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EpilepsyNet: Novel automated detection of epilepsy using transformer model with EEG signals from 121 patient population

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ABSTRACT

Background: Epilepsy is one of the most common neurological conditions globally, and the fourth most common in the United States. Recurrent non-provoked seizures characterize it and have huge impacts on the quality of life and financial impacts for affected individuals. A rapid and accurate diagnosis is essential in order to instigate and monitor optimal treatments. There is also a compelling need for the accurate interpretation of epilepsy due to the current scarcity in neurologist diagnosticians and a global inequity in access and outcomes. Furthermore, the existing clinical and traditional machine learning diagnostic methods exhibit limitations, warranting the need to *create* an automated system using deep learning model for epilepsy detection and monitoring using a huge database.

Method: The EEG signals from 35 channels were used to train the deep learning-based transformer model named (EpilepsyNet). For each training iteration, 1-min-long data were randomly sampled from each participant. Thereafter, each 5-s epoch was mapped to a matrix using the Pearson Correlation Coefficient (PCC), such that the bottom part of the triangle was discarded and only the upper triangle of the matrix was vectorized as input data. PCC is a reliable method used to measure the statistical relationship between two variables. Based on the 5 s of data, single embedding was performed thereafter to generate a 1-dimensional array of signals. In the final stage, a positional encoding with learnable parameters was added to each correlation coefficient's embedding before being fed to the developed EpilepsyNet as input data to epilepsy EEG signals. The ten-fold cross-validation technique was used to generate the model.

Results: Our transformer-based model (EpilepsyNet) yielded high classification accuracy, sensitivity, specificity and positive predictive values of 85%, 82%, 87%, and 82%, respectively.

Conclusion: The proposed method is both accurate and robust since ten-fold cross-validation was employed to evaluate the performance of the model. Compared to the deep models used in existing studies for epilepsy diagnosis, our proposed method is simple and less computationally intensive. This is the **earliest** study to have uniquely employed the positional encoding with learnable parameters to each correlation coefficient's embedding together with the deep transformer model, using a huge database of 121 participants for epilepsy detection. With the training and validation of the model using a larger dataset, the same study approach can be extended for the detection of other neurological conditions, with a transformative impact on neurological diagnostics worldwide.

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1. Introduction

Epilepsy is a common neurological condition affecting over 65 million people of all ages worldwide [1]. The Global Burden of Epilepsy Report estimates over 13 million disability-adjusted life years due to epilepsy each year, demonstrating that epilepsy is one of the top priorities for improved care globally [2]. In particular, there is a huge disparity between healthcare outcomes related to epilepsy in high and low to middle-income countries: over 80% of the global 125 000 deaths per year related to epilepsy are in low and middle-income countries. Delays in diagnosis and inadequate access to treatment and monitoring are major challenges in epilepsy care worldwide, especially in low and middle-income countries with significant shortages of appropriately trained diagnostic and clinical staff. Thus efforts to improve access and quality of epilepsy diagnostics are of utmost importance to address this health inequity challenge [3].

Epilepsy is characterized by recurrent non-provoked seizures, represented by short, excessive discharges of electrical activity in the brain, that impact an individual's behavior, awareness, cognition and/or motor control [4]. During a seizure, the normal balance between excitation and inhibition in the brain is disrupted, which can be detected by electroencephalogram (EEG) recordings. There are multiple causes of such an imbalance [5]. Globally the leading diagnosable causes of epilepsy are acquired causes, for example, cerebral infarcts or bleeds, tumors or cerebral infections including intrauterine 'TORCH' (toxoplasma, rubella, cytomegalovirus, and herpes) infections, viral or bacterial meningitis and encephalitis and complications related to pregnancy and birth including hypoxia-ischemia related to perinatal complications [6]. However, it is now recognized that for a growing number of individuals, an underlying genetic cause can be identified: the highest genetic diagnostic yield is for developmental and epileptic encephalopathies (DEEs), which are defined by the International League Against Epilepsy as the fusion of severe epilepsy with an impact on development [7]. Over 600 individual genes have been linked to epilepsy, with that number growing each week: many genes encode proteins important for neuronal development and synaptic function, such as ion channels [8].

