Eng. Sci., 2025, **38**, 1899

Engineered Science
DOI: https://dx.doi.org/10.30919/es1899

Optimized Electroencephalogram Preprocessing with Discrete Wavelet Transform and EfficientNet for High-Accuracy Seizure Detection

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Abstract

Abnormal neuronal activity in the brain leads to seizures which seriously affect quality of life and can become life-threatening in certain situations. Automatic seizure detection research matters because timely intervention requires early accurate detection. Deep learning achieves high effectiveness in seizure detection while its success relies strongly on how well EEG signals undergo pre-processing. The accuracy and reliability of models require effective pre-processing of raw EEG data because it contains noise and patient variability. The research introduces a deep learning model dedicated to seizure detection while emphasizing advanced pre-processing and flexible adaptability. The model transforms EEG signals into a two-dimensional feature representation to enhance spatial and temporal pattern recognition capabilities. The model's modular structure provides adaptability across various hardware platforms which facilitates both optimization processes and custom solutions. The model reached a 93.27% classification accuracy on two seizure datasets when utilizing EfficientNet with DWT showing its powerful generalizability and practical effectiveness in real-world situations.

Keywords: EEG; Deep learning; DWT; EfficientNet; Seizure.
Received: 05 August 2025; Revised: 09 November 2025; Accepted: 20 November 2025
Article type: Research article.

1. Introduction

A deep learning-based approach for seizure detection that converts EEG features into a two-dimensional format. Whether using single-channel or multi-channel EEG data, the model is designed to be flexible, allowing different components to be optimized or replaced as needed. To enhance performance and adaptability, we integrate the EfficientNet architecture, which can dynamically adjust its depth, width, and resolution based on available hardware resources and input data.[1] This flexibility ensures the model remains efficient and accurate across different computing environments. This is based on two publicly available epilepsy datasets, where we explore key parameter settings and assess the impact of transfer learning on model performance. The model is built around two key principles: first, representing EEG features in a two-dimensional format to capture richer patterns, and second, utilizing a scalable neural network that adapts to different hardware constraints and data variations.

The seizure detection method utilizes deep learning to transform EEG features into two-dimensional representations. The model functions effectively with both single-channel and multi-channel EEG data because its design allows for optimization and substitution of various components according to requirements. Our model performance and adaptability receive improvements by adopting the EfficientNet architecture which allows automatic modifications of its depth, width and resolution according to hardware resources and input data. The model maintains its efficiency and accuracy throughout multiple computing settings because of its flexible design. Our research utilizes two public epilepsy datasets to examine essential parameter settings and evaluate transfer learning's effect on model performance. The model is built around two key principles: Two-dimensional EEG feature representation captures deeper patterns while scalable neural networks adjust for hardware and data differences. EfficientNet plays a crucial role in improving classification accuracy through transfer learning while also enhancing adaptability by allowing dynamic adjustments to network architecture for better feature extraction.

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The model follows a structured process with five main stages. It begins with EEG decomposition, where EEG signals are divided into smaller time-segmented slices. We analyse how different time window lengths affect epilepsy detection accuracy. Next, the feature extraction step identifies key patterns in the EEG data, which are then transformed into a 2D representation for better processing. EfficientNet is then used for deep feature extraction,[2] learning meaningful patterns from the transformed data. Finally, in the classification stage, the processed EEG signals are categorized as seizure or non-seizure. By organizing the model in this way, we aim to provide a highly accurate yet practical solution for EEG-based seizure detection. The combination of modular design, adaptable architecture, and deep learning techniques ensures that the model remains effective across different hardware setups and datasets, making it a promising tool for epilepsy detection and monitoring.

Although much of the recent literature has used deep learning models, including CNNs, RNNs, and hybrid models, the models have been used with raw or minimally pre-processed EEG data and this can lower accuracy because of noise and artifacts. Some concentrate on other standard classifiers such as ANN and SVM which are also more costly in terms of training and have problems with generalization. Other papers have investigated the use of wavelet feature extraction,[3] although they have not incorporated the use of sophisticated pre-processing techniques. The novelty of the given work is based on the unification of PCA and ICA-based pre-processing and DWT-driven EfficientNet architecture to detect the seizures. In contrast to the previous studies that applied PCA/ICA individually or concentrated on the traditional neural networks, our model uses both methods of dimensionality reduction (PCA) and artifact removal (ICA) to clean the EEG signals prior to their classification. The application of EfficientNet, a lightweight but high-performing deep learning model, allows reaching a faster convergence (50 epochs vs. 200 steps with ANN) and much higher accuracy (93.27% with the CHB-MIT dataset). Combining these methods, the study fills the blank between effective signal cleaning and deep-learning-based methods, showing a more trustworthy set up to detect seizures than the current methods.

2. Literature survey

In this study, we evaluate the effectiveness of the Enhanced Epileptic Seizure Classification (EESC) methodology using real-world EEG data from the widely recognized CHB-MIT database. This open-source dataset consists of scalp EEG (sEEG) recordings from 23 paediatric patients, collected continuously over 844 hours, with 163 recorded epileptic seizures. The majority of the signals were recorded from 23 channels at a sampling rate of 256 Hz. Since neurologists typically classify a seizure only if abnormal EEG patterns persist for at least 6–10 seconds,[4] we focused on patients with seizures exceeding this duration. To assess the reliability of EESC, we conducted extensive comparisons with existing epilepsy classification algorithms. Our findings contribute to improving automated seizure detection, aiding clinicians in timely and accurate epilepsy diagnosis. By leveraging machine learning techniques, we aim to enhance seizure classification, ultimately benefiting patient care and treatment planning. Recent advancements in deep learning have significantly improved epilepsy diagnosis and seizure prediction using EEG signals. Developed[5] a graph neural network (GNN) model that integrates local and global connectivity to predict seizure freedom in paediatric patients with refractory epilepsy. Their approach, which applies graph convolutions and multi-scale attention mechanisms, achieved an impressive 92.4% accuracy in binary classification. Key brain regions, such as the anterior cingulate and frontal pole, were identified as critical in determining seizure outcomes. Similarly,[6] provided a comprehensive review of deep learning techniques for EEG-based epilepsy detection, discussing architectures like CNNs, RNNs, and hybrid models while highlighting challenges such as data scarcity and model interpretability.

Other researchers have focused on refining seizure prediction models through specialized deep learning techniques. Introduced a multiresolution convolutional neural network approach,[7] leveraging wavelet transforms to decompose EEG signals into different frequency bands, enhancing feature extraction and prediction accuracy. Explored both[8] supervised and unsupervised deep learning methods to detect preictal EEG states, tailoring models to individual patients for improved accuracy. Meanwhile, a study[9] combined Dense Net and Vision Transformer (ViT) architectures with attention fusion to enhance EEG-based seizure prediction. By integrating these models, researchers were able to capture complex temporal patterns, further improving the reliability of automated seizure forecasting. Improving interpretability and robustness in epilepsy detection has also been a key research focus. Applied deconvolutional[10] networks to visualize the features contributing to seizure predictions, making deep learning models more transparent and clinically relevant. Developed a hybrid ResNet-LSTM model,[11] where ResNet captured spatial features, and LSTM handled temporal dependencies, achieving better prediction performance. Proposed[12,14] a similar approach, combining one-dimensional CNNs with LSTM networks for epileptic seizure recognition. Additionally,[13] introduced an adversarial representation learning method to develop robust, patient-independent seizure detection models, ensuring that learned features generalize across different patients without requiring extensive retraining.

