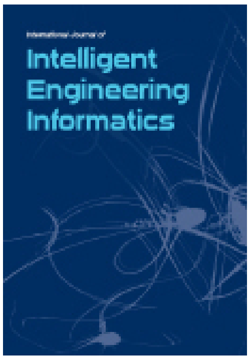

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New approaches to epileptic seizure prediction based on EEG signals using hybrid CNNs

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Abstract: This study employs the University of Bonn Dataset to address the importance of frequency information in EEG data and introduces a methodology utilising the short-time Fourier transform. The proposed method transforms conventional 1D EEG signals into informative 2D spectrograms, offering an approach for advancing the detection of neurological diseases. Integrating advanced CNN architectures with the conversion of EEG signals into 2D spectrograms forms the foundation of our proposed methodology. The 1D CNN model utilised in this study demonstrates exceptional performance metrics, achieving a specificity of 0.996, an overall test accuracy of 0.991, a sensitivity of 0.987, and an F1 score of 0.989. Shifting to the 2D approach discloses a slight reduction in accuracy to 0.987, sensitivity of 0.976, specificity of 0.988, and an F1 score of 0.97. This analysis provides nuanced insights into the performance of 1D and 2D CNNs, clarifying respective strengths in the context of neurological disease detection.

Keywords: seizure prediction; epilepsy; EEG signals; 1D convolutional neural network; deep learning; classification.

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1 Introduction

Epilepsy is a chronic neurological disease resulting from sudden abnormal and synchronous electrical activities of brain neurons, affecting nearly 1% of the world's population (Wang et al., 2021). Seizures are caused by a high level of electrical discharge in a cluster of brain neurons. Consequently, electroencephalography (EEG) is widely used for diagnosing and treating various neurological disorders. It does this by recording electrical activity in the brain (Roy et al., 2018). Recurrent and unpredictable seizures, which are brief episodes of involuntary movements and sometimes even result in a momentary loss of consciousness, are the hallmarks of epilepsy, a chronic brain disease (Fisher et al., 2014).

Neurological diseases present significant challenges in diagnosis and treatment, necessitating innovative solutions that harness the power of deep learning, a powerful technique for analysing complex data. Deep learning methods have recently become very popular in medical analysis because deep learning with autonomous learning capabilities can analyse statistical patterns in large datasets, offering applications from medical diagnoses to predicting stages in neurological diseases with results surpassing human accuracy (Lima et al., 2022). Deep learning methods, achieved through the combination of nonlinear modules, enable effective learning of intricate functions, especially in neurological disease classification, by emphasising crucial input aspects in higher layers and suppressing irrelevant variations for sharper and more meaningful outcomes (Lecun et al., 2015). Most current approaches focus on seizure prediction, detection, and classification of seizures. Research indicates that when antiepileptic medications (AEDs) are used appropriately, up to 70% of patients can receive successful treatment (Fisher et al., 2014). EEG is commonly used to diagnose epilepsy, but manual analysis by neurologists is time-consuming. Automated seizure detection techniques aim to speed up diagnosis and enhance accuracy. Examining frequency features in EEG seizure data is crucial for understanding seizure EEG (Rashed-Al-Mahfuz et al., 2021).

This study delves into neurological disease detection, explicitly focusing on epileptic seizures, and utilises advanced 1D and 2D convolutional neural networks (CNNs) for EEG signal analysis. The complexity of EEG signals requires a sophisticated approach for accurate neurological disease detection. Traditional methods often treat EEG data as one-dimensional time series, overlooking crucial frequency information in the signals. Our study proposes a methodology that transforms 1D EEG signals into informative 2D spectrograms using the STFT to address one-dimensional limitations. This transformation enhances analysis by capturing frequency patterns, providing a more comprehensive understanding of neural activity.