1.1. Current diagnostic methods

The prompt and correct diagnosis of epilepsy is imperative for effective treatment and monitoring. The primary diagnostic method for epilepsy is the recording and characterization of electroencephalogram (EEG) signals. Additionally, neuroimaging, for example, structural and functional neuroimaging techniques such as magnetic resonance imaging (MRI), computed tomography (CT), positron emission tomography (PET), single-photon emission computed tomography (SPECT) scans are helpful in identifying underlying structural abnormalities, and a screen of blood, urine and cerebrospinal fluid, as well as increasingly genetic tests, are often employed to identify the underlying cause for epilepsy [9]. The process of acquiring EEG signals is noninvasive and relatively inexpensive [10]. The accurate analysis of EEG signals requires high sensitivity, given, for example, that individual epileptic spikes, reflecting electrical imbalances, last only about 20–70 ms [11]. However, the major challenge in epilepsy diagnosis lies with the limited numbers of trained diagnostic and clinical neurological experts, especially in developing countries, who have the appropriate skills to accurately interpret EEG signals to ensure correct diagnoses are made in a timely manner so that appropriate anti-seizure medications can be started and treatment monitored. Hence, there is an urgent need for the automatic analysis of EEG signals to mitigate the challenges of supporting, facilitating and expediting the diagnosis of epilepsy in all countries worldwide [12].

1.2. Related work using traditional machine learning techniques with EEG signals

Recently, machine learning techniques are emanating as crucial supportive tools in the automated diagnosis of EEG signals [13]. For instance, Acharya et al. [14] explored various types of entropy-based features with seven conventional classifiers for detecting seizures. In another study, Chen et al. [15] investigated eight different types of entropy features for the classification of ictal, inter-ictal, and normal EEG classes and achieved an accuracy of 99.5%. In a different study, Selvakumari et al. [16] similarly investigated the entropy feature, root mean square, variance, and energy features. A classification accuracy of about 96% was obtained with the support vector machine (SVM) and naïve Bayesian classifiers. Other authors have zealously explored other approaches; for instance, Satapathy et al. [17] developed the SVM and neural network classifiers using different kernel methods for seizure detection. The performance of each classifier was assessed using majority voting, wherein the SVM classifier was reported to be more capable than other networks. Contrastingly, Subasi et al. [64] investigated a hybrid approach involving the SVM classifier, genetic algorithm, and particle swarm optimization for seizure detection. While an impressively high accuracy of about 99.4% was achieved, the authors concur that the proposed method is time-consuming due to the classifier needing to train the dataset twice, for the SVM with genetic algorithm and particle swarm optimization, respectively. In a recent study, Tasci et al. [13] proposed a novel hypercube-based feature extraction technique for extracting seven feature vectors. The most discriminatory features were selected using the neighbourhood component analysis selector, wherein the best features were fed to the k-nearest neighbor classifier, with the leave one subject out cross-validation strategy. The authors reported a high classification accuracy of about 88%. More studies on the successful implementation of conventional machine-learning techniques for epilepsy detection are discussed in the article by Tasci et al. [13]. While many articles on machine learning techniques are being employed for seizure detection [65], Natu et al. [18] contended that implementing advanced deep learning methods mitigates the challenges posed by traditional machine learning algorithms due to the reduced computational complexity of deep models.

Deep learning methods combine feature extraction and classification processes, unlike conventional classifiers, reducing computational cost and complexity. For these reasons, deep learning models are favored over conventional classifiers. Table 1 summarizes recent studies (past five years; 2019–2023) that employed deep learning methods for epilepsy detection.

2. Methodology

Recurrent neural networks are widely recognized as a state of the art techniques in sequence modeling and transduction intricacies [57]. Recurrent networks work by considering the symbol locations of the input and output sequences. These networks produce a series of hidden states h_t, as a function of the preceding hidden state, h_{t-1}, and in the input for position $_t$, as they arrange the positions to steps during computation [57]. Recent work has achieved substantial improvements in computational efficiency through factorization tricks [58] and conditional computation [59] hence enhancing the performance of models due to the second-mentioned factor. However, despite these improvements, the basic limitation of sequential computations still remains.

Attention mechanisms have become an essential element of persuasive sequence modeling and transduction models in innumerable tasks, enabling the modeling of dependencies without consideration of the distance in the input or output structures [60]. Hence, such attention mechanisms are usually employed in combination with a recurrent network. To mitigate the challenges of recurrent models, Vaswani et al. [57] proposed a unique Transformer model, which works entirely based on the attention mechanism to generate global dependencies between

Table 1
Summarized studies that employed deep learning methods with EEG signals for epilepsy detection.

