Spectrum of Engineering Sciences

SPECTRUM OF ENGINEERING SCIENCES

Online ISSN
3007-3138
Print ISSN
3007-312X

A Hybrid Deep Learning Model for Precise Epilepsy Detection and Seizure Prediction

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Abstract

Manually classifying brain activity linked to epilepsy can be a lengthy, expensive process that varies depending on the observer. This study utilizes deep learning, particularly Convolutional Neural Networks (CNNs), to streamline this task using the Epileptic Seizures dataset. The CNN models are trained on spectrograms derived from brain signal plots, enabling the automatic detection of brain activity associated with epilepsy, such as generalized rhythmic delta activity, lateralized rhythmic delta activity, and

epileptic seizures. This automated approach aims to lower diagnostic costs, reduce variability between observers, and lessen the manual workload, providing neurologists with a more reliable and efficient tool for diagnosing epilepsy. With an impressive accuracy of 97.11%, the proposed model shows its capability to effectively classify epilepsy-related brain activity. Additionally, this research includes a comparative analysis of different deep learning models, assessing their performance and appropriateness for automatic epilepsy detection. The insights gained from this analysis will contribute to the development of dependable classification systems, facilitating earlier diagnoses and enhancing patient outcomes.
Keywords: Epilepsy Detection, Image Processing, Machine Learning

1. Introduction

Brain tumors and other brain illnesses like epilepsy frequently show up as aberrant electrical activity in the brain that can be identified by neurophysiological signals (Idris et al., 2024) as shown in Fig 1. Traditionally, diagnosing epilepsy has involved manually interpreting brain signals, which is a lengthy and human error-prone process. Hundreds of pages of brain signal data are frequently reviewed by neurologists by hand to find abnormal patterns. Significant effort and experience are needed, and interpretations can vary, which could lead to inconsistent diagnoses and higher patient expenses. Epilepsy is still one of the most common neurological conditions, affecting over 50 million individuals worldwide and presenting a serious public health concern (Habijan et al., 2024). Both physical and mental health can be severely harmed by epileptic seizures, which are typified by irregular and frequent brain activity. The need for automated, effective systems that can precisely categorize brain activity and recognize seizures is growing due to the importance of early detection.

Fig 1. Neurophysiological Signals of Epilepsy

In order to automatically classify brain activity into groups including seizures, lateralized rhythmic delta activity, and generalized periodic discharges, this study suggests a deep learning-based method. Our goal is to create a reliable model that standardizes the interpretation of brain activity by utilizing sophisticated signal processing methods such as the Continuous Wavelet Transform and Short-Time Fourier Transform. In addition to speeding up the diagnostic procedure, this will lessen the inter-observer variability that is now present in manual analysis. To precisely identify aberrant brain activity, this research trains a group of neural network models using spectrograms and signal plot pictures using the epilepsy seizures dataset (Islam et al., 2023). To reduce noise and increase computing performance, our method includes thorough data pretreatment and augmentation, which includes standardizing and normalizing spectrograms. To ensure optimal efficiency during training, the structure of the model places a strong emphasis on checkpointing and learning rate adjustment. The time and effort needed for diagnosis might be greatly decreased with the implementation of an automated classification system, which would also save patients' expenses.

This study goes beyond the necessity for automated epilepsy detection by evaluating multiple deep-learning models to determine the best method for epilepsy classification. To enhance temporal feature extraction from epilepsy data, we experiment with other architectures in addition to CNNs. To ascertain which of these models offers the optimum balance for practical applications in clinical settings, they are assessed according to their accuracy, precision, and computational efficiency. To convert raw epliepsy data into spectrograms, the proposed approach framework combines several signal processing methods, including the Continuous Wavelet Transform and Short-Time Fourier Transform (Jaipriya et al., 2024). By highlighting important frequency components of brain activity, this modification helps neural networks identify intricate patterns that conventional feature extraction techniques frequently overlook. By concentrating on these crucial spectral features, the model is better able to differentiate between different kinds of aberrant brain activity (Djemili et al., 2023).