2 Related work

A proposed method used Arnold and Chaotic encryption to encrypt generated spectrogram images, achieving an accuracy of up to 86.11% and 84.72% for seizure detection when employing pre-trained CNN models (Ein Shoka et al., 2023). Researchers proposed a data integration framework for EEG seizure detection, and their method achieved up to 96.87% accuracy (Alharthi et al., 2022). In a different approach, a study proposed a novel EEG instance matching-based epilepsy classification using a CNN that achieved an accuracy of 99.3% (Lian et al., 2020). The authors used a novel CNN to analyse time, frequency, and channel information of EEG signals to predict epileptic seizures and the model accurately achieved 80.5% accuracy, 85.8% sensitivity, and 75.1% specificity (Wang et al., 2021). Using a combination of raw EEG and frequency sub-bands as input, a CNN could detect interictal epileptiform discharges from EEGs at 90% sensitivity (Prasanth et al., 2020). The authors used a CNN with 1D and 2D kernels to achieve a high-accuracy prediction of 93.5% on the intracranial dataset and 98.8% on the CHB-MIT scalp EEG dataset (Xu et al., 2020). Deep learning structure based on CNNs was designed to detect epilepsy using EEG signals using Bonn University datasets, achieving an average accuracy of 98.67% (Abiyev et al., 2020) A proposed method involving the pre-processing of scalp EEG signals, automated feature extraction using a CNN, and classification with support vector machines achieved a sensitivity of 92.7% (Muhammad Usman et al., 2020; Zhou et al., 2018). Using CNNs, it was found that frequency domain signals yielded higher accuracies for epileptic signal detection than time domain signals, reaching 96.7% in Freiburg and 97.5% in CHB-MIT databases. The study found that using a 3D CNN with multi-channel EEG data outperformed traditional signal processing methods, achieving an accuracy of over 90% (Wei et al., 2018). In a different study using CNN and transfer learning, a % classification accuracy of 82.85% for epileptic seizure type recognition was achieved, surpassing conventional feature and clustering-based approaches (Raghu et al., 2020). The study presents CNN-based classifiers for seizure detection, incorporating signal-to-image conversion methods and proposing three classification methods with five classifiers, with the FT-VGG16 achieving a top accuracy of 99.21% (Rashed-Al-Mahfuz et al., 2021). The TF-HybridNet model outperformed other models in training and testing, particularly with ten-fold cross-validation, showcasing the potential for enhanced performance with increased EEG data and achieving a notable 94.3% accuracy compared to the state-of-the-art method (Sui et al., 2021). In a separate study, the conversion of original EEG signals into spectrograms using STFT and a dual self-attention residual network (RDANet) was introduced for enhanced forecasting performance, achieving 92.07% accuracy (Yang et al., 2021). The study achieves a remarkable 98.22% average accuracy in classifying epilepsy seizures using STFT for non-stationary signal processing and a CNN model on EEG spectrogram images from the Bonn University dataset (Mandhouj et al., 2021). The 2D CNN CWT + LSTM model applied to the Bonn AB-CD-E dataset achieved an accuracy of 97.30% (Varlı and Yılmaz, 2023). The combination of EEG signals processed STFT and continuous wavelet transform (CWT) has achieved an accuracy of 91.3% through training a CNN (Xia et al., 2021). The proposed method with CBAM-3D CNN-LSTM achieved an accuracy of 97.95% and a sensitivity of 98.40% on an EEG dataset of 11 patients (Lu et al., 2023).

Classification studies cover a diverse range of applications. In studies related to classification, the study focuses on breast cancer identification using mammography, introducing a multidimensional feature-based technique with enhanced grey-level co-occurrence matrix and contrast limited advanced histogram equalisation. Achieving 92% of accuracy on the MIAS dataset (Surya and Muthukumaravel, 2023). The article highlights the need for automatic recognition of aggressive actions in videos and emphasises the importance of detecting violence to protect children from inappropriate content. The proposed approach achieves a commendable accuracy of 76.79% on the specified database test set (Chelliah et al., 2023a). The article explores epilepsy as a chronic neurological disorder leading to life-threatening seizures due to irregular brain activity. It aims to develop an automated seizure detection system using machine learning algorithms.

The model evaluates eight algorithms on the Bonn University dataset, with random forest and Gaussian Naive Bayes achieving 100% accuracy, sensitivity, specificity, 0.01 FPR, and 0.99 AUC with feature extraction. Even without feature extraction, these algorithms perform exceptionally well (Patel et al., 2022). The study introduces a novel multi-view, multi-depth learning framework for soil temperature prediction, demonstrating its effectiveness, especially when employing support vector regression (SVR) as the base learner, and highlighting its unprecedented application in estimating soil temperature using both time series and machine learning methods (Tuysuzoglu et al., 2022). This paper introduces a two-stage approach, utilising multi-objective SALP optimisation for efficient detection of two-locus epistasis associations among single nucleotide polymorphisms, demonstrating superior performance compared to MACOED and CSE (Priya and Manavalan, 2022). The research focuses on deep learning in image classification, natural language process and speech recognition, emphasising the prevalence of unrealistic adversarial samples in model security. True hostile attacks are understudied but compromise real-world applications. The study assesses the efficacy of unreal hostile samples in protecting models using real-world cases, revealing comparable success with realistic examples. The findings contribute insights into neural network adversarial resilience (Chelliah et al., 2023b). The study utilised geocell as a ground enhancement technology to improve the tensile properties of poor soil, exploring the effects of varying reinforcement depths, layers, and relative densities. Settlement predictions in poor sand were made using the recommended recurrent neural network (RNN) method, outperforming alternative models when applied to geocell with independent variables (Jeyanthi et al., 2023).

3 Proposed methodologies

This section applies automated methods for classifying epilepsy diseases using the University of Bonn dataset (Andrzejak et al., 2001). Our proposed approach comprises two key stages: feature extraction and classification.