Author, year	Features and methods	Participant/ data information	Findings/Results
Yao et al. [19], 2019	• Independently recurrent neural network • Extraction of spatial and temporal features	686 EEG recordings from 23 subjects; CHB-MIT database	The proposed approach outperforms current techniques
Avcu et al. [20], 2019	• SeizNet (Convolutional neural network) • Implementation of baseline classifier using spectrum band power features with support vector machines • Leave-one-out cross validation technique	EEG data from 29 paediatric patients; KK Woman's and Children's Hospital	SeizNet outperforms the baseline classifier with a higher sensitivity of 95.8% and 17% false alarm per hour.
Yao et al. [21], 2019	• Integration of recurrent neural network and attention mechanism • Leave-one-out cross validation technique	EEG data from CHB-MIT dataset	Average sensitivity, specificity, precision: 88.8%, 88.60%, 88.69% respectively.
Lesmantas et al. [22], 2019	• Convolutional neural network (CNN) • Phase locking value, entropy, energy features • Area under the curve	EEG data from Temple University Hospital	Sensitivity, specificity: 68%, 67% respectively
Covert et al. [23], 2019	• Temporal graph convolutional network • Five performance metrics	Scalp EEG data from 1063 patients	Proposed model performs as well as other state-of-the-art models.
Hussein et al. [24], 2019	• Deep long short-term memory model • Fully connected layer for extraction of robust EEG features • SoftMax layer for prediction	5 different sets of EEG datasets from Bonn University EEG database	Accuracy, sensitivity, specificity: 100% respectively
Hossain et al. [25], 2019	• Deep CNN • Extraction of spatial and temporal features • Correlation maps to link spectral amplitude features to output data	EEG dataset of 23 patients from Boston University Hospital	Accuracy, sensitivity, specificity: 98.05%, 90,% 91.65% respectively
Emami et al. [26], 2019	• Patient-specific autoencoder model • Error in segmentation of images used for seizure detection	EEG dataset comprising 24 test subjects	Sensitivity (22 test subjects): 100% Proposed model performed better than commercially available software for half the subjects.
San- Segundo et al. [27], 2019	• CNN • EEG signal transformations such as Fourier, wavelet, empirical model decomposition	Bern-Barcelona EEG, Epileptic seizure recognition datasets	Proposed method yielded an increase in accuracies for seizure versus non-seizure classification.
Akut [28] 2019	• Wavelet based deep learning method for feature extraction • 2-class and 3-class classifications	EEG dataset	Accuracy: 100% Proposed model is more accurate than current state-of-the-art methods
Turk & Ozerdem [29] 2019	• Scalogram based CNN • Continuous wavelet transform	Bonn University EEG database	Proposed method is efficient is discerning EEG signals of different classes.
Liu & Woodson [30] 2019	• CNN • Single channel EEG	Publicly available dataset: 5 sets consisting of 100 single channel EEG segments of 23.6 s	Accuracy: >90%
Tian et al. [31], 2019	• Deep multi-view feature extraction • Fast Fourier Transform and wavelet packet decomposition • CNN • Multi-view rule-based classifier	EEG dataset	Proposed method yields an improved classification accuracy of at least 1% compared to prevalent feature extraction methods.
Cao et al. [32], 2019	• CNN • Mean amplitude of spectrum map • Adaptive and discriminative feature weighting fusion	CHB-MIT EEG database	Proposed algorithm yields superior results than other existing algorithms.
Boonyakitanont et al. [33], 2019	• Convolution neural networks • Artificial neural networks • Concatenation of dominant features	CHB-MIT EEG database	Both models yielded a high accuracy of about 97%, with ANN generating more dominant features than CNN and CNN yielding a slightly higher accuracy than ANN.
Craley et al. [34], 2019	• Hybrid probabilistic graphical model convolutional neural network • Clinically pertinent information retained through the latent PGM prior	Clinical EEG data from hospitals	Proposed system generates better results than existing systems
Lu & Triesch. [35], 2019	• CNN with residual connections • Model trained using raw EEG data	EEG datasets from Bonn University and Bern-Barcelona	Developed model achieved an accuracy of 99%.
Wei et al. [36], 2019	• CNN • Merger of increasing and decreasing sequences • Wasserstein Generative Adversarial Nets	CHB-MIT EEG database	Proposed data augmentation technique increases the model's sensitivity and specificity from 70.68% to