Additionally, to improve model robustness and lessen overfitting, data augmentation methods including temporal shifting, flipping, and random noise addition are used. This makes the model more dependable for real-world applications by ensuring that it can generalize successfully to unseen data. To maximize model performance and avoid overfitting during training, we also employ several hyperparameter tuning techniques, such as learning rate scheduling and dropout. Since it reveals how the model analyses epilepsy data and spots anomalous patterns, this openness is essential for fostering confidence in medical practitioners.

This model is a flexible tool in the field of neurology since it may detect not only epilepsy but also other brain disorders like sleep disorders and brain tumors. The model's versatility under different circumstances demonstrates its potential to develop into a comprehensive tool for using epliepsy data to diagnose a variety of neurological illnesses. In this study, we evaluate our hybrid neural network's performance against many benchmark models, including pure CNNs, as well as traditional machine learning algorithms like support vector machines and decision trees. By comparing various models, we hope to determine the best architecture for epliepsy categorization while accounting for computational cost and accuracy.

With possible uses in both clinical and research settings, this comparison enables us to offer well-informed suggestions regarding the optimal methodology for automated epliepsy analysis. Lastly, this study aims to tackle the persistent problem of striking a balance between clinical utility and model performance. The ultimate objective is to create a dependable, scalable system that enhances diagnostic precision while blending in smoothly with current medical procedures, allowing neurologists to diagnose patients more quickly and reliably. This study represents a breakthrough in the use of artificial intelligence in healthcare and adds to the expanding field of automated brain illness detection by utilizing cutting-edge deep learning and signal processing techniques. The ultimate goal of this research is to give medical personnel a trustworthy tool that improves overall patient outcomes, lowers human error, and increases diagnostic accuracy. The research aims to help and provide more efficient and timely medical care by expediting the detection of epilepsy and other brain illnesses.

2. Literature Review

The diagnosis and analysis of epilepsy have made great strides, especially with the advent of computational techniques. As a neurological disorder that affects over 50 million people worldwide, epilepsy poses a significant public health challenge

(Khorev et al., 2024). Traditionally, diagnosing epilepsy has depended heavily on the manual interpretation of neurophysiological signals, a process that is not only time-consuming but also susceptible to human error, often resulting in inconsistent diagnoses. In light of these difficulties, there is a growing need for automated systems that can effectively classify brain activity and detect seizures. Research has investigated various computer-based classification models to improve the analysis of brain signals. These models generally include essential stages such as pre-processing, feature extraction, and classification, all of which are crucial for enhancing overall accuracy. Feature extraction, in particular, plays a key role in identifying important patterns within the data. Techniques like chaotic feature extraction, time-domain analyses, and frequency-domain methods have been employed to boost classification accuracy (Thahniyath et al., 2022; Alshaya et al., 2023).

Some studies have suggested hybrid approaches that combine multiple feature extraction techniques, showing better classification results compared to traditional methods (Shivwanshi et al., 2023). The advancement of brain signal acquisition technologies has also resulted in the creation of portable devices that can capture neurophysiological data with accuracy similar to that of conventional medical equipment. Devices like Emotiv have become popular due to their cost-effectiveness and suitability for non-clinical uses (Rajwal et al., 2022). However, the diversity of data sources and inconsistencies in data formats such as sampling frequencies and signal lengths often undermine data integrity. This scenario underscores the need for adaptive classification algorithms that handle various input characteristics.