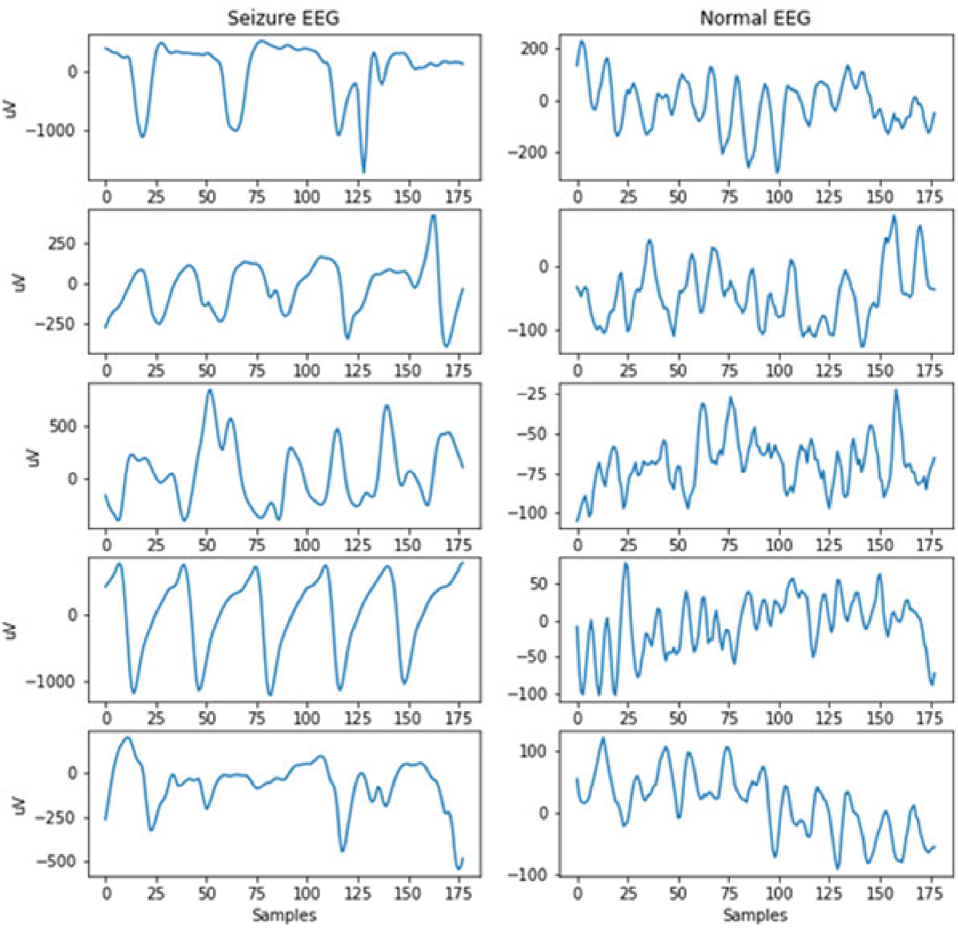
The crucial first stage involves extracting informative features from raw EEG data. We leverage a technique that integrates time-frequency domain analysis via the STFT. This innovative approach captures richer temporal and spectral information compared to traditional methods. Further, we transform these extracted features into spectrogram images, providing a readily interpretable visual representation for improved classification.

For the subsequent classification task, we employ a CNN as the model. CNNs excel at processing image data like spectrogram images, extracting visual patterns directly from the pixel-based input.

3.1 Dataset description

The dataset utilised for this study was acquired by a research team affiliated with the University of Bonn (Andrzejak et al., 2001). It comprises five subsets labelled A through E, amounting to 500 EEG signals. Each signal within the A to E sets comprises 100 channels, and each dataset includes 4,096 sampling points, reflecting 23.6 seconds. To remove artefacts related to muscle activity and eye movements, the gathered data was visually inspected. In EEG recordings, noises from various muscle movements have been eliminated. The EEG recording was conducted following standardised techniques for electrode placement. Five patients experiencing epileptic seizures were chosen for this study. Five segments were carefully selected and extracted from the continuous multi-channel EEG recordings after a visual inspection to identify contaminants. Segments A and B were explicitly taken from the EEG recording surface and represent data from healthy individuals. Segment A reflects the eyes-open state, while segment B pertains to the eyes-closed state of a healthy volunteer. The remaining C, D, and E segments are associated with brain activity during epileptic seizures. Sets C and D exclusively contain intervals of seizure-free brain activity. Set E comprises EEG signals exclusively recorded during seizure activity. The EEG signal was recorded at 173.61 Hz after being converted from analogue to digital by a 12-bit converter.

Figure 1 Seizure and normal EEG signal samples (see online version for colours)



The dataset's limited number of instances presents a challenge for training an effective deep-learning model. Obtaining a substantial quantity of EEG signals for this issue is impractical, and the expert labelling required by neurologists adds to the difficulty (Wu and Fokoue, 2017). To address this, we require an augmentation approach to augment the dataset sufficiently for training a generalised CNN model, which demands ample training data for optimal performance. While the EEG dataset (Andrzejak et al., 2001) is small enough to train a model, the risk of overfitting is apparent. To address this challenge, the original dataset (Andrzejak et al., 2001) has undergone modifications and restructuring, resulting in an enhanced version derived from a commonly utilised epileptic seizure detection dataset (Wu and Fokoue, 2017) for improved usability. The original dataset, segmented into 23 chunks, each representing one second of EEG recording, results in

11,500 rows of data. Each row contains 178 data points, comprehensively representing EEG signals across different segments. The dataset is divided into two classes: a non-epileptic class of 9,200 rows and an epileptic class of 2,300.

Figure 2 Scatter plot of maximum and minimum values (see online version for colours)