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Table 1 (*continued*)

Author, year	Features and methods	Participant/ data information	Findings/Results
	data augmentation technique		92.03%–72.11% and 95.89% respectively.
Meisel et al. [37], 2019	• Multimodal wristband sensor data • Recording of physiological parameters from epilepsy patients • CNN • Leave-one-out validation	Sensor data from 50 patients with epilepsy	Proposed method achieved an accuracy of 86.3% and paves the way towards developing easier and non-invasive methods for seizure risk assessments in epileptic patients.
Roy et al. [38], 2019	• Recurrent neural network, ChronoNet • 1D convolution layers, deep gated recurrent unit	TUH Abnormal EEG Corpus dataset	Proposed technique yields an accuracy of 90.6%.
Karim et al. [39], 2019	• Autoencoder deep model • Energy spectral density function	Medical EEG waveform datasets	Proposed technique lowers the processing time of model and increases accuracy, yielding an accuracy of 100%.
Fukumori et al. [40], 2019	• Neural networks • Data-driven filter bank with supervised learning • Area under the receiver operating characteristic curve	Clinical EEG data (15 833 epileptic spike waveforms) from 50 patients	Proposed method yielded an area under the receiver operating characteristic curve of about 0.97.
Choi et al. [41], 2019	• Multi-scale 3-dimensional CNN with deep neural network • Short Time Fourier Transform for extraction of spectral features • Extraction of spatial and temporal features	CHB-MIT & Seoul National University Hospital Scalp EEG databases	Developed model yielded an accuracy of 99.4%.
Liu et al. [42], 2019	•6 conventional machine learning models •3 deep neural networks •Area under the curve	Epileptic seizure recognition dataset (4097 EEG readings from 500 patients)	Ensemble classifiers, random forest and gradient boosting classifiers yielded an accuracy above 95%. Deep learning models outperformed machine learning models in multi-label classification tasks.
Zhao et al. [43], 2020	• CNN (one dimensional) • Two, three, and five class classifications of EEG signals	EEG dataset from Bonn University (five different sets of EEG signals)	Developed model achieved a high accuracy of 97.63%–99.52% for 2 class, 96.73%–98.06% for 3 class and 93.55% for 5 class classifications.
Pisano et al. [44], 2020	• CNN • Detection of nocturnal frontal lobe epilepsy • Cross-patient seizure detection model • Transfer learning	Datasets from epilepsy centers in Coimbra, Portugal and Freiburg Germany	Proposed system yields an accuracy of about 94%.
Gao et al. [45], 2020	• CNN • Conversion of EEG signals to power spectrum density energy diagrams • Classification of four epileptic states	CHB-MIT EEG data	Proposed method achieved an accuracy of over 90%.
Zhou & Li [46] 2020	• CNN • Extraction of nonlinear features (entropies) from EEG signals input to radial basis function model	EEG dataset from Bonn University	Recommended algorithm has been proven to have a high epileptic signal recognition rate.
Jaoude et al. [47], 2020	• CNN • Nested 5-fold cross-validation • Receiver operating characteristic curve	Intracranial EEG recordings from 46 epileptic patients	An area under the curve (close to 1) was achieved.
Sui et al. [48], 2021	• Time-frequency hybrid network • Short-Time Fourier Transform • Fusion of time-frequency features and feature maps	Bern-Barcelona IEEG dataset	Recommended method discerns focal from nonfocal EEG signals with an accuracy of 94.3%.
Malekzadeh et al. [49], 2021	• Tunable Q-Wavelet Transform for signal decomposition • Extraction of statistical, frequency and nonlinear features • CNN- recurrent neural network-based model • 10-fold cross-validation	EEG datasets from Bonn and Freiburg	Proposed method yielded the highest accuracy of 99.7% for the Bonn dataset.
Sahani et al. [50], 2021	• CNN • Optimized variational mode decomposition • Multi-kernel random vector functional link network • Improved particle swarm optimization to compute values of band-limited intrinsic mode functions • Ten-fold cross-validation technique	Bonn University, New-Delhi single-channel EEG, Boston Children's Hospital, Boston Children's Hospital Multichannel Scalp EEG datasets	Proposed method has obtained a classification accuracy of 100% for the datasets.
Peng et al. [51], 2021	• Fourier neural network • CNN • Estimation of spectral power ratios of raw recordings	Intracranial and scalp EEG datasets	Recommended method has proven to achieve higher performance and generalization as compared to