Deep learning technologies have emerged as a promising way to tackle these challenges. By using algorithms that learn from data on their own, researchers can avoid the complexities of manual feature extraction. Recent studies have effectively applied deep learning techniques to analyze brain activity signals, transforming one-dimensional time-series data into two-dimensional images for classification (Chen et al., 2023). This method improves the adaptability and accuracy of models when working with datasets that vary in duration and frequency. A key advancement in this area is the creation of deep convolutional neural network models specifically tailored for classifying brain activity. These models adeptly learn the features of neurophysiological signals, helping to differentiate between normal and abnormal brain activity (Shoka et al., 2022). The thorough training processes and data augmentation techniques further boost model performance, resulting in improved diagnostic outcomes (Assali et al., 2024).

Signal processing techniques are also essential in preparing brain activity data for deep learning applications. Among these methods, Continuous Wavelet Transform, Short-Time Fourier Transform, and Constant-Q Transform are frequently used. The CWT has shown superior abilities in capturing complex patterns within brain signals compared to STFT-based models (Zeng et al., 2023). Its flexibility in adjusting scale and translation parameters allows for a detailed signal representation, making it particularly suitable for deep-learning applications.

In conclusion, the literature highlights a significant shift towards integrating advanced computational techniques and signal processing methods in the analysis of epilepsy. This move from manual interpretation to automated systems improves diagnostic accuracy and streamlines the process of detecting and classifying epilepsy and other brain conditions.

3. Methodology

The proposed methodology employs a Convolutional Neural Network (CNN) to classify data related to epilepsy as shown in Fig 2.

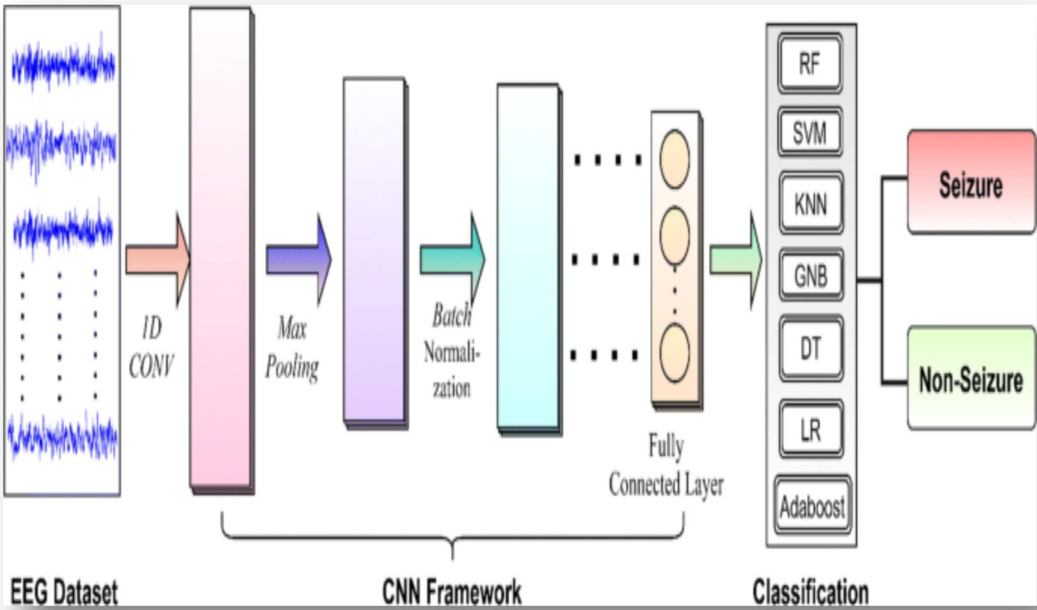

Fig 2. Proposed Model

This CNN is built to automatically learn features from the raw signals, which improves classification accuracy and reduces the reliance on manual feature extraction. The CNN architecture for this research is designed with the following layers:

Input Layer

This layer takes in the pre-processed data, organized as a 2D array.

Convolutional Layers

A series of convolutional layers are stacked to automatically extract important features from the signals (Abbasi et al., 2024). Each layer employs a set of learnable filters (kernels) that convolve over the input data, generating feature maps that highlight essential patterns.