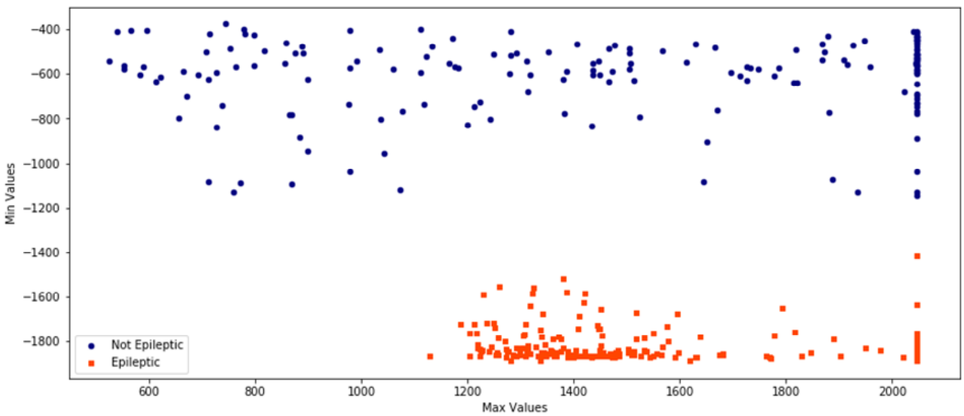
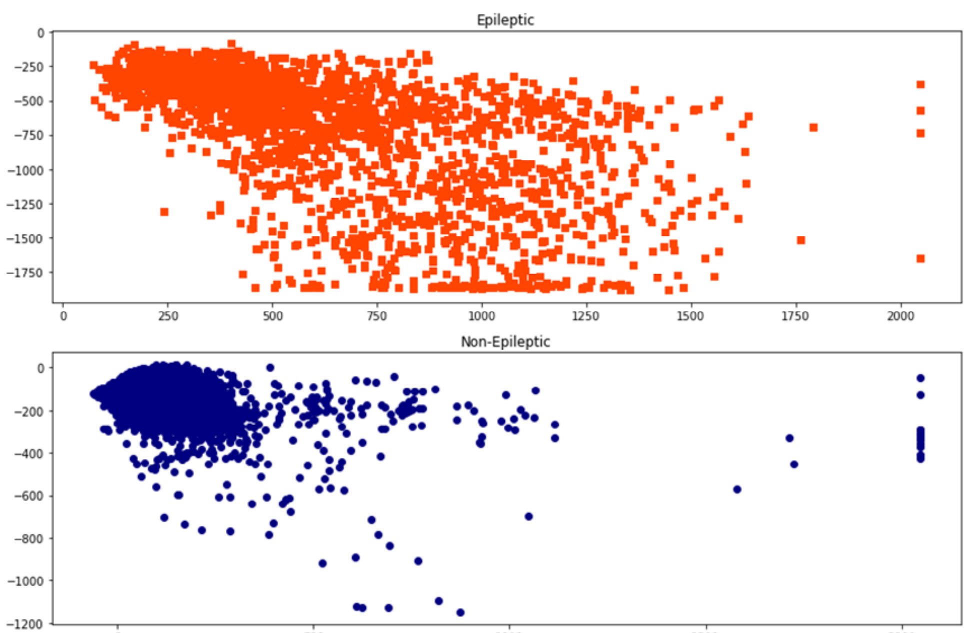


Figure 3 Visual representation of epileptic and non-epileptic conditions (see online version for colours)



Class 1 signifies recordings of seizure activity, indicating that the individual is experiencing an epileptic seizure. Class 2 indicates EEG recordings from the area where the tumour was located, providing insights into the tumour's potential impact on brain activity. Class 3 identifies the tumour region in the brain with EEG activity recorded from the healthy brain area, aiding in understanding the tumour's location and extent.

Class 4 indicates recordings with the patient's eyes closed, reflecting the patient's state of rest or relaxation. Class 5 denotes EEG recordings taken with the patient's eyes open. In this approach, the epileptic seizure class is considered the positive class, and the remaining categories are the negative class. This allows focusing on identifying the characteristics distinguishing seizure segments from non-seizure segments.

Figure 3 visualises epileptic and non-epileptic conditions, representing the dataset obtained during the analysis of EEG recordings. Most points in the epileptic class are concentrated in an area with higher x and y values. Conversely, most points in the non-epileptic class are concentrated in an area with lower x and y values. This distinction suggests that two features of EEG signals could potentially be utilised in diagnosing epilepsy.

The widespread distribution of signals representing epilepsy symptoms suggests abnormal electrical activity in various brain regions, offering insights into the origins and mechanisms of seizures. On the other hand, the clustering of non-epileptic signals in a narrow area implies regular brain function. These observations could inform the development of new strategies for epilepsy diagnosis and treatment, representing a crucial step in improving patient interventions and quality of life.

3.2 Feature extraction

The short-time Fourier transform (STFT) was introduced by Gabor in 1946 and has since been extensively utilised to analyse nonlinear and non-stationary signals. Fourier transform (FT) provides valuable insights into the frequency components of a signal. FT assumes a signal's frequencies remain constant over time. This assumption becomes problematic when dealing with non-stationary EEG signals where frequencies fluctuate dynamically (Sui et al., 2021).

Extracting distinct frequency components (delta, theta, alpha, beta, and gamma) from EEG signals unlocks the potential for in-depth frequency-dependent analysis. This analysis can inform the identification of these bands as biomarkers, contributing to a deeper understanding of brain activity (Beeraka et al., 2022). To address the limitations of FT with EEG, the STFT offers a refined approach. The STFT is a technique in which the fast Fourier transform (FFT) is calculated for each data frame (Keerthi Krishnan and Soman, 2021). It divides the signal into multiple, shorter segments, each assumed to be approximately stationary within its limited timeframe. This segmentation is achieved by applying a window function, which isolates individual segments for analysis. The FT is then applied to each stationary segment, yielding a time-dependent spectral representation known as the spectrogram. This 2-dimensional representation captures temporal and spectral variations within the signal, allowing us to visualise how frequencies change over time (Loh et al., 2022). The inherent non-stationarity of EEG signals often renders conventional time-frequency analysis methods, like the FT, less effective in extracting key features. However, the spectrograms generated by STFT effectively capture the dynamic nature of EEG signals, enabling the extraction of features that can successfully distinguish between EEG signals associated with epilepsy (Sui et al., 2021). By segmenting the signal and analysing each segment's frequency content independently, STFT acts as a moving window, revealing the frequency evolution of the signal over time. A large window provides less resolution in time and more resolution in frequency. Along with the window length, window type decides the time frequency distribution, since the strong time-variable signal causes frequency aliasing