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Table 1 (*continued*)

Author, year	Features and methods	Participant/ data information	Findings/Results
			previous methods.
Islam et al. [52], 2022	• Epileptic-Net deep model • Convolutional blocks • Hypercolumn methods	EEG dataset from Bonn University	Proposed technique yields a high accuracy of about 99% in all classification tasks with the highest (99.8%) in three-class classification of signals.
Gramacki & Gramacki [53] 2022	•CNN •Sliding window design •Five-fold cross-validation	79 neonatal EEG recordings with seizure annotations	Highest classification accuracy between 96% and 97% was achieved.
Chen et al. [54], 2023	• CNN • Extraction of nonlinear features (entropies) • Decomposition of signals using Discrete Wavelet Transform • Random forest algorithm for feature selection	Bonn University and New Delhi EEG datasets	Proposed model yielded the highest accuracy of 100% with the New Delhi dataset.
Ilias et al. [55], 2023	•CNN •Pretrained models •Short-time Fourier transform for conversion of signals to images •Gated multimodal unit	EEG dataset from Bonn University	Recommended method achieves comparable results to existing methods.
Chanu et al. [56] 2023	• Self-organizing neural network and multilayer perceptron hybrid model • Genetic algorithm • Discrete wavelet transform • Clustering technique	EEG dataset from Bonn University	Proposed method yielded a high accuracy of 99.2%.
This work	• **Transformer deep model** • **Pearson Correlation Coefficient** • **Positional encoding**	**EEG data from 71 healthy subjects, 50 epileptic patients**	**Proposed method yielded a high accuracy of 85%.**

the input and output while avoiding recurrence. The Transformer model is advantageous and lauded for its ability to accommodate much more parallelization, reaching a new avant-garde in translational quality after being trained for only 12 h on eight P100 graphics processing units. Imbued by the success of Vaswani et al. [57], the Transformer model was employed in this study with a unique methodology.

2.1. Data acquisition

The EEG signals used in this study were acquired from 35 channels encompassing the parietal, temporal, frontal, occipital, frontopolar, central and auricular regions, using the standard 10–20 electrode position system with a sampling frequency of 500 Hz. These 8.5 min long EEG recordings were obtained from 71 healthy subjects and 50 epileptic patients. More information regarding the demographic properties of participants can be retrieved from this link in the published article by Tasci et al. [13].

2.2. Preparation of training data

The EEG signals from all 35 channels were used for training the model. For each training iteration, 1-min-long data were randomly sampled from each participant. This allows the model to generalize better with an effect akin to augmentation. Thereafter, each 5-s epoch was mapped to a matrix (12 × 35 x 35) using Pearson Correlation Coefficient (PCC) [61]. The PCC method is useful in describing the relationship between two variables [61]. PCC measures the strength and direction of correlation between two variables, measured on an interval scale [62]. While Pearson's Correlation aims at drawing a best-fit line through the data of two variables, Pearson's Correlation Coefficient, denoted by r, specifies how far the data points are from the best-fit line. The PCC is used based on four assumptions; (i) the two variables are measured at the interval or ratio scale, (ii) a linear relationship exists between the two variables, (iii) there should be zero significant outliers within the data that do not follow the standard pattern, (iv) the data should generally be normally distributed [62]. Hence, for a given bivariate set (x_1, y_1), (x_2, y_2), …., (x_n, y_n), Pearson's Product Moment Correlation Coefficient (r) is expressed as $\frac{S_{xy}}{S_x S_y}$ wherein r is defined as the Pearson's Product Moment Correlation Coefficient, S_{xy} refers to the covariance of x and y values and S_x and S_y refer to standard deviations of x and y values, respectively. The bottom part of the triangle was discarded and only the upper triangle of the matrix was vectorized as input (12 × 595). Thereafter, single embedding was performed based on the 5 s of data to generate a 1-dimensional array of signals. In the final stage, a positional encoding with learnable parameters was added to each correlation coefficient's embedding before being fed to the developed deep model, as input data, for the classification of signals.