Activation Function

The Rectified Linear Unit (ReLU) activation function is applied after each convolution to introduce non-linearity into the model, enabling it to learn complex relationships between inputs and outputs (Srihari et., al 2023).

Pooling Layers

After the convolutional layers, pooling layers are used to down-sample the feature maps. Typically, max pooling is employed, which selects the maximum value from each region of the feature map, reducing dimensionality while preserving key features (Hu et al., 2023).

Fully Connected Layer

Following several convolutional and pooling layers, the flattened output is passed into one or more fully connected layers. These layers connect every neuron from the previous layer to the next, allowing the model to integrate features learned from earlier layers and make final classifications (Ma et al., 2023).

Output Layer

The final layer utilizes a softmax activation function to generate class probabilities, indicating the likelihood of the input signal belonging to each class (e.g., epileptic vs. non-epileptic) (Liu et al., 2023).

Model Training

Dataset

The Epilepsy dataset is used in this research as shown in Fig 3. To prepare the data for training, resampling techniques from the SciPy signal processing library are used (Qi et al., 2023). This step adjusts the signals to a uniform length and frequency, which helps the CNN learn more effectively from the dataset. Before training, the data goes through several preprocessing steps, including:

Normalization

This involves scaling the data to a range that is suitable for CNN input, which enhances the model's convergence during training (Ra et al., 2023).

Augmentation

Techniques like MixUp and RandomCutout are utilized to boost the diversity of the training data. These methods help mitigate overfitting by exposing the model to a wider variety of input variations (Rivera et al., 2023).

Noise Reduction

Filtering techniques are applied to lessen the effects of artifacts and noise in the signals (Shanmugam et al., 2023).

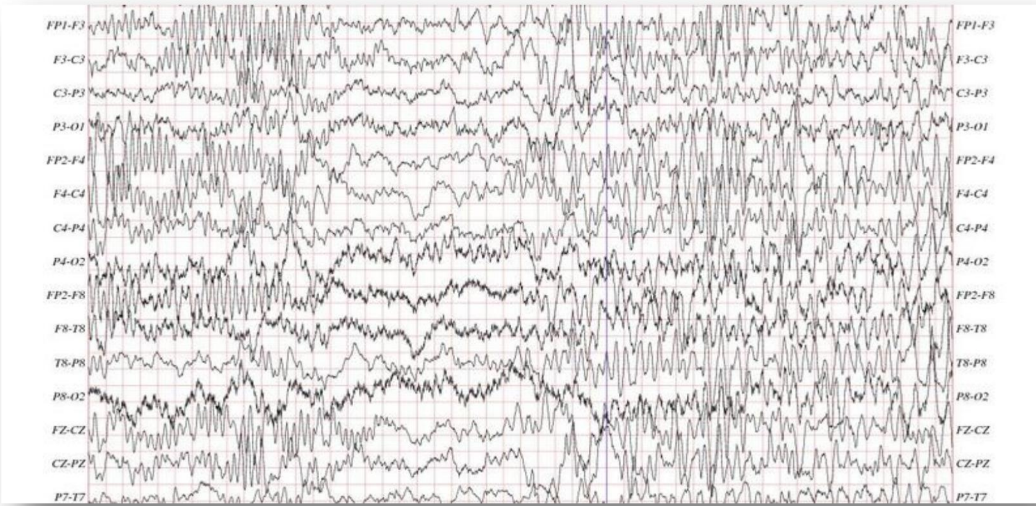

Fig 3. Epilepsy Seizures Dataset

Model Training

The model is trained using a strong optimization algorithm, usually Adam, which dynamically adjusts the learning rate based on how well the model is performing. The training process includes the following steps:

Loss Function

A categorical cross-entropy loss function is used to assess the model's performance by measuring the difference between predicted probabilities and actual class labels (Lebal et al., 2023).

