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Pair-wise Matching of EEG signals for Epileptic Identification via Convolutional Neural Network

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ABSTRACT Electroencephalogram (EEG) have been extensively analyzed to identify the characteristics of epileptic seizures in the literature. However, most of these studies focus on the properties of single channel EEG data while neglecting the association between signals from diverse channels. To bridge this gap, we propose an EEG instance matching-based epilepsy classification approach by introducing one convolutional neural network (CNN). First of all, each pair of EEG signals are exploited to form one 2 dimensional matrix, which could be used to reveal the interaction between them. Secondly, the generated matrices are fed into the proposed CNN that would discriminate the input representations. To evaluate the performance of the presented approach, the comparison experiments between the state-of-the-art techniques and our work are conducted on publicly available epilepsy EEG benchmark database. Experimental results indicate that the proposed algorithm could yield the performance with an average accuracy of 99.3%, average sensitivity of 99.5%, and average specificity 99.6%.

INDEX TERMS Convolution; Machine learning; Classification algorithms.

I. INTRODUCTION

Being a typical brain recording modality, Electroencephalogram (EEG) has been widely applied in the detection and identification of epileptic seizures. Generally, those electric fields from brain are captured by scalp EEG equipment that could provide an economical and non-invasive fashion. Originally, the precise interpretation of EEG data were implemented manually. Since it is a time-consuming and laborious task, the automated classification of EEG samples had become a buzzing field in current studies [1]–[5].

Previously, large amount of researches have paid attention to this domain. For instance, Gotman [6] proposed the first epileptic EEG recognition algorithm, in which the EEG signals were decomposed into elementary waves whose peak amplitude, duration, slope, and sharpness were then simultaneously as the representations for epilepsy in EEG samples. Then, Adeli et al. [7]–[9] introduced the wavelet (WT) features including discrete Daubechies and harmonic wavelets to characterize the EEG samples with seizures. Adeli et al. [10] presented an advanced computational model for automatic neurological disorder diagnosis in EEG by using neural networks, wavelets, and chaos theory. In the work of [11], Acharya et al.proposed a convolutional neural network (CNN)-centric algorithm for classifying the types of EEG signals. A method using the local binary pattern (LBP) was proposed by Qi et al. [13] based on the WT to discriminate the EEG behaviors. Within this framework, the LBP operator was conducted on the WT-based representations and fed into a support vector machine (SVM) classifier. In the work presented in [14], Li et al.proposed an automatic EEG signal classification method for epileptic seizure recognition with a continuous WT. Both Gaussian Mixture model (GM-M) and Gray Level Co-occurrence Matrix (GLCM) features were employed. Recently, U.R. Rajendra Acharya et al. [12] reviewed the automated EEG-based identification of epilepsy including the techniques that are developed for seizure pre-

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diction.

Commonly, these automated techniques for epilepsy detection in EEG follow a straightforward procedure including pre-processing, feature extraction, feature selection, and classification as illustrated in Fig. 1. These techniques have shown their great performance in various aspects. However, most of them did not take the association between multiple channels of EEG signals as an extracted feature for the discrimination of ictal, interictal, and normal EEG activities. The relationship between multi-path EEG signals could contribute to the identification of epilepsy since the multi-path signals are generated simultaneously. Although multiple channels have been leveraged into these studies, most of them deal with the channels in a serial fashion rather than a parallel pattern. To be specific, the multi-channel EEG signals are incorporated into the classification pipeline one after another.

Meanwhile, since deep learning-based algorithms have become a hot topic in recent applications including image analysis and signal processing [121], [122]. A large amount of them have also been applied in brain-machine interface (BCI) applications. Specially, a number of works have presented the employment of CNNs in EEG information analysis and processing. For instance, Oshea et al. [16] proposed a end-to-end deep learning framework that could automatically extract the hierarchical representations from EEG signals for neonatal seizure detection. And the presented CNN was exploited both as a feature extractor and the classifier. In [17], a CNN-based pipeline was proposed to implement the classification of intracranial and scalp EEG data. It could produce the optimal feature sets over the manual descriptors. It is notable that the deep learning-based techniques heavily rely on the quantity and quality of the training set, which is usually inadequate for the publicly available EEG datasets.