2.3. Proposed transformer model

The encoder stack of the Transformer model was developed based on the Multi-Head and Feedforward mechanisms. The multi-Head self-attention mechanism was developed using seven heads and a dropout of 0.3. The Feedforward mechanism was developed using the dense layer (85), gelu activation function, followed by another dense layer (85). The classifier component in the model was developed using the global max pooling layer and dense layer (1) with a sigmoid activation function. The signals were classified as normal or epilepsy thereafter. The Transformer model was developed and trained using 100 epochs with a batch size of 30, binary cross entropy loss function and Adam optimization algorithm [63] with a learning rate of 1e-5. The proposed technique and developed model is explicitly shown in Fig. 1.

3. Classification results

As a small dataset was used in this study, the acquired data was split into training and testing data, wherein 90% of the data was used for training and 10% was used for both testing and validation. The accuracy, sensitivity, specificity and positive predictive values were used to assess the performance of the Transformer model. Table 2 shows the classification results of the model. The table shows that high classification accuracy, sensitivity, specificity and positive predictive values of 85%, 87%, 82% and 87% were obtained for the classification of healthy and epileptic EEG signals. Confusion matrix obtained using the proposed Transformer model is shown in Fig. 3.

4. Discussion

From the classification results, it is evident that the Transformer model for the classification of healthy and epileptic EEG signals yielded a high classification accuracy of 85%. Although we used the same