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Seizure localization remains a crucial aspect of epilepsy treatment, particularly in cases of temporal lobe epilepsy, where identifying the precise origin of seizures can determine surgical eligibility. If a seizure is localized to either the left or right hemisphere, surgical intervention may be an option when medication is ineffective. Combining deep CNN with wavelet synchro-squeezing transform to achieve a high classification accuracy of 94.15%. These studies underscore the potential of machine learning in improving epilepsy diagnosis and treatment planning, offering hope for more accurate and personalized care for patients.

3. Materials and methods

EEG signal analysis plays a crucial role in diagnosing and classifying epilepsy, as these patterns reflect the brain's electrical activity at any given moment. Researchers follow a structured process to detect epilepsy from EEG signals, which includes:

Data acquisition – EEG data is collected using electrodes placed on the scalp, and voltage fluctuations in the brain are measured. Publicly available EEG datasets are used in many studies.

1. **Pre-processing** – Raw EEG data is cleaned to remove noise and artifacts.
2. **Feature extraction** – Key statistical attributes are identified to distinguish epileptic and non-epileptic events. The quality of these features significantly impacts detection accuracy.
3. **Classification** – EEG signals are classified based on extracted features using deep learning algorithm.
4. **Evaluation** – The model's performance is evaluated by measuring its accuracy.

Since accurate feature extraction is essential for reliable epilepsy detection, researchers often apply dimensionality reduction techniques to improve data quality and enhance classification performance.

3.1 Signal processing

In signal processing, the Fourier Transform (FT) has traditionally been the primary tool for analysing one- and two-dimensional signals, allowing the conversion between time and frequency domains. However, it provides only limited information about both aspects simultaneously.[15] The Short-Time Fourier Transform (STFT) improved upon this by offering time-localized frequency information, but it still had constraints. To overcome these limitations, the Wavelet Transform (WT) was introduced, enabling more detailed analysis of signals across different time and frequency scales. In this research, we explored the effectiveness of wavelet transform in processing brain electrical signals. By analysing these signals, we can extract valuable insights for advanced diagnostic applications. As computational methods advance, brain signal processing has become more refined, allowing for the identification of key brain wave patterns - alpha, beta, theta, gamma, and Sensory Motor Rhythm (SMR).[16] These patterns are closely linked to epilepsy and can be used to develop intelligent systems capable of distinguishing normal from abnormal brain activity.

The Fourier Transform represents periodic signals using sine and cosine series and was later adapted for non-periodic signals.[17] Eq. (1) allows the conversion of a signal between the time and frequency domains, making it a fundamental tool in signal analysis.

$$x(f) = \int \int_{--}^{+\infty} x(t) \,.\, e^{-jwt} . dt \tag{1}$$

The Fourier Transform struggles with discrete signals because it only provides frequency information without indicating when those frequencies occur, frequency and time scale is shown in Fig. 1. To address this limitation, the Short-Time Fourier Transform (STFT) was developed, allowing for both time and frequency analysis. STFT addresses the limitations of the traditional Fourier Transform by using a fixed-width window to analyse both time and frequency.[18] By sliding this window along the signal, it provides a time-frequency representation. However, STFT has trade-offs - small windows offer high precision for rapidly changing signals but lose accuracy for slower changes, while large windows do the opposite. Due to these limitations, STFT provides only an approximate view of signal characteristics, making it less effective for complex signals like brain activity. To achieve greater accuracy in processing brain signals, the Wavelet Transform (WT) was developed, offering a more detailed and precise analysis.

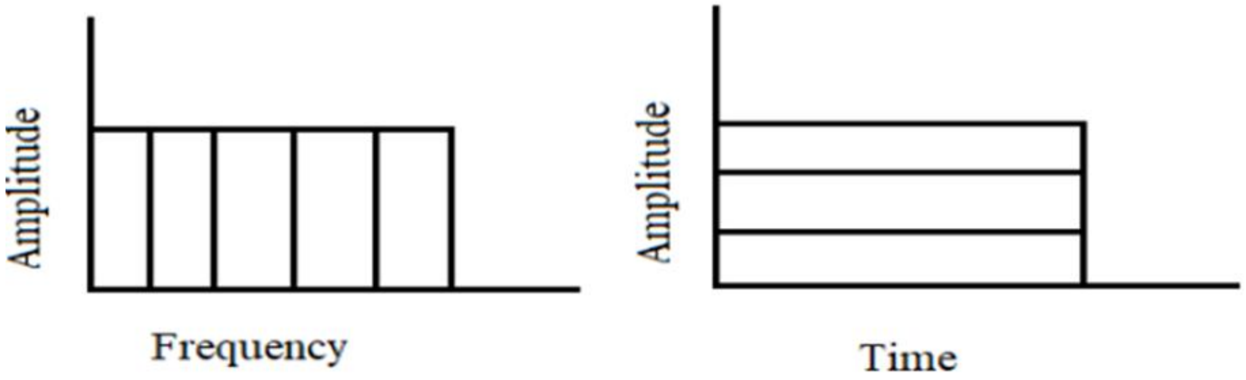

Fig. 1: Frequency and time scale representation.

3.2 Wavelet theory

Wavelet theory provides a powerful method for analysing signals by breaking them down into smaller, localized wave-like functions. Unlike the Fourier Transform, which represents signals using only sine and cosine waves, wavelets can analyse both time and frequency components with high precision. Wavelet theory provides a mathematical framework for analysing signals in both time and frequency domains, offering advantages over traditional Fourier analysis. It represents signals using localized wavelet functions,[19] making it suitable for non-stationary signals such as brain activity.

Continuous wavelet transform (CWT): CWT analyses signals at different scales by continuously shifting and scaling a wavelet function. It provides a detailed time-frequency representation, making it useful for identifying patterns in complex signals like brain activity. However, CWT requires significant computational resources due to its continuous nature. The Continuous Wavelet Transform (CWT) of the signal is computed using the formulation shown in Eq. (2). The scaled and translated version of the mother wavelet is expressed in Eq. (3)

The CWT of signal x(t) is defined as:

$$\mathrm{C(a,b)} = \int_{-\infty}^{\infty} x(t)\psi^{*}_{a,b}(t)dt \qquad (2)$$

Where $\psi^{*}_{a,b}(t)$ *is the scaled and translated version of the mother wavelet* $\psi(t)$, *given by*

$$\psi_{a,b}(t) = \frac{1}{\sqrt{|a|}}\boldsymbol{\psi}(\frac{t-a}{a}) \qquad (3)$$

α(scale parameter) controls the frequency resolution.

