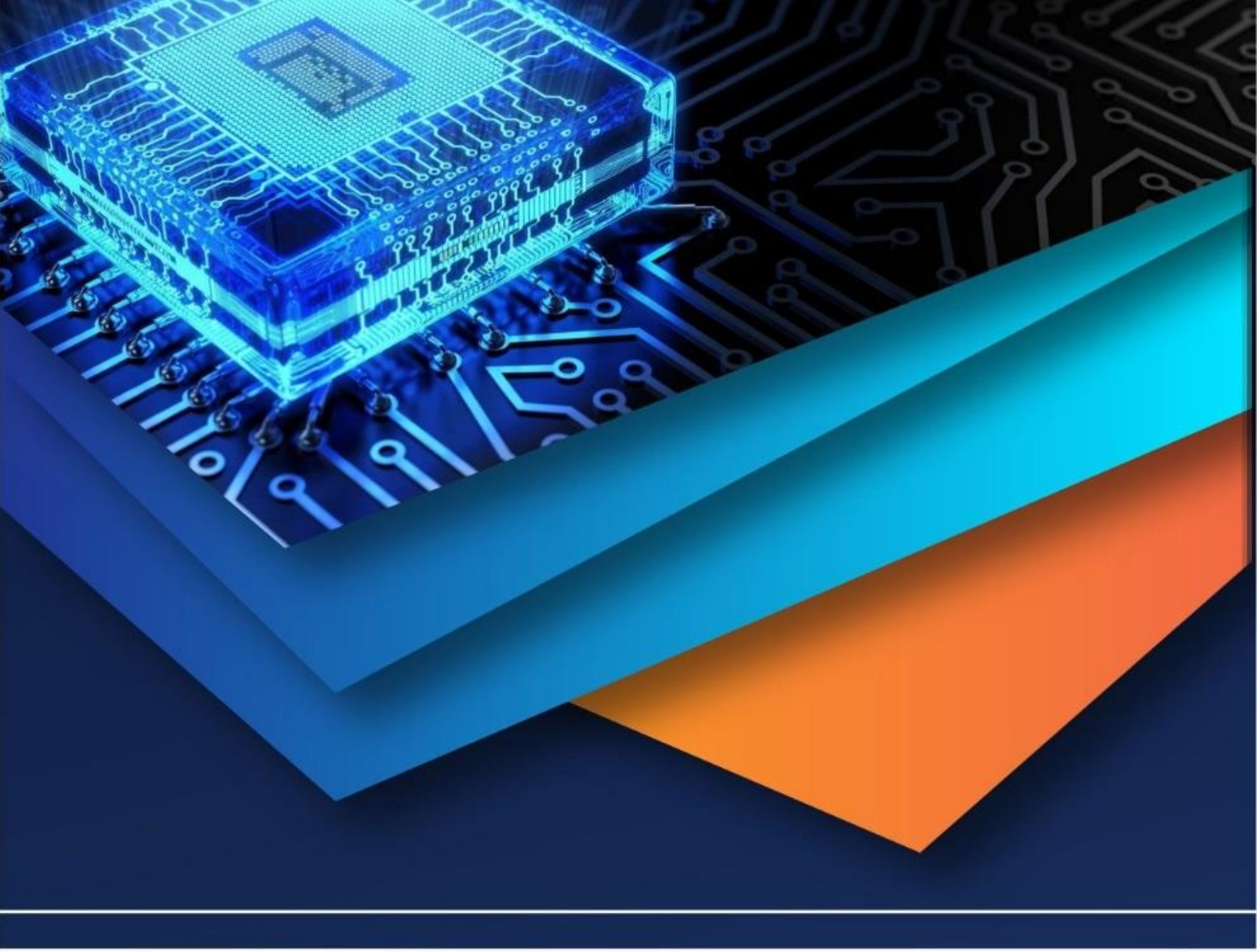
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