Batch Processing

The data is split into batches to enable efficient training. Each batch is processed one at a time, updating the model weights according to the calculated gradients (Lebal et al., 2023).

Learning Rate Scheduler

A learning rate scheduler with cosine annealing is employed to modify the learning rate during training, which helps achieve quicker convergence and reduces the risk of overfitting (Dutta et al., 2024).

Checkpoints

Model checkpoints are saved at different points during training, allowing for recovery in case of interruptions and aiding in model evaluation.

Results and Discussion

The Convolutional Neural Network (CNN) model achieved an impressive accuracy of 97.11% in classifying signals associated with epilepsy as shown in Fig 4. This level of accuracy suggests that the model effectively learns the key patterns in the dataset, allowing it to distinguish between epileptic and non-epileptic signals with very few errors.

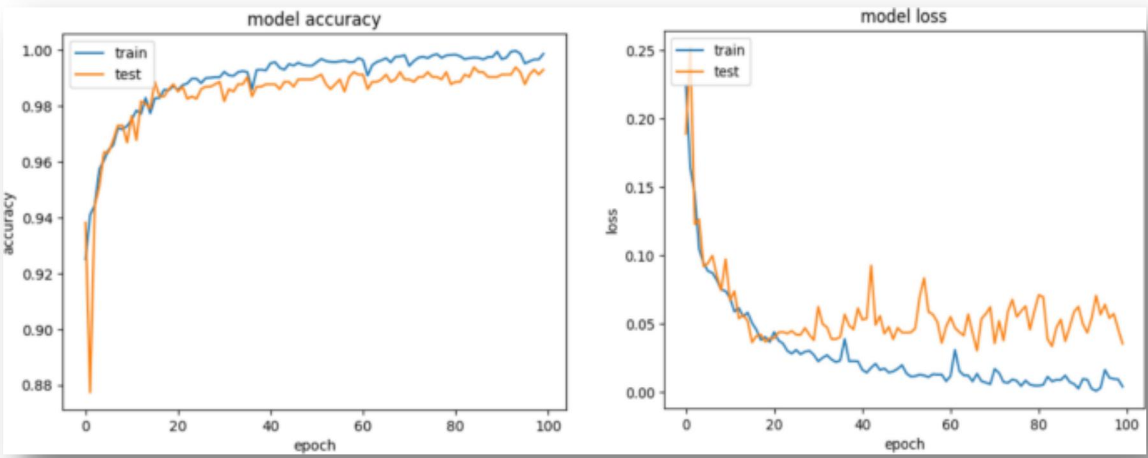

Fig 4. Accuracy and Loss of Proposed Model

When comparing the CNN-based approach to traditional classification methods, it was evident that the CNN outperformed others by automatically extracting relevant features from the signals, eliminating the need for manual feature engineering. This advantage is particularly important when handling the complex data patterns often present in epilepsy-related signals.

Comparison of Results with Other Models

A clear comparison of the different models is shown in Table 1 below, which shows that the suggested CNN model performs better than the others in correctly identifying brain activity linked to epilepsy. The higher accuracy attained demonstrates how well spectrogram analysis and sophisticated CNN architectures work together to improve feature extraction and overall performance in automatic epilepsy identification.

Table 1. Comparison of Proposed Model

Model	Accuracy
Proposed Model	97.11%
SVM-CNN (Wang et al., 2023)	93.5%
LSTM-CNN (Wang et al., 2024)	92.7%
CNN (Chen et al., 2023)	96%

Conclusion

This study introduced a CNN-based model designed to classify brain activity associated with epilepsy, achieving impressive accuracy while addressing the shortcomings of traditional feature extraction methods. Unlike standard techniques that often face challenges with varying sampling frequencies and data lengths, the proposed CNN model effectively adapts to these issues by automatically learning features from raw signals. Its ability to generalize across different data conditions highlights its potential to enhance automatic epilepsy detection and diagnosis, as demonstrated by its remarkable accuracy of 97.11%.