β(translation parameter) shifts the wavelet along the time axis.

CWT provides a detailed time-frequency representation but requires significant computational resources due to its redundancy.

Discrete wavelet transform (DWT): DWT simplifies wavelet analysis by applying specific scales and shifts, minimizing redundant calculations. It breaks down a signal into approximation and detail coefficients, enabling efficient multi-resolution analysis. DWT is widely used in areas like signal compression, feature extraction,[20] and medical applications, including EEG signal analysis. Unlike the Continuous Wavelet Transform (CWT), DWT is a more computationally efficient approach, as it operates on discrete values of scale and shift (typically powers of two). It achieves signal decomposition using filter banks, making it a practical choice for many real-world applications. The Discrete Wavelet Transform (DWT) of the signal is computed using the formulation presented in Eq. (4). The scaled and translated wavelet function used in the DWT is expressed in Eq. (5)

The DWT is defined as

$$\mathrm{X(j,k)} = \int x(t)\psi^{*}_{j,k}(t)dt \qquad (4)$$

where,

$$\psi_{j,k}(t) = 2^{\frac{j}{2}}\psi(2^{j}t - k) \qquad (5)$$

j controls the decomposition level

Overall, wavelet transforms provide a more flexible and precise approach to signal processing than traditional methods, making them ideal for analysing non-stationary signals such as brain waves. DWT uses a multi-resolution approach with low-pass and high-pass filters to separate the signal into coarse and detailed components. This decomposition is fundamental in EEG signal analysis, where brain waves (alpha, beta, theta, gamma, and SMR) can be extracted for medical diagnosis. CWT provides a continuous time-frequency analysis but is computationally intensive,[21] while DWT offers an efficient, multi-level representation suitable for real-time signal processing.

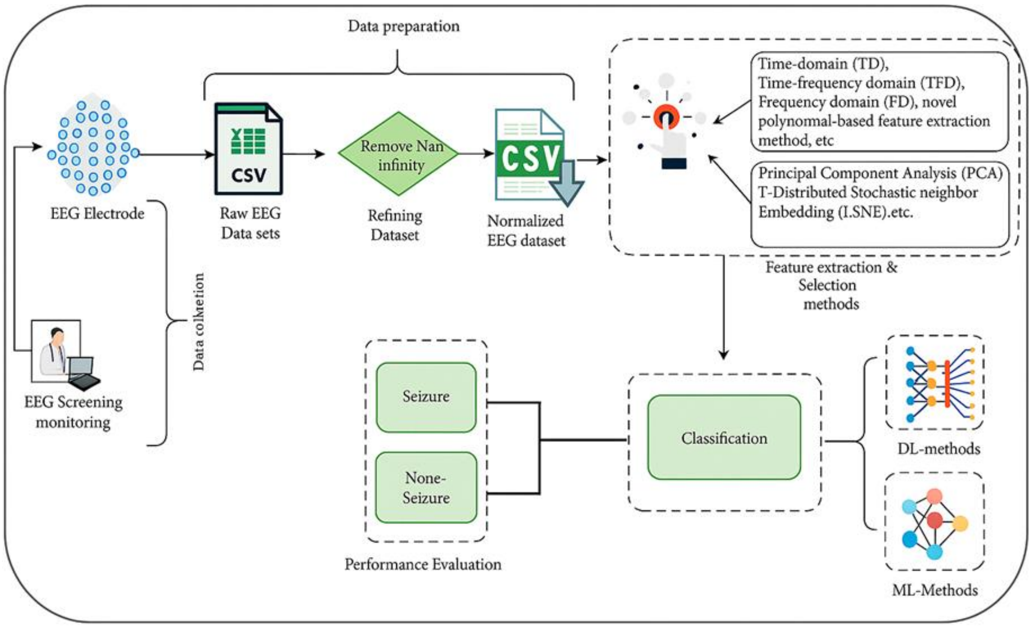

Fig. 2: Architecture of the proposed system.

In pre-processing stage, a noise removal filter is applied to EEG signals, followed by a band-pass filter (0.5–40 Hz) to isolate frequencies relevant to epilepsy detection. Our research is based on data from Dr. Andrzejak, which includes five EEG datasets (A–E). Groups A and B contain normal signals (eyes open/closed), while C and D capture interictal activity. Group E represents epileptic seizures. EEG recordings were taken using 19 surface electrodes (10-20 system), with each subset containing 100 files. Each signal lasts 23.6 seconds, with 4097 samples recorded at 173.61 Hz, ensuring high-resolution data for epilepsy analysis, architecture shown in Fig. 2. Wavelet Transform is used to extract frequency-based features for machine learning classification. Unlike Fourier Transform,[22] which loses time information in the frequency domain, and Short-Time Fourier Transform (STFT), which suffers from fixed window limitations, Wavelet Transform overcomes these issues by using variable-width windows for better time-frequency analysis.