(Keerthi Krishnan and Soman, 2021). The usual mathematical expression of the STFT (1) is shown by:

$$STFT(t, \omega) = \int_{-\infty}^{+\infty} x(t)\omega(t-\tau)e^{-j\omega t}dt \quad (1)$$

The variable t represents the specific moment in the signal, while ω stands for the angular frequency. The signal function in the time domain is denoted as $x(t)$. The term $\omega(t - \tau)$ represents a window function centred around $t - \tau$ in the time domain. The complex exponential term $e^{-j\omega t}$ modulates the signal in the frequency domain, and dt signifies an infinitesimal change in time. The integral is computed over all time, from negative infinity to positive infinity, capturing the product of the signal, window function, and the complex exponential for different values of τ and ω.

3.3 Convolutional neural networks

Artificial neural networks refine their functions by adjusting weights through iterative learning from training data. This process aims to minimise prediction errors and improve accuracy over time. Generalising for unseen inputs is a key advantage of machine learning models, achieved by connecting multiple units in a neural network (Aggarwal, 2018).

CNNs represent a subset of deep learning architecture, comprising an input layer, an output layer, and multiple hidden layers. The initial hidden layers typically consist of convolutional layers, which extract feature maps by applying convolution kernels to input data (Sui et al., 2021). These convolutional layers, also known as filters, form the foundational elements of the network. They generate a feature map of the input data through repetitive application, achieved by sliding a window across the dataset (Beeraka et al., 2022).

The convolutional layer detects local patterns. The pooling layer merges similar features by calculating the maximum of local patches. The technique helps in expanding the position of each feature for reliable perception. Combining two or three stages of convolution, linearity, and pooling, followed by additional convolutional and fully connected (FC) layers, facilitates backpropagation through the CNN, allowing training of all weights in the filters (Lecun et al., 2015).

In deep learning, each layer's learning process depends on completing the previous layer's learning. Although input values are standardised during normalisation, layers may face challenges such as gradient loss or slower, less stable training (Varlı and Yılmaz, 2023). Neural networks rely on nonlinear activation functions to translate incoming data into meaningful outputs, enabling them to tackle complex tasks (Rosenberg Johansen et al., 2018). Rectified linear unit (ReLU) function is utilised following each convolutional layer. ReLU (2) denoted as:

$$f(x) = \max(0, x) \quad (2)$$

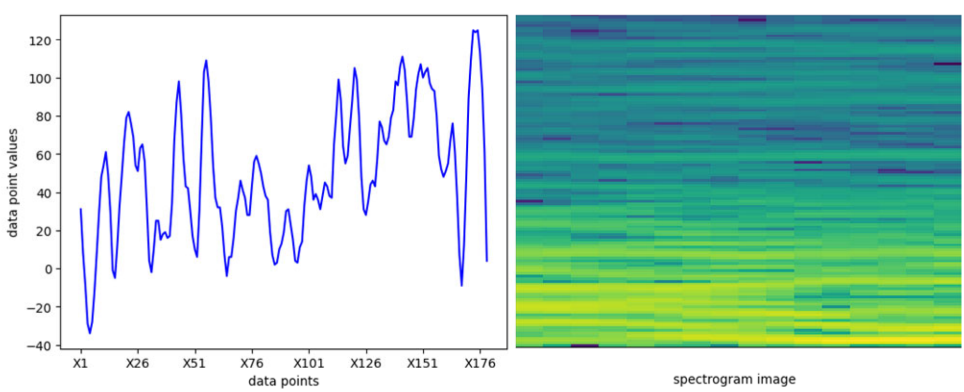
As the CNN progresses to deeper layers, the focus shifts to learning higher-level features and breaking down inputs into intricate structures. In contrast, the initial layers concentrate on understanding basic features through filtering (Keerthi Krishnan and Soman, 2021). Pooling layers play a crucial role in CNNs by strategically reducing the dimensionality of data, effectively mitigating overfitting, and easing computational demands. They operate by down-sampling the output matrix of the preceding convolutional layer, either selecting the maximum value within each region or averaging the values. During the training phase, dropout layers deactivate a randomly chosen set of neuron units, reducing the model's workload and preventing overfitting. The learned features combine the previously extracted features in the FC layer by linking each node in the previous layer to each node in the FC layer. Each FC layer, except the last one, incorporates an activation function to optimise CNN network performance (Xia et al., 2021). The flattened layer plays a crucial role in this process by converting the data into a one-dimensional array, serving as the input for the FC layer. This prepares the data for subsequent FC layers, where each input is linked to every neuron in the network (Varlı and Yılmaz, 2023).

3.4 Transformation from 1D signals to 2D spectrograms using STFT

CNN is a deep learning network that can be used on single, two, or three-dimensional data (Varlı and Yılmaz, 2023). CNNs have become widely adopted in machine learning research, particularly in adapting 1D and 2D architectures for diagnosing and predicting diseases using biological signals (Shoeibi et al., 2021).