Bearing the above-mentioned analysis in mind, we propose a convolutional neural network (CNN)-based pipeline for classifying the types of input EEG signals. In this approach, the relationship between each pair of EEG firstly are integrated into one matrix. By using the 1D convolution operation, the interaction between pair of EEG channels can be generated. Then, the generated matrices are fed into the proposed CNN, which could accurately identify the type of input data samples. Totally, there are nine categories of combinations for the pairwise EEG activities as followings.

(1) (normal, normal)
(2) (normal, ictal)
(3) (normal, interictal)
(4) (ictal, normal)
(5) (ictal, ictal)
(6) (ictal, interictal)
(7) (interictal, normal)
(8) (interictal, ictal)
(9) (interictal, interictal)

To note that numerous pairs of EEG data are taken as the input for this presented CNN in the following experiments. While in the practical applications, one single channel EEG signal is used as the baseline, which would be combined with each input EEG sample.

To evaluate the performance of the proposed approach, the comparison experiments between the state-of-the-art techniques and our work were carried out on one publicly available dataset. The experimental results indicate that the accuracy of our work is superior over the state-of-the-arts.

In general, our work offers the following contributions:

(I) To the best of our knowledge, this is an early work of Pairwise matching-based deep learning strategy for epileptic seizure detection in EEG data.
(II) We propose a novel deep learning architecture with an input of the association between each pair of EEG signals.
(III) Experimental results indicate that the proposed approach could outperform the state-of-the-arts in accuracy.

The remainder of this article is organized as follows. Firstly, the details about the proposed approach is described in Section II. In Section III, we provide the comparison experiments, results, and the corresponding discussion. Finally, both the conclusion and our future work were given in Section IV,.

II. METHODOLOGY

A. CONVOLUTIONAL EEG SIGNAL MODEL

Firstly, we propose a novel convolutional framework for modeling the EEG activity. As demonstrated in Fig. 2, the EEG signals aligned sequentially are taken as the input of the proposed convolution operator. Each row in the input data represents one epoch of the original EEG sample from each subject while each column stands for the $\frac{1}{16}$ of an epoch of EEG signal. Then, the representation vector with a fixed length would be generated by using a sequence of convolutional and pooling layers.

1) Convolution

The employed convolution operators are realized in a sliding window fashion, simultaneously. In general, assuming that an input is x, the corresponding outcome of class-c at layer-l is formulated as following:

$$z_i^{(l,c)} = z_i^{(l,c)}(x) = \sigma(w^{(l,c)} z_i^{(l-1)} + b^{(l,c)}), c = 1, 2, ..., C \tag{1}$$

where $w(.)$ and $b(.)$ is the weight and bias function, respectively. $\sigma(.)$ represents the activation function like sigmoid [18] and ReLU [19] while C denotes the maximal types of the EEG signals. To note that the matrix form of Eq. (1) is:

$$z_i^{(l)} = z_i^{(l)}(x) = \sigma(W^{(l)} \bar{z}_i^{(l-1)} + b^{(l)}, \tag{2}$$

where $z_i^{(l,c)}$ denotes the output feature map for type-c at layer-l of location i, $w^{(l,c)}$ is the weighting parameters for