Future research will aim to broaden the validation of the CNN model across a wider array of datasets to confirm its robustness and applicability in various clinical environments. A key focus will be on improving the model's ability to visually represent the features it learns, which will enhance interpretability.

Furthermore, we intend to investigate advanced data augmentation methods, real-time processing capabilities, and user-friendly interfaces for practical use in patient monitoring and medical diagnostics. Integrating the CNN model with other machine-learning techniques could further refine classification accuracy and aid in the creation of a more comprehensive epilepsy detection system.

References

Idris, Z., Zakaria, Z., Yee, A. S., Fitzrol, D. N., Ismail, M. I., Ghani, A. R. I., ... & Suardi, N. (2024). Light and the Brain: A Clinical Case Depicting the Effects of Light on Brainwaves and Possible Presence of Plasma-like Brain Energy. *Brain Sciences*, *14*(4), 308.

Habijan, M., Šojo, R., Tolić, I. H., & Galić, I. (2024, September). Harmful Brain Activity Classification Using Ensemble Deep Learning. In *2024 International Symposium ELMAR* (pp. 109-112). IEEE.

Shams, M. Y., Abd El-Hafeez, T., & Hassan, E. (2024). Acoustic data detection in large-scale emergency vehicle sirens and road noise dataset. *Expert Systems with Applications*, *249*, 123608.

Islam, M. R., Zhao, X., Miao, Y., Sugano, H., & Tanaka, T. (2023). Epileptic seizure focus detection from interictal electroencephalogram: a survey. *Cognitive neurodynamics*, *17*(1), 1-23.

Jaipriya, D., & Sriharipriya, K. C. (2024). Brain-computer interface-based signal processing techniques for feature extraction and classification of motor imagery using EEG: A literature review. *Biomedical Materials & Devices*, *2*(2), 601-613.

Djemili, R., & Djemili, I. (2023). Nonlinear and chaos features over EMD/VMD decomposition methods for ictal EEG signals detection. *Computer Methods in Biomechanics and Biomedical Engineering*, 1-20.

Khorev, V., Kurkin, S., Badarin, A., Antipov, V., Pitsik, E., Andreev, A., ... & Hramov, A. (2024). Review on the use of brain-computer interface rehabilitation methods for treating mental and neurological conditions. *Journal of Integrative Neuroscience*, *23*(7), 125

Thahniyath, G., Yadav, C. S. G., Senkamalavalli, R., Priya, S. S., Aghalya, S., Reddy, K. N., & Murugan, S. (2024). Cloud-based prediction of epileptic seizures using real-time electroencephalogram analysis. *International Journal of Electrical & Computer Engineering (2088-8708)*, *14*(5).

Alshaya, H., & Hussain, M. (2023). EEG-based classification of epileptic seizure types using deep network model. *Mathematics*, *11*(10), 2286.

Shivwanshi, R. R., & Nirala, N. (2023). Hyperparameter optimization and development of an advanced CNN-based technique for lung nodule assessment. *Physics in Medicine & Biology*, *68*(17), 175038.

Rajwal, S., & Aggarwal, S. (2023). Convolutional neural network-based EEG signal analysis: A systematic review. *Archives of Computational Methods in Engineering*, *30*(6), 3585-3615.

Chen, W., Wang, Y., Ren, Y., Jiang, H., Du, G., Zhang, J., & Li, J. (2023). Automated detection of epileptic seizures EEG using CNN classifier based on feature fusion with high accuracy. BMC Medical Informatics and Decision making, 23(1), 96.

Shoka, A. A. E., Dessouky, M. M., El-Sayed, A., & Hemdan, E. E. D. (2023). An efficient CNN-based epileptic seizure detection framework using encrypted EEG signals for secure telemedicine applications. *Alexandria Engineering Journal*, *65*, 399-412.