Transforming 1D EEG data into 2D spectrograms, presenting a comprehensive approach to enhance signal analysis for epileptic seizure detection. The method employs an STFT to convert the time-domain EEG signals into a frequency-domain representation, providing valuable insights into the underlying patterns and dynamics of the neural activity. Analysing EEG data is essential in neurology and medical signal processing to identify abnormalities like epileptic seizures. Conventional methods frequently ignore the rich frequency information inherent in EEG signals by treating them as 1D time-series data. An approach to convert the 1D EEG data into 2D spectrograms is introduced to take advantage of this frequency-domain information.

Figure 4 Example of a signal and its spectrogram-transformed version (see online version for colours)



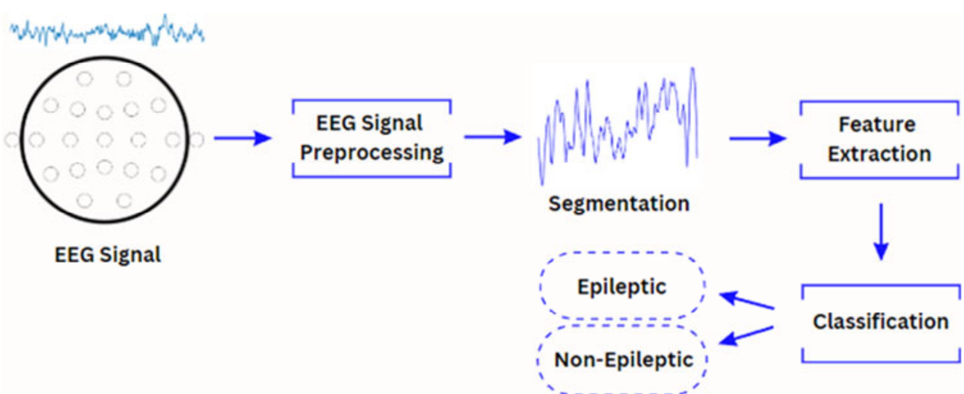
The transformation process is executed using a sliding window technique, where each segment of EEG data undergoes STFT. The parameters for this transformation include a window size of 100 samples and a specified number of frequencies set at 256. The sampling frequency is also set to 1,000 Hz, ensuring an accurate representation of the EEG signals. The resulting spectrograms are saved as images, where each image corresponds to a unique EEG recording. The resulting spectrograms provide a visually rich representation of the frequency content of EEG signals. This approach holds promise for enhancing the accuracy of epileptic seizure detection algorithms by capturing intricate frequency patterns that may not be fully discernible in the time domain. The images can be seamlessly integrated into machine learning models, paving the way for more comprehensive and practical EEG signal analysis in neurology.

3.5 1D CNN

1D CNN was trained on EEG signals, while 2D CNN was trained using corresponding spectrogram images. The dataset was evenly split for both models, with 80% allocated for training and 20% for testing. This balanced distribution aimed to evaluate the model's performance comprehensively. The strategy involved utilising 80% of the data for training to optimise the model's learning and generalisation capabilities, with the remaining 20% reserved for thorough assessment. The proposed 1D CNN architecture was developed for epilepsy detection, featuring various layers tailored to effectively capture and analyse EEG data. The model uses three convolutional layers with 32, 64, and 128 filters. Each convolutional layer uses a kernel of size 6 and 3. The model's structure encompasses an input layer, convolution layers equipped with batch normalisation, and max-pooling layers to systematically extract hierarchical features from the EEG signals. The initial convolution layer processes a signal of size 173 with 32 filters with a five-unit kernel, is followed by batch normalisation and max-pooling.

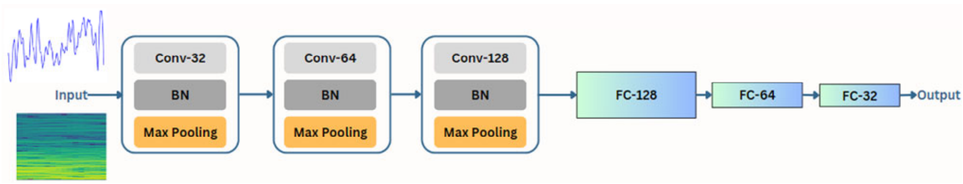
Further enhancing its capacity, the architecture introduces two additional convolution layers, each incorporating larger filter sizes, 64 and 128, respectively. Batch normalisation is strategically applied to these layers to bolster model stability and convergence.

Figure 5 Framework of the proposed 1D CNN method (see online version for colours)



Utilising max-pooling layers facilitates the down-sampling of feature maps, thereby reducing dimensionality while preserving crucial information. The flattened layer transforms the output into a one-dimensional array, seamlessly connecting to dense layers for robust classification. Two FC dense layers with 64 and 32 neurons contribute to the model's ability to comprehend intricate patterns within the data. Dropout layers are seamlessly integrated to prevent overfitting in the training phase. The final dense layer housing two neurons is the output layer, effectively conveying binary classifications indicative of epilepsy detection.