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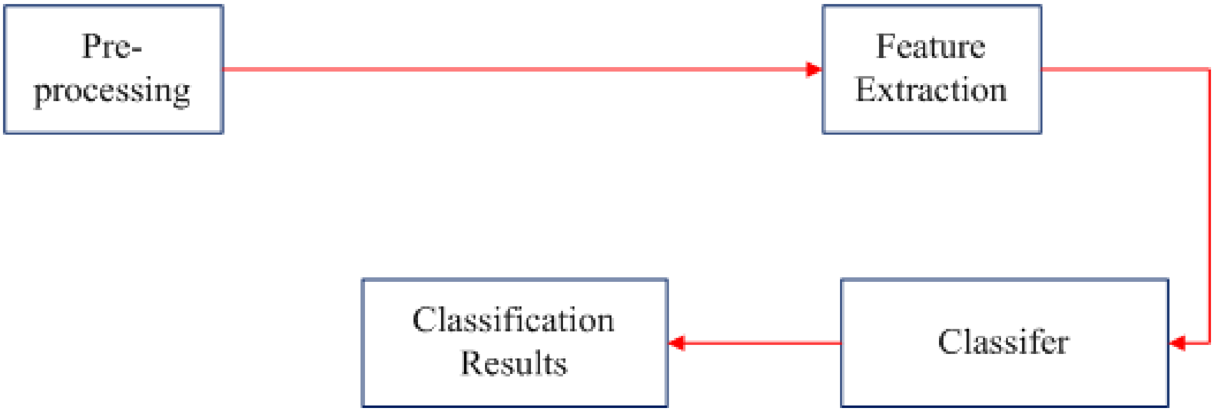

FIGURE 1: The pipeline for general anomaly detection algorithms.

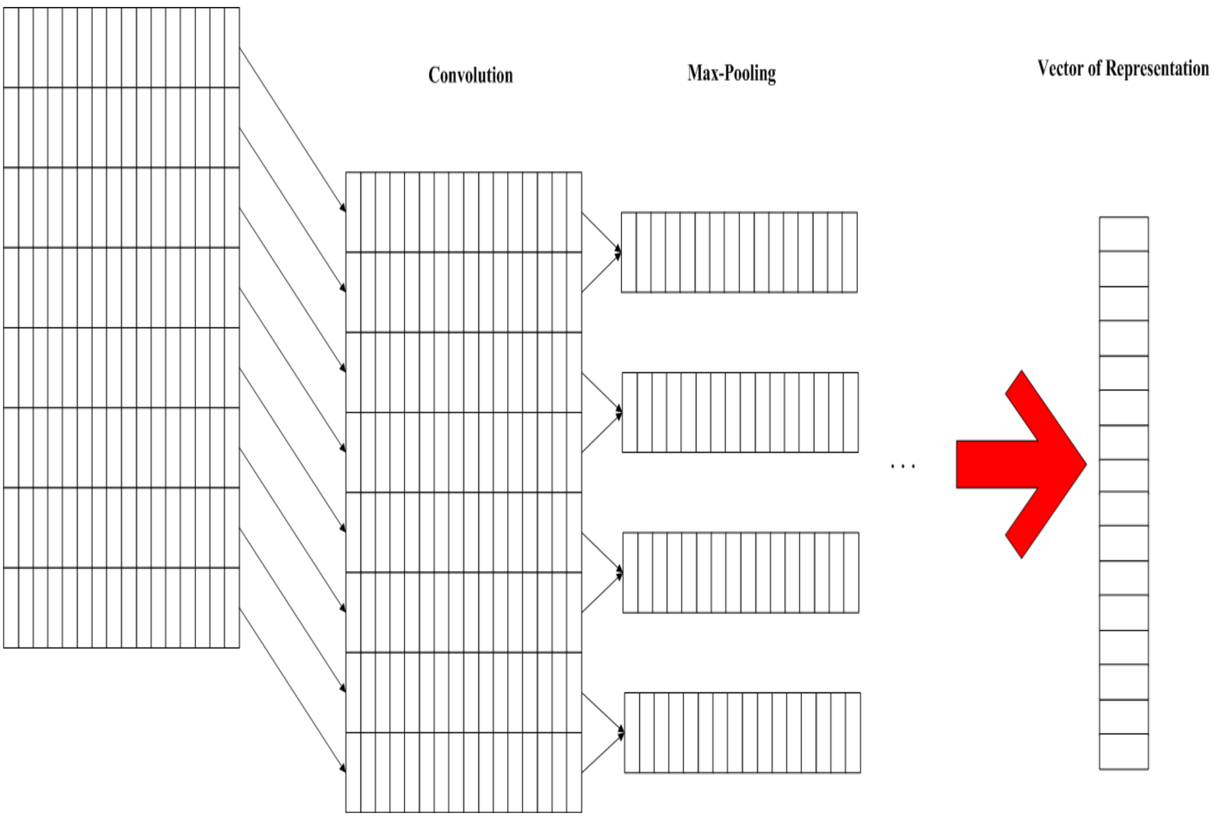

FIGURE 2: The proposed convolution operator on EEG signals. Each row represents one epoch of the original EEG sample from each subject while one column stands for the $\frac{1}{16}$ of an epoch.