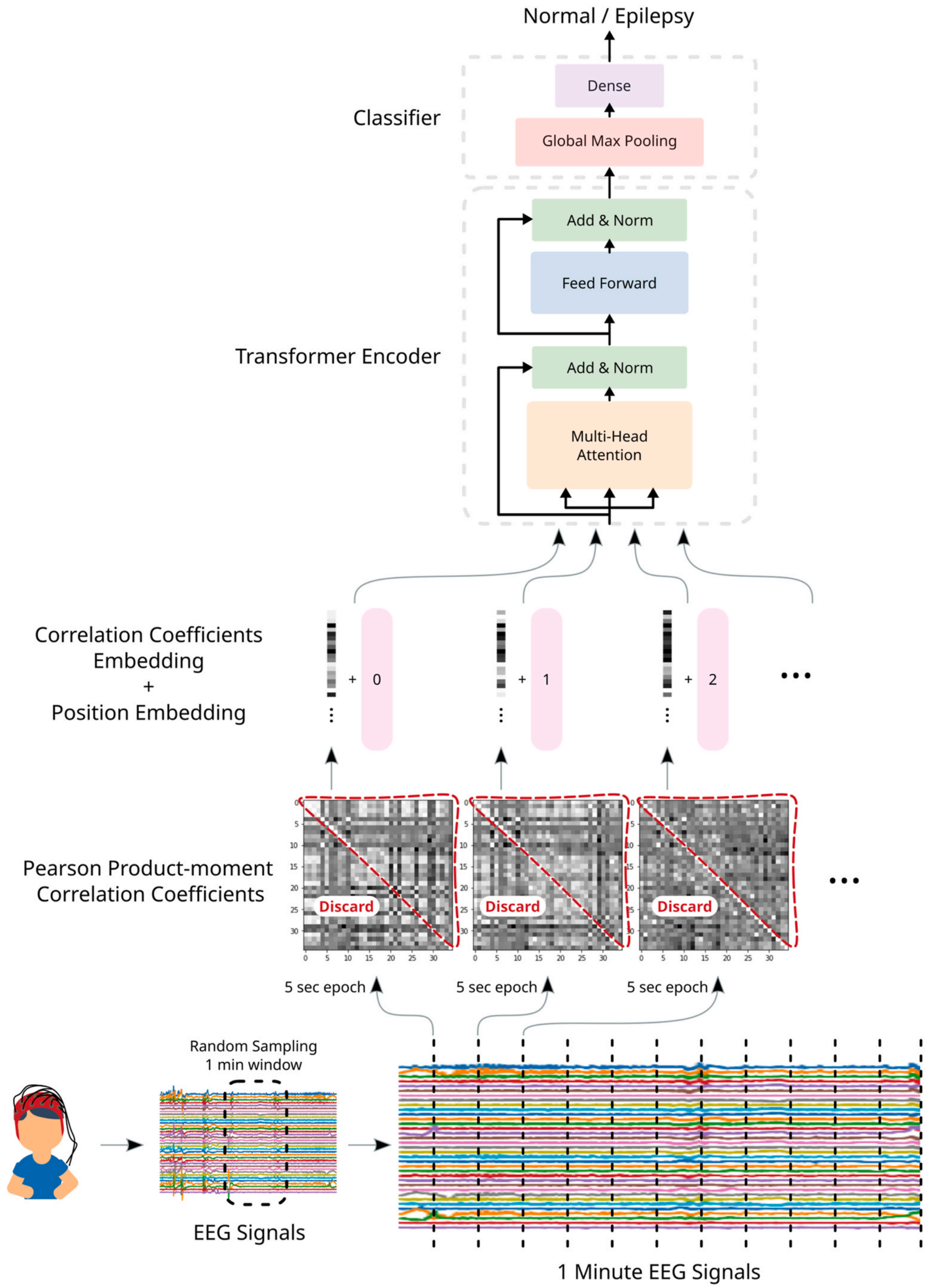

Fig. 1. Proposed EpilepsyNet model.

Table 2
Classification results obtained for the proposed EpilepsyNet model.

Performance parameters (%)	Healthy class	Epilepsy class
Accuracy	85	85
Sensitivity	87	82
Specificity	82	87
Positive predictive value	87	82

epilepsy dataset as Tasci et al. [13], it is observable that we have employed a different approach from the authors. While the authors employed a novel hypercube-based feature extraction technique for the extraction of feature vectors, they employed the conventional k-nearest neighbor classifier for the classification task. In contrast, we have employed a novel deep learning technique involving the transformer model and achieved a comparable classification accuracy. This proves that our proposed method is remarkable as deep learning models such as the Transformer model can be trained faster due to the automatic extraction of features compared to conventional classifiers such as the k-nearest neighbor. From Table 1, it is evident that Hussein et al. [24], Hossain et al. [25], Akut et al. [28], Liu & Woodson [30], Boonyakitanont et al. [33], Lu & Triesch. [35], Roy et al. [38], Karim et al. [39], Choi et al. [41], Haotian et al. [40], Wei et al. [36], Gao et al. [45], Sui et al. [48], Malekzadeh et al. [49], Mrutyunjaya et al. [48], Rashed et al. [50], Islam et al. [52], Gramacki et al. [53], Chen et al. [54], Chanu et al. [56] had obtained higher classification accuracies (above 85%).

However, these authors had employed the CNN likewise, wherein the Transformer model was uniquely employed only in our study. In our study, we have converted the acquired EEG signals to a 2-dimensional image using the correlation plot. The signals were then fed to the developed deep Transformer model for classification. The conversion of EEG signals to 2-dimenional image is a crucial step in finding the correlation present in the signals. This helps the Transformer model in classifying the EEG signals according to the physiology of classes. We have obtained high performance due to the presence of the attention module present in our developed model. The subtle changes in the EEG are picked up by the proposed correlation plot coupled with the Transformer model to yield high performance. Furthermore, while these authors had developed CNNs of a few layers, the unique deep Transformer model was developed using a single transformer encoder module and is hence both less computationally intensive and expensive to develop as compared to the CNNs or recurrent neural networks employed in existing studies. This proves that our proposed method is superior as compared to the deep models used in Table 1 for epilepsy diagnosis. Fig. 2 shows the accuracy plot of the Transformer model. From the Figure, it is apparent that the model generally learns the data well, as the accuracy versus epoch plots for both training and validation converge well. The convergence is less stronger after 20 epochs probably due to the small dataset used for training. Fig. 3 depicts the confusion matrix of the developed model. From the matrix it can be gathered that very low misclassification rates of 13% and 18% were obtained for the classification of healthy and epilepsy classes, respectively. Hence, both the accuracy plot and confusion matrix serve as an attestation to the good performance of the Transformer model developed in this study. The advantages and limitations of our study are discussed below.

4.1. Advantages

1. A high accuracy of 85% was achieved by using only a single transformer encoder module.
2. This is the **earliest** study that employed the deep Transformer model (EpilepsyNet) using a huge database of 121 participants for epilepsy detection.
3. A unique method was employed to add a positional encoding with learnable parameters to each correlation coefficient's embedding.
4. The proposed system is accurate and may be useful to health professionals managing epileptic patients.
5. Proposed system is both less computationally intensive and expensive to develop as compared to the deep models used in existing studies.
6. The proposed system is novel and the EEG signals used for this work is available at https://www.kaggle.com/datasets/buraktaci/turkish-epilepsy.