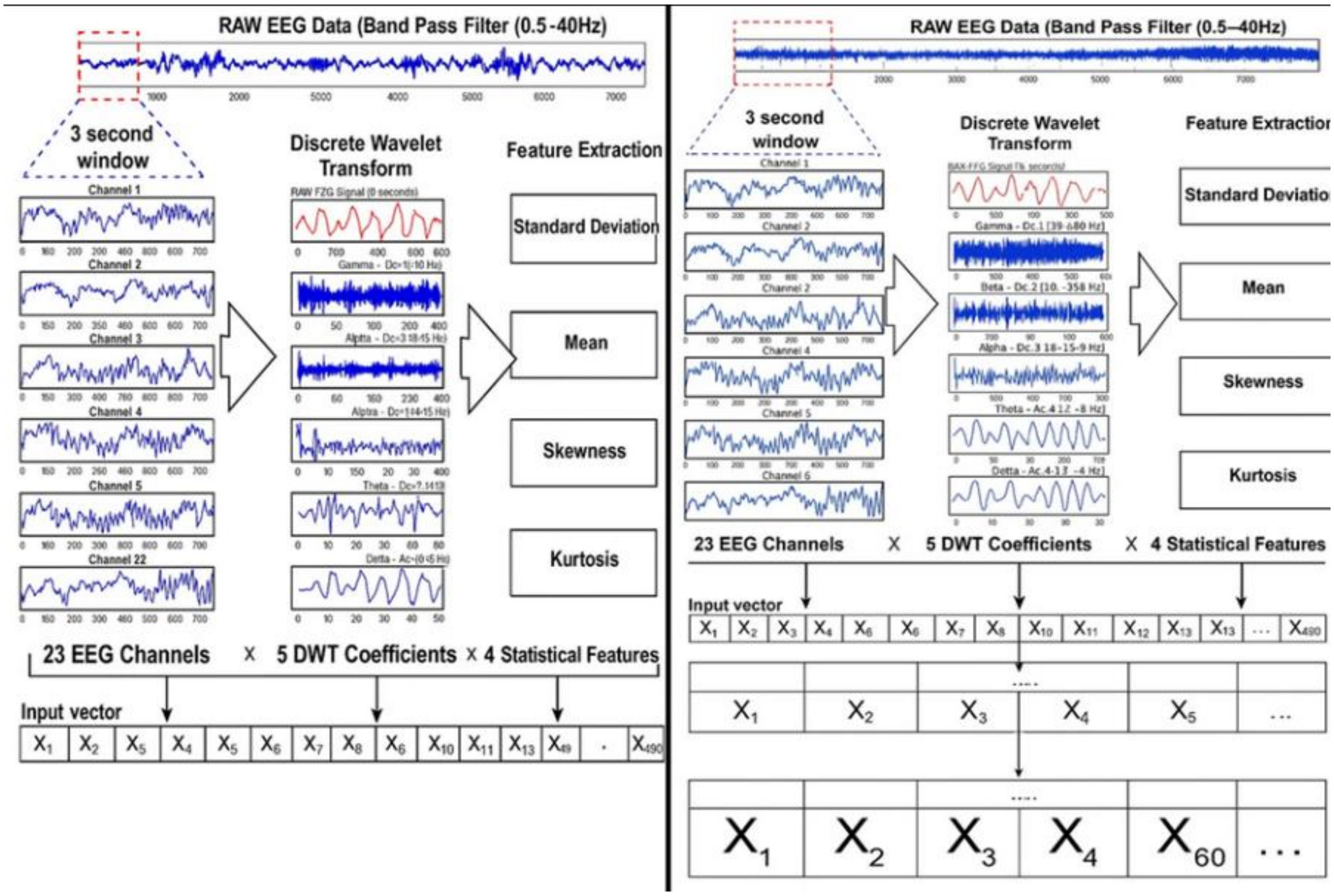

Fig. 3: Preprocessing EEG data and extracting key features for seizure detection using EfficientNet.

3.3 Feature extractions

Wavelet coefficients extracted from EEG signals capture both frequency and time characteristics of brain activity. These coefficients help analyse how signal frequencies change over time. By deriving statistical features from these wavelet coefficients, researchers can effectively represent the frequency-time dynamics of EEG signals, aiding in the detection and classification of epilepsy. We analyse EEG signals by breaking them into five frequency bands[23] and calculating four key stats for each—standard deviation, mean, kurtosis, and skewness. These features help detect conditions like epilepsy or Alzheimer's. Each EEG segment gets turned into a 460-value feature vector (23 channels × 5 bands × 4 stats). The dataset contains 2,730 labelled segments, marked as seizure (1) or non-seizure (0).

Mean

The mean, or arithmetic mean, is calculated by adding up all the values in a group and then dividing the total by the number of elements. It provides a simple way to determine the average value of a dataset.

Median

The median is the middle value in a sorted list of numbers. Unlike the average (mean), it is often a better representation of a dataset, especially when there are extreme values or outliers.

Kurtosis

Kurtosis in EEG signal analysis measures the sharpness or peakness of the signal's distribution. It helps identify abnormalities, such as sudden spikes or bursts in brain activity, which can be useful in detecting epileptic seizures. A higher kurtosis value indicates more extreme variations, while a lower value suggests a more uniform signal.

Skewness

Skewness tells us if an EEG signal's data is lopsided—whether most readings cluster on the high or low end. A positive skew means more low values with a tail stretching right, while a negative skew shows more high values with a tail stretching left. This helps spot unusual brain activity, like seizures.

Since ECG data can be high-dimensional, analysing all features simultaneously may introduce redundancy and computational challenges. Principal Component Analysis (PCA) is applied to reduce dimensionality while retaining the most important information. It works by transforming the original features into a smaller set of principal components, making the data more manageable without losing key insights, we aim to retain essential variations in the signal while discarding less relevant details.[24] A key aspect of this approach is finding the optimal number of principal components. For example, retaining eight principal components might explain around 90% of the variance in the data in Fig. 3 as shown, making it a reasonable choice for further analysis. However, variance alone does not guarantee effective classification. Therefore, it is important to evaluate whether the transformed features maintain the ability to distinguish between different heart conditions. By reducing the number of features while preserving critical patterns, PCA helps make ECG signal analysis more efficient and interpretable.

To improve the detection of EEG seizures, we need to enhance the distinction between seizure and non-seizure states. One way to achieve this is by expanding our feature space using Principal Component Analysis (PCA). The following plot illustrates how much variance in the EEG data is retained as we include more principal components (PCs) shown in Fig. 4. With just eight PCs, we capture 90% of the total variance, making it a reasonable choice for feature selection. However, it's important to note that while variance explains data distribution, it does not necessarily indicate how well the features separate seizure and non-seizure patterns.[25] Therefore, further evaluation is needed to determine the optimal number of components for effective classification.

A smaller set of features or specific combinations of them can create a space where seizure and non-seizure EEG signals become linearly separable. We use PCA to shrink the data down to its most important features, cutting complexity without losing key details in Fig. 5. The goal is to determine if a lower-dimensional representation of the EEG data can still effectively distinguish seizure patterns from normal brain activity, making classification both accurate and efficient. Each EEG time series is described using 26 different features that capture important patterns in brain activity.[26] These features include statistical measures, frequency components, and temporal variations that help distinguish between seizure and non-seizure states. By analysing these features, we can determine whether a smaller subset can effectively represent the data while maintaining important information for accurate classification.