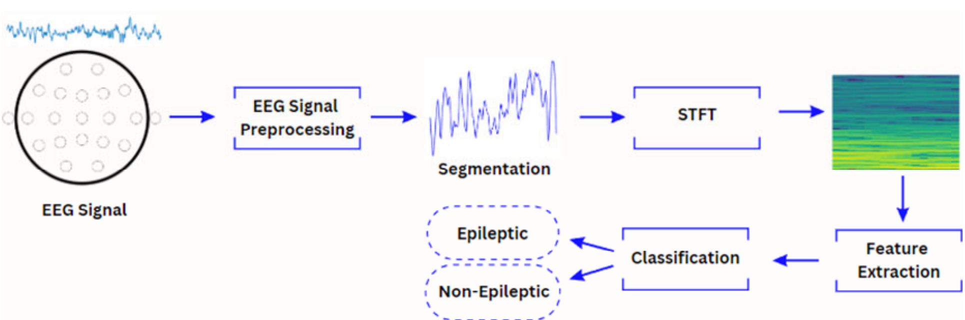
Figure 6 Proposed 1D CNN and 2D CNN models (see online version for colours)



3.6 2D CNN

The optimised network is designed as a 2D CNN to improve classification performance in detecting epileptic seizures. This CNN structure encompasses multiple layers strategically designed to extract hierarchical features from the input EEG data. Commencing with an input layer, the model incorporates three convolutional layers, each leveraging ReLU activation functions to facilitate robust feature extraction. Following each convolutional layer, batch normalisation is applied to bolster the stability and efficiency of the network. After these layers, max-pooling operations with 2 × 2 pooling sizes are employed to down-sample spatial dimensions, effectively capturing crucial patterns while mitigating computational complexity. The output from the final max is in Figure 7.

Figure 7 Framework of the proposed 2D CNN method (see online version for colours)



The pooling layer is then fed into two FC dense layers, with 128 and 64 neurons, utilising ReLU activation functions. A dropout layer is introduced after the second dense layer to prevent overfitting. The ultimate layer is a dense layer featuring two neurons, employing a SoftMax activation function to yield probability distributions for the two classes relevant to seizure detection. The training process utilises the Adam optimiser, and sparse categorical cross-entropy is the chosen loss function.

Figure 8 2D CNN architecture for EEG spectrogram classification (see online version for colours)

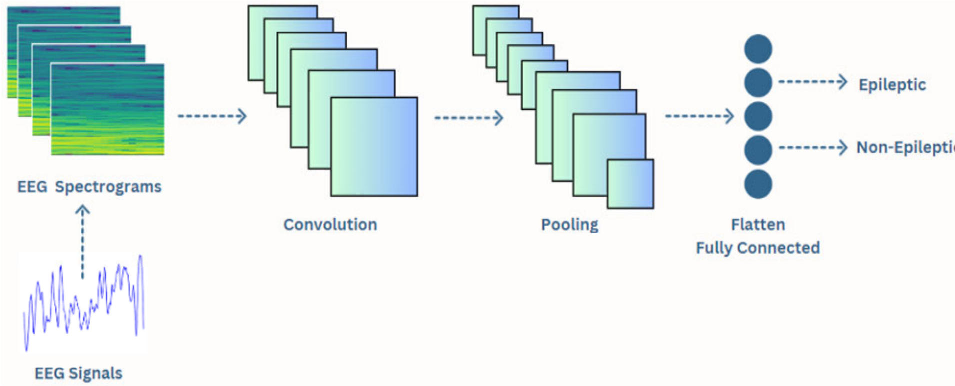


Table 1 Proposed methods for neural networks

1D CNN layers	*Output shape*	*2D CNN layers*	*Output shape*
Conv1D	(173, 32)	Conv2D	(28, 28, 32)
Batch normalisation	(173, 32)	Batch normalisation	(28, 28, 32)
MaxPooling1D	(87, 32)	MaxPooling2D	(14, 14, 32)
Conv1D	(85, 64)	Conv2D	(14, 14, 64)
Batch normalisation	(85, 64)	Batch normalisation	(14, 14, 64)
MaxPooling1D	(43, 64)	MaxPooling2D	(7, 7, 64)
Conv1D	(41, 128)	Conv2D	(7, 7, 128)
Batch normalisation	(41, 128)	Batch normalisation	(7, 7, 128)
MaxPooling1D	(21, 128)	MaxPooling2D	196
Flatten	128	Flatten	128
Dense	64	Dense	128
Dropout	64	Dropout	64
Dense	32	Dense	64
Dropout	32	Dropout	32
Dense	2	Dense	2

4 Results and discussion

A successful deep learning model generates highly classifiable features through multi-layered feature extraction. To evaluate the performance of a model, various metrics are used in this study. These include true positive (*TP*), true negative (*TN*), false positive (*FP*), and false negative (*FN*), which indicate the model's ability to identify and differentiate between positive and negative cases correctly. Additionally, accuracy (*Acc*) (3), sensitivity (*Sen*) (4), specificity (*Spe*) (5), precision (*Pre*) (6), and *F*1-*score* (7) provide comprehensive insights into the model's overall effectiveness and balance in terms of correct predictions and error rates.

$$Acc = \frac{TP + TN}{TP + TN + FP + FN} \tag{3}$$

$$Sen = \frac{TP}{TP + FN} \tag{4}$$

$$Spe = \frac{TP}{FP + TN} \tag{5}$$

$$Pre = \frac{TP}{TP + FP} \tag{6}$$

$$F1\text{-}score = \frac{2 * Pre * Sen}{Pre + Sen} \tag{7}$$

1D CNN demonstrated exceptional performance, achieving a specificity of 0.996, signifying its proficiency in correctly identifying instances without seizures. The overall test accuracy reached 0.991, underscoring the model's robustness. Furthermore, the sensitivity 0.987 highlights the model's effectiveness in accurately detecting seizure occurrences. The calculated F1-score is 0.989, confirming the outstanding performance of the 1D CNN. Upon converting the dataset into a 2D format, the CNN's accuracy experienced a slight decrease to 0.987.