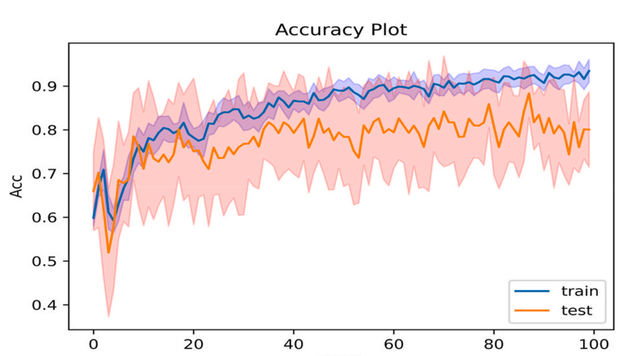

Fig. 2. Accuracy plot of Transformer model.

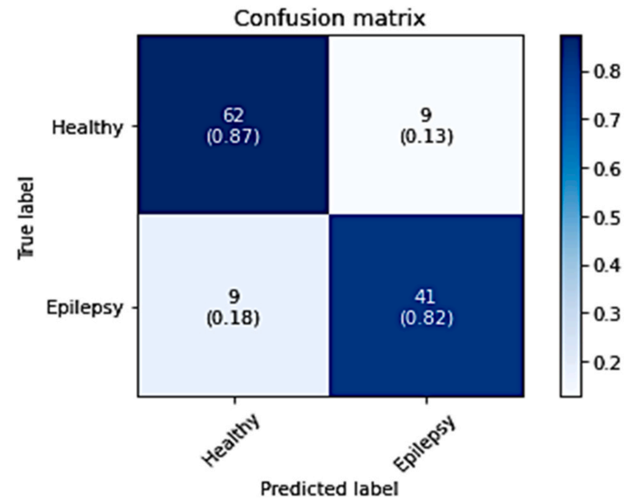

Fig. 3. Confusion matrix of Transformer model.

4.2. Limitations

1. The deep Transformer model was developed using a small number of epileptic patients.
2. Validation of the results in larger datasets may be needed before the proposed system can be clinically accepted widely.

For future work, we intend to analyze epileptic EEG signals from larger datasets. The developed model could be better trained and validated using a larger dataset for wider clinical acceptance. Furthermore, training and validating the model with larger data would make it more robust, thus enabling it to be employed for detecting other neurological disorders.

5. Conclusion

Epilepsy is a common neurological disorder that impacts the quality of one's life significantly. Presently, the paucity in neurologist diagnosticians and a global inequity in access to epilepsy diagnostics warrants the need for accurate interpretation of epilepsy. Existing clinical and traditional machine learning diagnostic methods exhibit limitations. Thus, there is a compelling need to develop reliable and accurate automated systems using deep learning models, for epilepsy detection and monitoring. Hence, this study used EEG signals from 35 channels to train our novel model. For each training iteration, 1-min-long data were randomly sampled from each participant. Thereafter, each 5-s epoch was mapped to a matrix using the Pearson Correlation Coefficient, wherein the bottom part of the triangle was discarded and only the upper triangle of the matrix was vectorized as input. Based on the 5 s of data, single embedding was performed thereafter to generate a 1-dimensional array of signals. In the final stage, a positional encoding with learnable parameters was added to each correlation coefficient's embedding before being fed to the developed deep Transformer model, as input data, for the classification of signals. The k-fold (k = 10) cross-validation technique was used to evaluate the model's performance. High classification accuracy, sensitivity, specificity and positive predictive values of 85%, 82%, 87%, and 82% were achieved, respectively. Our proposed method is both accurate and robust since ten-fold cross-validation was employed for the evaluation of the model's performance. It also presents as a less computationally intensive and expensive method for epilepsy diagnosis, in comparison to the deep models used in existing studies. This is the **earliest** study to have uniquely employed the positional encoding with learnable parameters to each correlation coefficient's embedding, with the deep Transformer model using a huge database of 121 participants for epilepsy detection. With the training and validation of the model using a larger dataset, the same study approach can be extended to detect other neurological conditions [66].

Declaration of competing interest

There is no conflict of interest in this work.

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