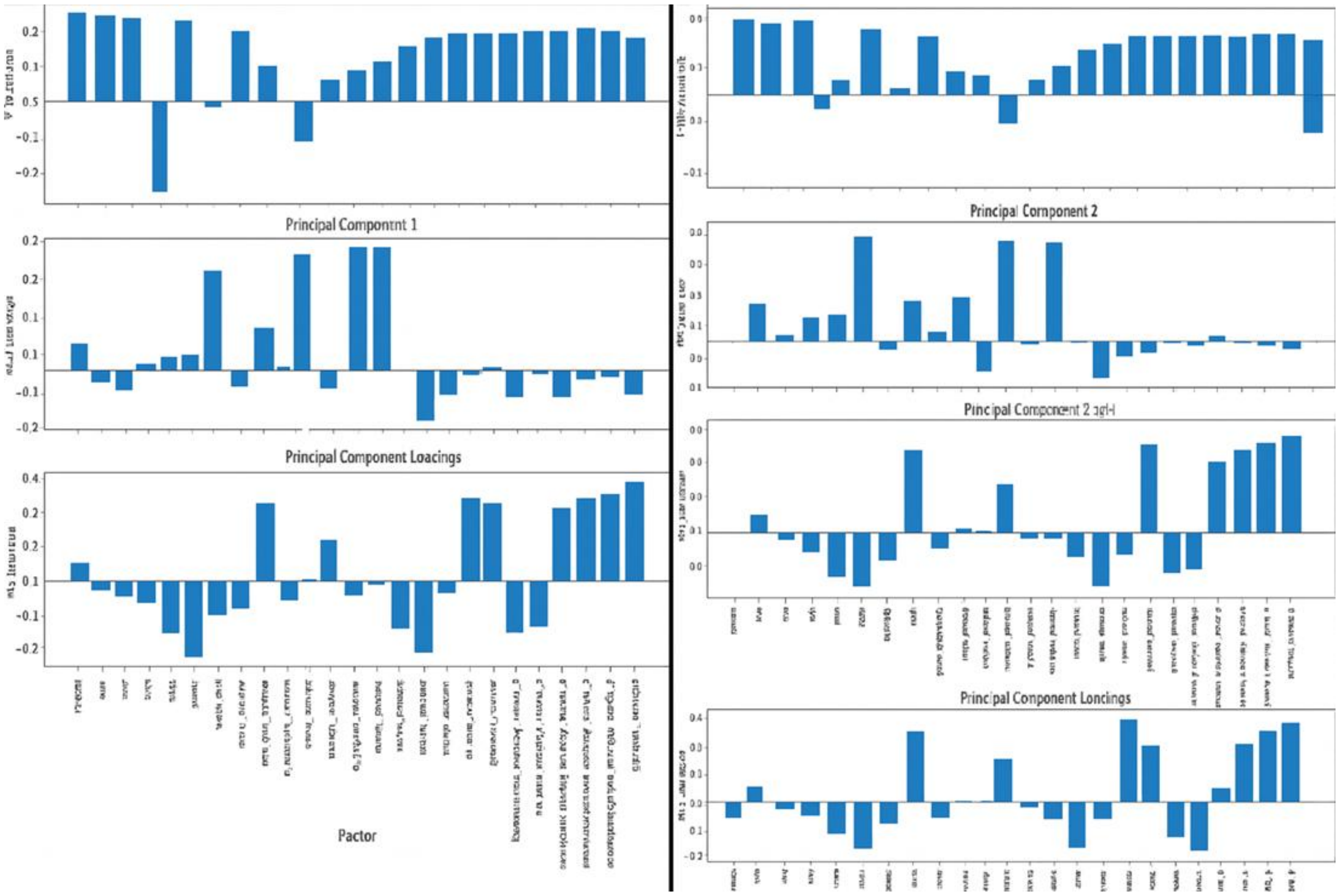

Fig. 4: Feature representation using component.

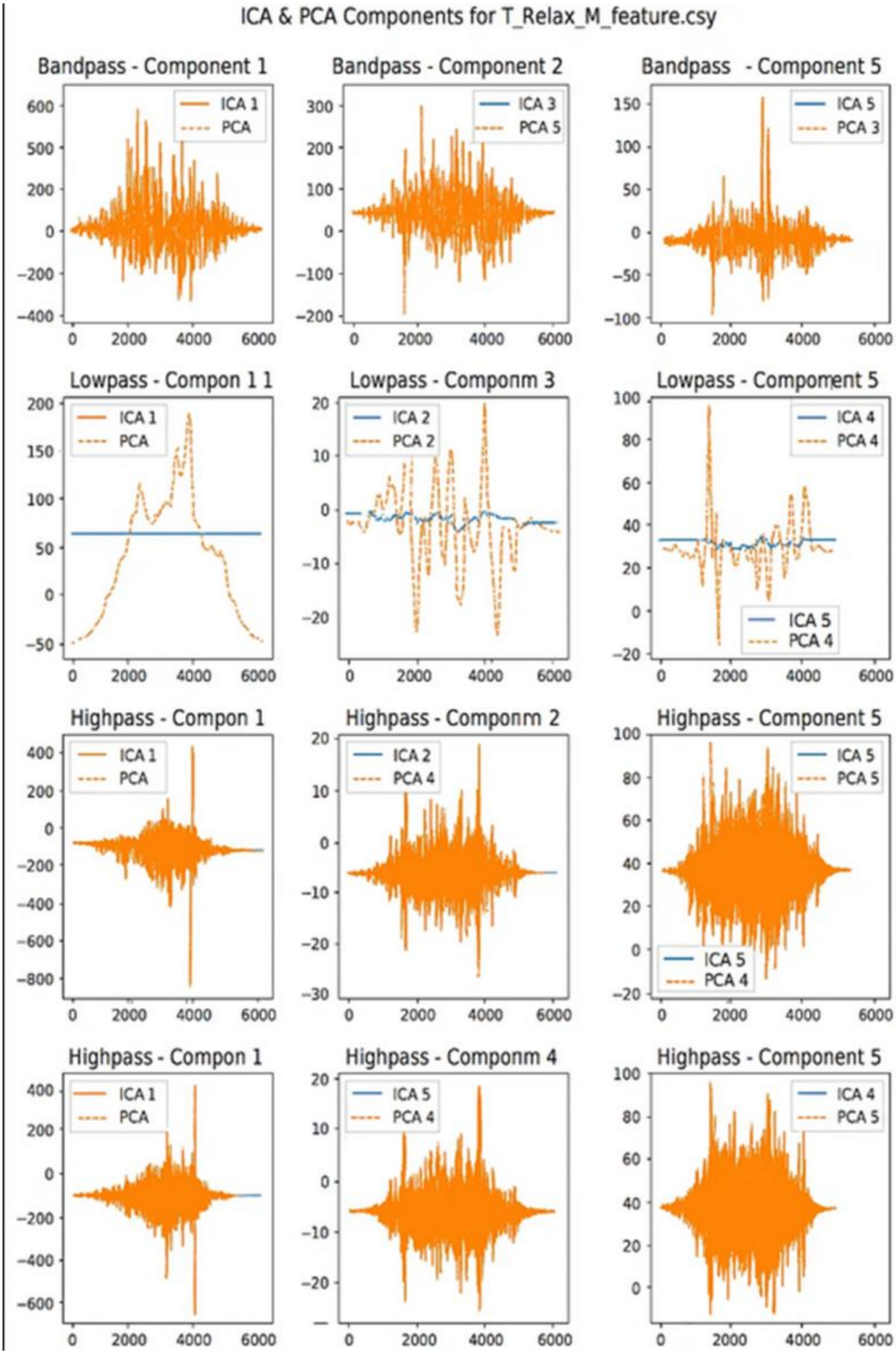

Fig. 5: ICA and PCA components.

Table 1: Different frequency bands accuracy analysis.

Frequency Sub-Band	Accuracy	Sensitivity	Specificity
Gamma(30-60Hz)	68.52	54.21	88.37
Beta (15-30Hz)	72.74	56.23	90.12
Alpha (8-15Hz)	78.36	62.87	92.48
Theta (4-8Hz)	79.04	71.24	91.35
Delta (0-4Hz)	82.78	78.46	86.01

For classification, a EfficientNet model is used. The architecture includes:

- Input layer with 460 neurons, matching the feature vector size.
- Hidden layer with 20 neurons, optimized through trial and error.
- Output layer with a single neuron for binary classification.

The model has undergone multiple training and testing cycles with varying data splits and learning rates to achieve optimal performance. The epilepsy seizure classification model uses EfficientNet and is tested on two EEG datasets: the BONN dataset (single-channel intracranial signals) and the CHB-MIT database (multi-channel surface recordings). To assess its performance, we tweak key settings like training/testing splits, learning rates, and frequency analysis methods, ensuring a robust evaluation of how well the model works.