class-c at layer-l. And $\bar{z}^{(l-1)}$ represents the segment of layer-l at location i with:

$$\bar{z}_i^{(0)} = x_{i:i+k_1-1} = [x_i^T, x_{i+1}^T, ..., x_{i+k_1-1}^T]^T \quad (3)$$

where k_1 denotes the width of each row for the input EEG data.

2) Max-pooling

The max-pooling operator is performed on each pair of rows for the input, which could be mathematically defined as:

$$z_i^{(l,c)} = max(z_{2i-1}^{(l-1,c)}, z_{2i}^{(l-1,c)}), l = 2, 4, ... \quad (4)$$

The role of max-pooling in the proposed CNN architecture includes compressing the size of extracted features and removing the redundant components in the data samples.

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B. NETWORK ARCHITECTURE

The novel CNN architecture is built upon the association between pairwise EEG signals. The EEG behaviors on multiple channels are captured rather than the information from one single channel. Both the characteristics of each single signal and the relationship between two EEG samples could be preserved before feeding into the proposed CNN. To be specific, all of the combinations for the EEG data are generated by using the convolution operation presented in Section II-A1. We assume that sample x and y are denoted by S_x and S_y, for segment m of S_x and segment n in S_y we obtain:

$$z_{m,n}^{(l,c)} = z_{m,n}^{(l,c)}(x,y) = g(\bar{z}_{m,n}^{0}).\sigma(w^{(l,c)}.\bar{z}_{m,n}^{0} + b^{(l,c)}), \quad (5)$$

where $\bar{z}_{m,n}^{0} \in \mathbb{R}$ denotes the concatenating vectors of S_x and S_y.

$$\bar{z}_{m,n}^{0} = [x_{i:i+k_1-1}^{T}, y_{j:j+k_1-1}^{T}]^{T}. \quad (6)$$

From the concatenation, the spatial alignment of the segments are preserved in the first layer. And the following layers both leverage the 2D convolution and pooling operators Fig. 3. In layer-2 and layer-3, the output could be respectively expressed as:

$$z_{m,n}^{(2,c)} = max(z_{2m-1,2n-1}^{(1,c)}, z_{2m-1,2n}^{(1,c)}, z_{2m,2n-1}^{(1,c)}), \quad (7)$$

and

$$z_{m,n}^{(3,c)} = g(\bar{z}_{m,n}^{2}).\sigma(W^{3,c}\bar{z}_{m,n}^{2} + b^{3,c}). \quad (8)$$

Through leveraging the 1D convolution as mentioned Section II-A1, a representation of the interactivity between pairwise EEG signals, $z_{m,n}^{(l)}$ contains the information from both of them. And the 2D convolution could formulated as:

$$z_{m,n}^{(l)} = g(\bar{z}_{m,n}^{(l-1)}).\sigma(W^{(l)}\bar{z}_{m,n}^{(l-1)} + b^{(l,c)}), l = 3, 5, \ldots \quad (9)$$

where $\bar{z}_{m,n}^{(l)}$ connects the representation vectors in layer-$l-1$.

In general, the architecture of the proposed CNN is illustrated in Fig. 4.

Besides the 1D convolution layer, there are the following layers described as:

- Convolutional. 48 kernels of size $3 \times 9 \times 9$ are used in the first layers followed by one ReLU layer.
- Convolutional. 128 kernels of size $3 \times 7 \times 7$ combined with the ReLU layer
- Convolutional. 128 kernels of size $3 \times 5 \times 5$ combined with the ReLU layer.
- Fully connected layer. 1024 neurons in total that are is used to realize the high-level reasoning.