Nevertheless, the sensitivity remained commendable at 0.976, indicating the model's sustained effectiveness in capturing TP instances of seizures. The specificity 0.988 underscores the model's capacity to accurately classify samples without seizures, comparable to the 1D CNN. Although there was a slight decrease in accuracy, the 2D CNN demonstrated an F1-score of 0.97.

5 Conclusions

This study explores the impact of dimensionality on the performance of CNNs in the context of epileptic seizure detection. First, the employed dataset was in a 1D format and subsequently transformed into 2D. We evaluated the model's effectiveness based on key metrics, including specificity, accuracy, sensitivity, and F1-score. The 1D CNN demonstrated noteworthy test results with an accuracy of 0.991 and sensitivity of 0.987. This shows its remarkable ability to identify seizure and non-seizure cases correctly. Despite limitations in frequency information utilisation and feature extraction flexibility, its efficiency and lightweight nature make it an appealing option for practical applications. While the 2D CNN showed slightly lower accuracy (0.987) than the 1D model, its sensitivity remained high at 0.976, indicating strong efficacy in detecting seizures. Additionally, its ability to learn richer spatiotemporal features holds potential for further accuracy improvements. However, the increased computational cost and data pre-processing requirement must be considered. Because of its lower time-frequency resolution, the STFT cannot capture some crucial time-frequency information in spectrograms, which results in insufficient input images for the deep learning model.

Nevertheless, it has drawbacks, including increased computational cost and the need for data pre-processing. In conclusion, the presented results highlight the nuanced performance variations between 1D and 2D CNNs in the context of epileptic seizure detection. Understanding these nuances is crucial for selecting the most suitable model architecture based on a given application's specific requirements and priorities.

Table 2 Comparative analysis between the proposed system and existing work

Method	*Accuracy (%)*	*Sensitivity (%)*	*Specificity (%)*
Arnold and Chaotic encryption + CNNs (Ein Shoka et al., 2023)	86.11, 84.72	-	-
Dominant channel selection + 1D-CNN, bi-LSTM and attention (Alharthi et al., 2022)	96.87	96.98	96.85
CNN-based EEG instance matching (Lian et al., 2020)	99.3	99.5	99.6
CNN for time, frequency and channel information (Wang et al., 2021)	80.5	85.8	75.1
CNN with raw EEG and frequency sub-bands (Prasanth et al., 2020)	-	90	79
1D and 2D CNN Kernels (Xu et al., 2020)	93.5, 98.8	-	0.981, 0.988
CNNs for Bonn University Datasets (Abiyev et al., 2020)	98.67	97.67	98.83
Scalp EEG pre-processing + CNN + SVM (Muhammad Usman et al., 2020)	-	92.7	90.8
Frequency domain CNN (Zhou et al., 2018)	96.7, 95.6, 59.5	-	-
3D CNN with multi-channel EEG Data (Wei et al., 2018)	90	88.90	93.78
CNN and transfer learning (Raghu et al., 2020)	82.85	-	-
CNN FT-VGG16 (Rashed-Al-Mahfuz et al., 2021)	99.21	99.04	99.38
RDANET (Yang et al., 2021)	92.07	93.02	91.26
2D CNN LSTM CWT (Varlı and Yılmaz, 2023)	97.3	97.3	98.35
CNN STFT (Mandhouj et al., 2021)	98.22	97.77	98.6
CNN CWT STFT (Xia et al., 2021)	91.3	-	-
TF-HybridNet STFT (Sui et al., 2021)	94.3	-	-
CBAM-3D CNN-LSTM (Lu et al., 2023)	97.95	98.4	-
1D CNN (ours)	*99.1*	*98.7*	*99.6*
2D CNN (ours)	*98.7*	*97.6*	*98.8*

This study provides valuable insights into the performance of 1D and 2D CNNs in epileptic seizure detection, but certain limitations need acknowledgment. Firstly, the study relies on the widely accepted University of Bonn dataset which may not fully capture the variability in diverse populations, potentially limiting generalisability. The small sample size also raises concerns about the broader applicability of the proposed methodology. Additionally, dataset modifications made for usability enhancements introduce the possibility of biases impacting real-world scenarios. The deep learning method employed has its constraints. The large dimensions of 2D CNN layers may strain GPU capacity, requiring larger GPUs or parallel processing and incurring additional costs. The computational cost, particularly with deeper models, can extend training times and increase resource intensity, especially with large datasets. Adding more layers and parameters increases model complexity, demanding more training data. While the 1D CNN demonstrated remarkable performance, the 2D CNN's slightly lower accuracy should be interpreted considering its potential for richer spatiotemporal feature learning. However, trade-offs must be considered, including increased computational costs and data pre-processing.

The findings contribute valuable insights to the ongoing research to optimise deep learning models for medical image analysis and seizure detection tasks. This study contributes to the evolving landscape of deep learning applications in neurology by unravelling the intricacies of CNN performance in epileptic seizure detection. The findings emphasise the significance of choosing the appropriate model architecture based on specific application requirements. As the field advances, optimising deep learning models for medical image analysis and seizure detection tasks remains a paramount objective, guided by insights from such studies.

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