4. Results

4.1 Data pre-processing with DWT

DWT is a key technique in EEG signal processing that helps break down complex brainwave data into simpler, more manageable parts. Imagine taking a detailed audio recording and separating it into bass (low-frequency) and treble (high-frequency) components - DWT does something similar with brain signals. It uses two filters: a low-pass filter that smooths out the signal to capture slow, rhythmic brain activity (like deep relaxation or drowsiness) and a high-pass filter that picks up sharp, fast fluctuations (like sudden bursts of neural activity or noise). The first pass splits the EEG signal into approximation coefficients (Ac-1), which represent the broader trends, and detail coefficients (Dc-1), which contain finer details. This process can be repeated, further refining the approximation coefficients into even smaller frequency bands, allowing researchers to zoom in on specific brainwave patterns. By adjusting the wavelet's shape and scale, DWT provides a flexible way to analyse EEG signals in both time and frequency, making it useful for detecting abnormalities, removing artifacts, and studying brain function at different levels of detail.

This study evaluates an EfficientNet -based model for epilepsy classification using two publicly available EEG datasets: BONN and CHB-MIT. The key difference between them lies in the type of electrodes used, which affects the spatial coverage and signal quality. The BONN dataset is smaller and consists of single-channel intracranial EEG recordings, offering higher spatial resolution and more precise neural activity measurements. Table 1 shows different frequency bands. In contrast, the CHB-MIT dataset is much larger,[27] featuring 23 channels of scalp EEG recordings, which provide broader but less detailed coverage.

After fine-tuning the model, it was tested on the larger CHB-MIT EEG dataset to classify seizure activity. To prepare the data, the study used Discrete Wavelet Transform (DWT) to split raw EEG signals into five key frequency bands: gamma (30–60 Hz), beta (15–30 Hz), alpha (8–15 Hz), theta (4–8 Hz), and delta (0–4 Hz). The Daubechies-4 (DB-4) wavelet was selected because its shape matches the spike-like patterns often seen in epileptic EEG readings in Fig. 6. By decomposing the signals, the method extracted both approximation coefficients (broad trends) and detail coefficients (fine fluctuations) from seizure and non-seizure EEG segments. To improve classification, statistical features - including mean, standard deviation, skewness, and kurtosis - were calculated for each frequency band, helping the model distinguish between normal and epileptic brain activity more effectively.

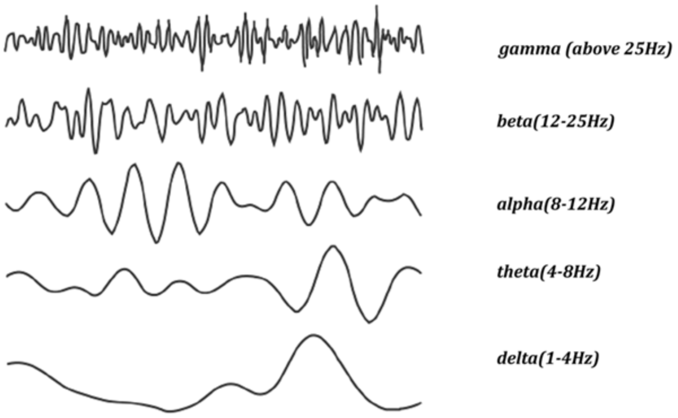

Fig. 6: Different band representation.

The scree plot illustrates how much information each principal component (PC) retains. The blue bars show the variance contributed by each component, while the red colour curve shows the cumulative variance. Green and the blue dashed lines indicate where 90% and 95% of the total variance are captured.[28] From the graph, the first few components hold most of the important information. The first component alone explains a significant portion of the variance, and by the time we reach the 8th to 10th component, over 90% of the total variance is retained as shown in Fig. 7. This means we can work with fewer features without losing essential details. The main objective is to check whether this reduced set of features still allows for clear separation between different categories. If the key patterns remain intact, we achieve an efficient way to analyse the data while reducing complexity.

The graph presents a promising outlook for the proposed deep learning model in detecting seizures using EEG signals. The model steadily improves, with decreasing loss and increasing accuracy, showing it effectively learns key patterns from the EEG data. The validation accuracy tracks closely with training accuracy, meaning it generalizes well to new data Fig. 8 depicts Loss and accuracy. Early stopping helps train the model just enough to detect seizure-related features without overcomplicating it. With an accuracy reaching close to 100%, this method shows great potential for real-time seizure detection, which could significantly benefit medical professionals and patients. The model's performance demonstrates its effectiveness in identifying seizure patterns, making it a strong candidate for further development and clinical applications.[29] This approach not only enhances diagnostic precision but also paves the way for more reliable and efficient seizure detection systems in healthcare.

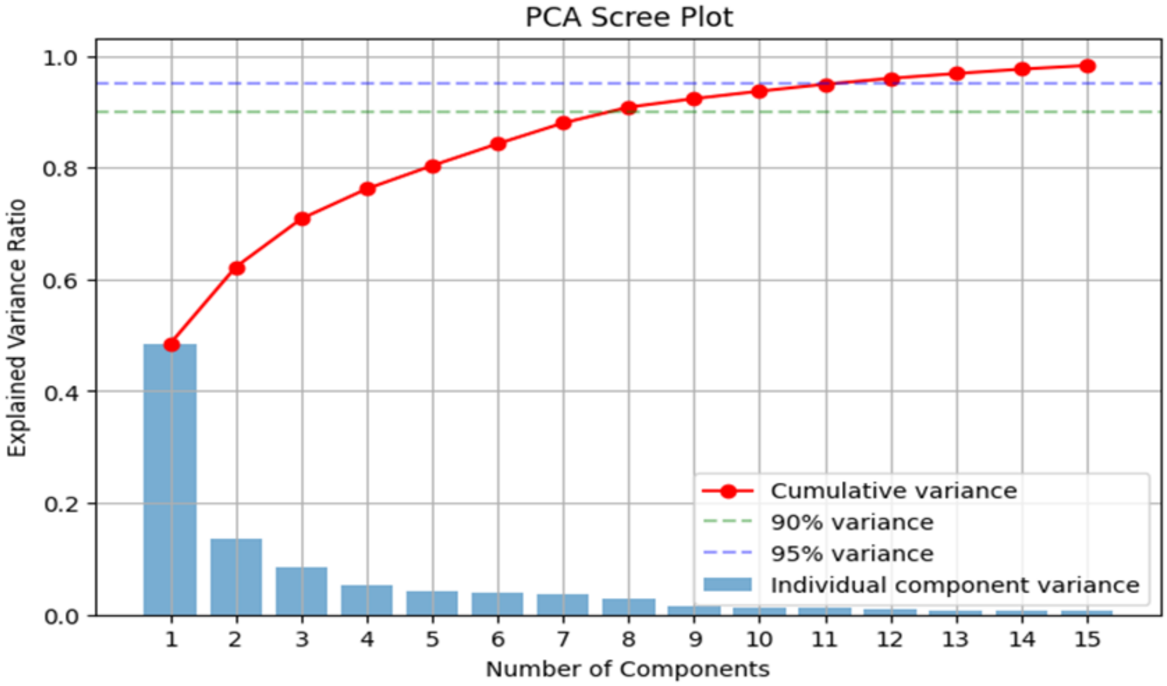

Fig. 7: PCA scree plot.