Assali, I., Blaiech, A. G., Abdallah, A. B., Khalifa, K. B., Carrère, M., & Bedoui, M. H. (2023). CNN-based classification of epileptic states for seizure prediction using combined temporal and spectral features. *Biomedical Signal Processing and Control*, *82*, 104519.

Zeng, W., Shan, L., Su, B., & Du, S. (2023). Epileptic seizure detection with deep EEG features by convolutional neural network and shallow classifiers. *Frontiers in neuroscience*, *17*, 1145526.

Abbasi, M. M., Daniyal, S. M., Abro, A. A., Hussain, D., Amjad, U., & Zahid, N. B. (2024). Applying Neural Networks to Predict Ventilator Demand: A Study of Pakistan's Healthcare Sector. *VFAST Transactions on Software Engineering*, *12*(3), 217-229.

Srihari, P., Santosh, V., & Ganapathy, S. (2023). An epileptic seizure diagnosis system using feature selection, fuzzy temporal naive Bayes, and T-CNN. *Multimedia Tools and Applications*, *82*(22), 34075-34094.

Hu, W., Cao, J., Lai, X., & Liu, J. (2023). Mean amplitude spectrum-based epileptic state classification for seizure prediction using convolutional neural networks. *Journal of Ambient Intelligence and Humanized Computing*, *14*(11), 15485-15495.

Ma, Y., Huang, Z., Su, J., Shi, H., Wang, D., Jia, S., & Li, W. (2023). A multi-channel feature fusion CNN-BI-LSTM epilepsy EEG classification and prediction model based on attention mechanism. *IEEE Access*, *11*, 62855-62864.

Liu, D., Dong, X., Bian, D., & Zhou, W. (2023). Epileptic Seizure Prediction Using Attention Augmented Convolutional Network. *International Journal of Neural Systems*, *33*(11).

Qi, N., Piao, Y., Yu, P., & Tan, B. (2023). Predicting epileptic seizures based on EEG signals using spatial depth features of a 3D-2D hybrid CNN. *Medical & Biological Engineering & Computing*, *61*(7), 1845-1856.

Ra, J. S., & Li, T. (2023). A novel epileptic seizure prediction method based on synchroextracting transform and 1-dimensional convolutional neural network. *Computer Methods and Programs in Biomedicine*, *240*, 107678.

Rivera, M. J., Sanchis, J., Corcho, O., Teruel, M. A., & Trujillo, J. (2024). Evaluating CNN Methods for Epileptic Seizure Type Classification Using EEG Data. *IEEE Access*.

Shanmugam, S., & Dharmar, S. (2023). A CNN-LSTM hybrid network for automatic seizure detection in EEG signals. *Neural Computing and Applications*, *35*(28), 20605-20617.

Lebal, A., Moussaoui, A., & Rezgui, A. (2023). Epilepsy-Net: attention-based 1D-inception network model for epilepsy detection using one-channel and multi-channel EEG signals. *Multimedia Tools and Applications*, *82*(11), 17391-17413.

Wang, B., Yang, X., Li, S., Wang, W., Ouyang, Y., Zhou, J., & Wang, C. (2023). Automatic epileptic seizure detection based on EEG using a moth-flame optimization of one-dimensional convolutional neural networks. *Frontiers in Neuroscience*, *17*, 1291608.

Wang, X., Gao, Z., Zhang, M., Wang, Y., Yang, L., Lin, J., ... & Cong, F. (2024). Combination of Channel Reordering Strategy and Dual CNN-LSTM for Epileptic Seizure Prediction Using Three iEEG Datasets. *IEEE Journal of Biomedical and Health Informatics*.

Chen, W., Wang, Y., Ren, Y., Jiang, H., Du, G., Zhang, J., & Li, J. (2023). Automated detection of epileptic seizures EEG using CNN classifier based on feature fusion with high accuracy. *BMC Medical Informatics and Decision making*, *23*(1), 96.