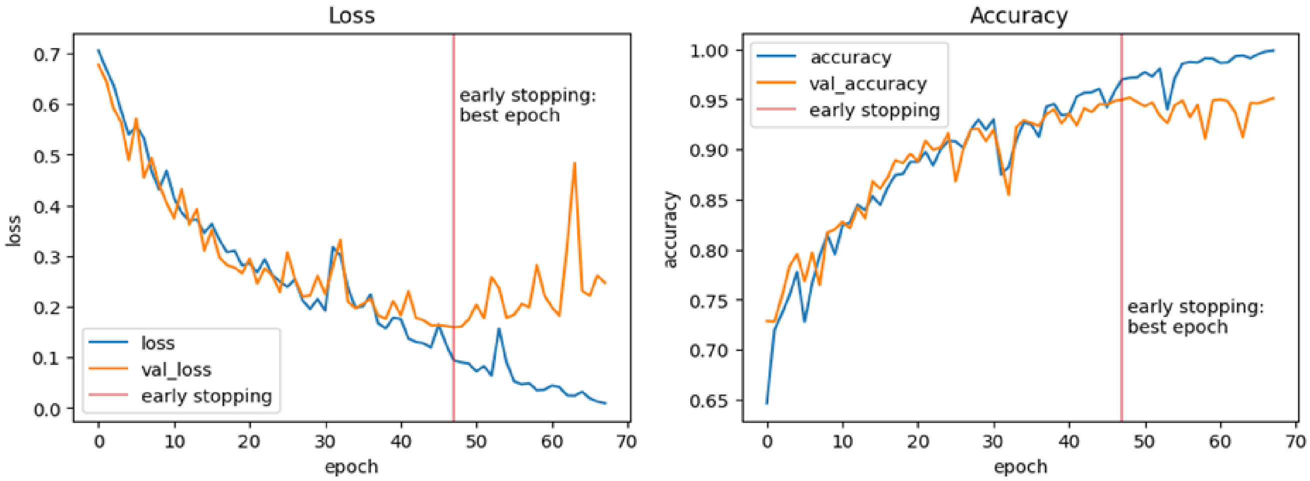

Fig. 8: Loss and accuracy graph.

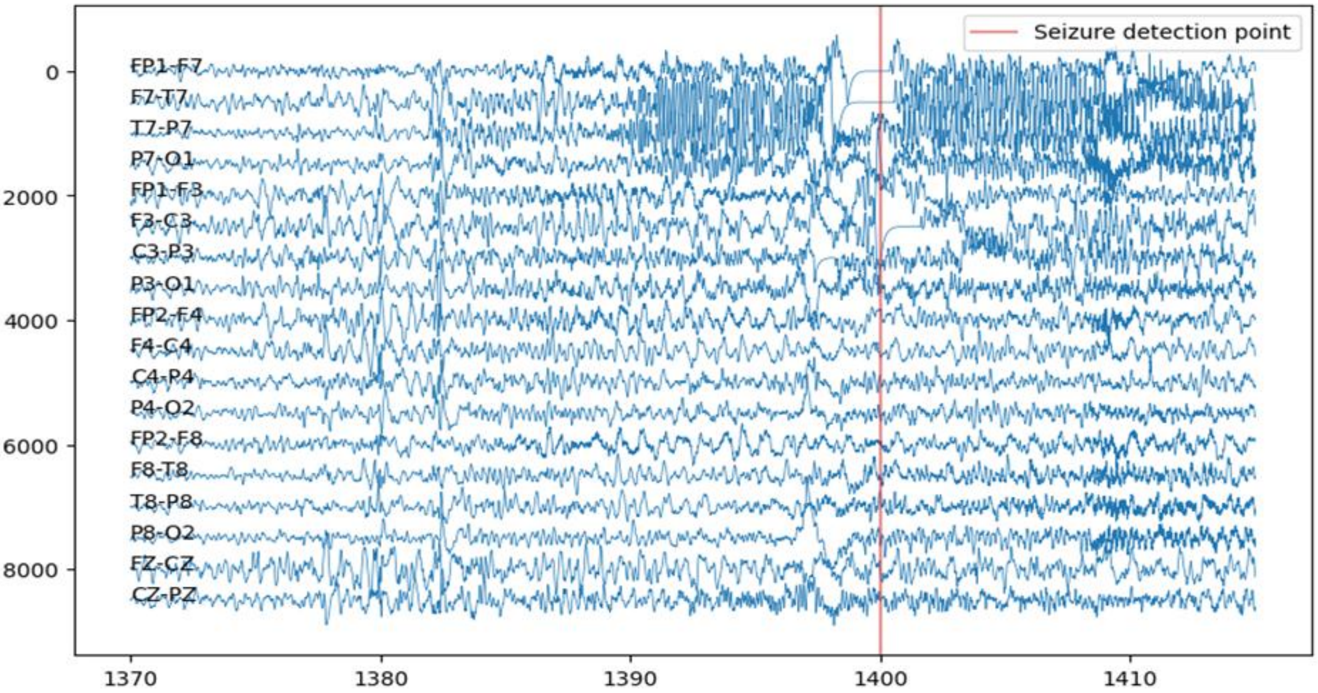

Fig. 9: Seizure detection point representation.

Each line represents brain activity recorded from different electrode positions over time. The red vertical line marks the moment a seizure is detected, clearly separating normal and seizure-related brain activity. Before this point, the signals appear stable, with natural fluctuations. However, as the seizure begins shown in Fig. 9, there is a sharp increase in amplitude and irregularity, key indicators of seizure onset. Accurately detecting this moment is essential for timely intervention and better patient care. By identifying seizure patterns with precision, this method can assist neurologists in monitoring and diagnosing seizures more effectively.[30,31] The ability to recognize these events in real time is invaluable for patients with epilepsy, improving both safety and treatment management. This approach demonstrates a promising step forward in seizure detection, offering a reliable solution for better healthcare and patient well-being.

This ROC curve represents Fig. 10 shows the effectiveness of the proposed seizure detection method. The x-axis shows the false positive rate, while the y-axis indicates the true positive rate. A higher curve means better accuracy in identifying seizures.[37] With an AUC score of 0.91, the method shows strong reliability in distinguishing seizure events from normal brain activity. The steep rise in the curve suggests that the detection method correctly identifies seizures with minimal false alarms. Table 2 shows the comparison of proposed work with existing work.

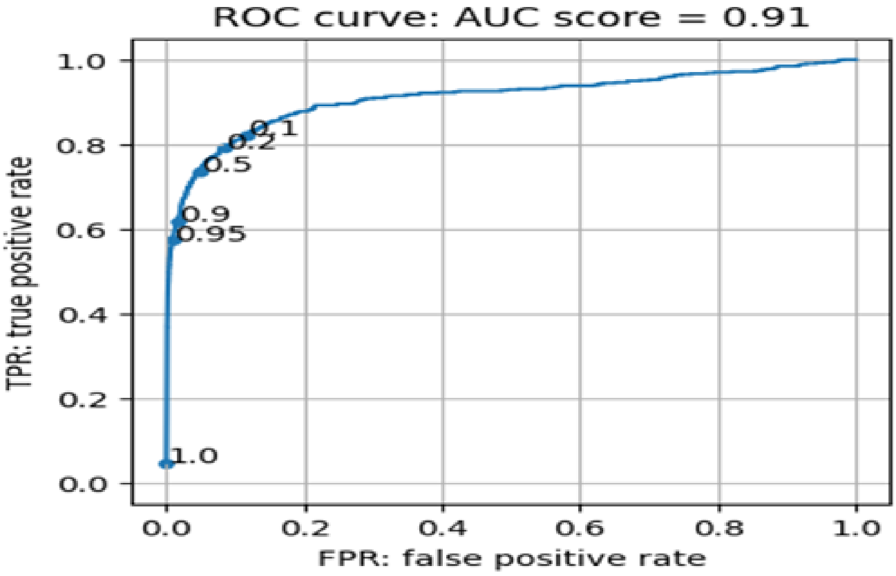

Fig. 10: ROC curve for seizure detection.

Table 2: Comparison of proposed work with existing work.

Author	Method	Accuracy	Sensitivity	Specificity
Lopes, F *et al.*[32]	DWT + ANN	90.17%	90.00%	91.00%
Natu, M *et al.*[33]	GNMF-based LogE + SSTFT+ FKNN	90.99%	90.53%	91.27%
Vieira *et al.*[34]	CNN + DWT	90.36%	86.27%	87.38%
Jahan *et al.*[35]	Entropy + STFT + MVAR + Sample	89.47%	90.26%	90.20%
Srinivasan S *et al.*[36]	SVM + DWT	91.70%	90.40%	89.10%
Proposed	DWT+ EfficientNet	93.27%	92.78%	92.86%

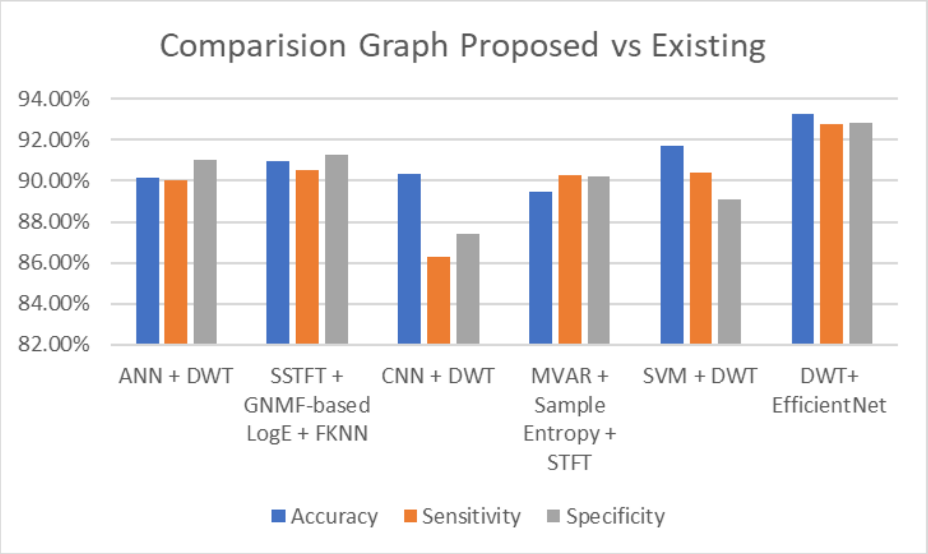

Fig. 11: Classification representation Graph.

The DWT-based EfficientNet model proved highly effective, delivering better results than other methods across both datasets. On the CHB-MIT dataset, it achieved an impressive 93.27% accuracy, surpassing traditional models like ANN (86.10%) and SVM (90.68%). Not only was it more accurate, but it also trained much faster reaching optimal performance in just 50 epochs, compared to the 200 epochs needed for ANN. When stacked against earlier research, such as Chen *et al.*'s study (which reported 89.01% accuracy using statistical features),[38] this model showed clear improvements in accuracy, sensitivity, and specificity, making it a stronger tool for detecting seizures in EEG data Fig. 11 shows the comparison.

5. Conclusion

Effective seizure detection starts with clean EEG signals. Since raw brainwave data is often cluttered with noise and varies from patient to patient, strong pre-processing is key to accurate analysis. This study highlights two powerful techniques PCA and ICA to refine EEG data before classification. PCA simplifies the signal by keeping only the most important features, cutting out unnecessary noise and speeding up model training. Meanwhile, ICA acts like a signal filter, isolating and removing interference like muscle twitches, eye movements, and electrode glitches. Together, these methods ensure the model works with clearer, more reliable data, reducing false alarms and improving seizure detection. The DWT-based EfficientNet model proved far more effective than traditional approaches like ANN and SVM, achieving 93.27% accuracy on the CHB-MIT dataset and doing so in just 50 epochs, compared to ANN's sluggish 200 epochs. By incorporating PCA and ICA in the pre-processing stage, the model successfully captured both the spatial and temporal patterns in EEG signals, resulting in stronger and more precise seizure detection. These results underscore just how crucial proper pre-processing is not just in theory, but in real-world medical settings where accuracy can make all the difference.

Future advancements in seizure detection could focus on integrating the model into wearable EEG devices, allowing real-time monitoring and instant alerts for patients and caregivers. Developing personalized models that adapt to an individual's unique EEG patterns can improve accuracy, reducing false alarms. Enhancing feature extraction by combining PCA, ICA, and other techniques may further refine signal processing. Beyond detection, predicting seizures before they occur could provide early warnings, improving patient safety. Expanding research across diverse datasets will strengthen reliability. Additionally, utilizing cloud and edge computing can enable faster, more accessible processing, making seizure detection more practical for everyday use.

Acknowledgments

We gratefully acknowledge the support, guidance, and valuable contributions from our institution

Conflict of Interest

There is no conflict of interest.

Supporting Information

Not applicable.

CRediT Statement

Amita Roshan Vakil: Conceptualization, Methodology, Investigation, Formal analysis, Data curation, Writing – original draft, Visualization. **Mangala Shetty:** Supervision, Validation, Writing – Review & editing, Methodology, Project administration. **Surendra Shetty:** Investigation, Validation, Resources, Writing – Review & editing. **Spoorthi Shetty:** Data curation, Software, Formal analysis, Visualization, Writing – Review & editing. **R. Anand:** Methodology, Supervision, Validation, Writing – Review & editing. **Shivananda Pai:** Supervision, Resources, Validation, Writing – Review & editing. **P. Rakshitha:** Investigation, Data curation, Writing – Review & editing.

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