One softmax loss function is located at the end of this network, which is formulated as:

$$L_s = -\sum_{i=1}^{N} log\left(P\left(\omega_k\right) | \left(L_i\right)\right), \quad (10)$$

where N denotes number of the input images, $P(\omega_k|L_i)$ indicates the probability of correct classification.

III. EXPERIMENTS

A. DATASET AND EVALUATION METRICS

1) Dataset

In our work, the dataset [20], which was presented by Department of Epileptology, University of Bonn, was exploited in the epileptic EEG classification experiments In general, the data samples were captured from five healthy subjects and five patients with epilepsy.

To be specific, there are five sets in the dataset denoted as A, B, C, D, and E. The EEG recordings of the health subjects were captured following the international 10-20 system. Meanwhile, the interictal and ictal samples were respectively collected from the depth electrodes and the same equipment with the electrodes planted into the lateral and basal regions of the neocortex. In each sequence, 100 EEG segments are incorporated and every segment consists of 4,096 sampling points while the duration for each segment is 23.6 seconds. All of the samples are divided into three categories including normal, interictal, and ictal that were collected from 128-channel EEG recordings after the pro-precessing like artifacts eliminations.

In the experiments, three types of recordings composing of the A (normal), D (interictal), and E (ictal) were used to evaluate the performance of the proposed approach. In general, we sequentially conducted the binary classification of set A and D, set D and E as well set A, D, and E.

2) Pre-processing

EEG has a low spatial resolution [21]. Therefore, the preprocessing of EEG recordings usually consists of the artifact elimination [22] from eye-movement [23], heartbeat [24], respiration [25], and electrical disturbance [26].

The EEG samples were captured from one 128-channel amplifier platform [20]. Furthermore, they were digitized at a sampling rate of 173.61Hz. And the corresponding output was then filtered by a band pass filter with 0.53 40Hz and 12 dB/octave.

3) Evaluation metric

In this study, $Accuracy$ was employed as the performance metric in the experiments that could be formulated as:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}, \quad (11)$$

where TP denotes true positive, FP is false positive, TN represents true negative, and FN is false negative. $Precision$ is commonly used to indicate the percentage of positive outcomes in total, and $Accuracy$ denotes the true samples comparing with the entire set.

To evaluate the presented method in a robust fashion, we adopted one 10-fold cross-validation strategy. Firstly, the entire EEG signal samples were separated into ten subsets and each set contains same number of samples. Generally,

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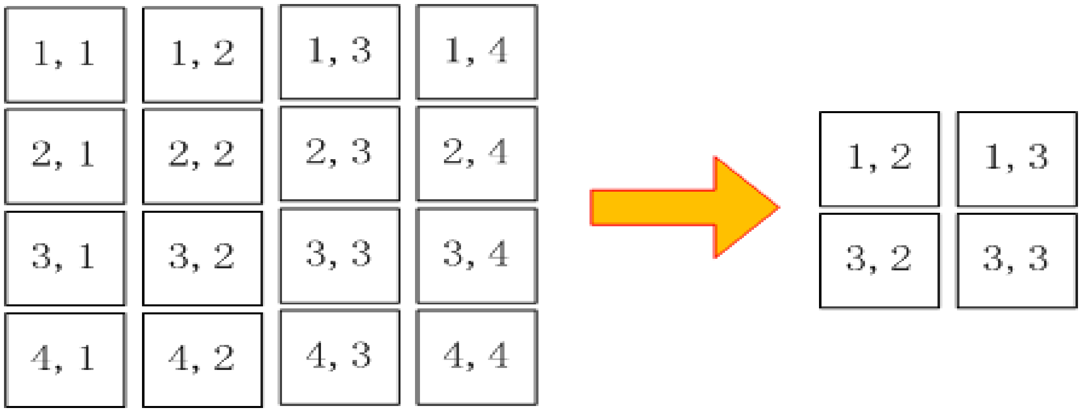

FIGURE 3: The 2D pooling operation that could preserve the spatial position in the proposed CNN.

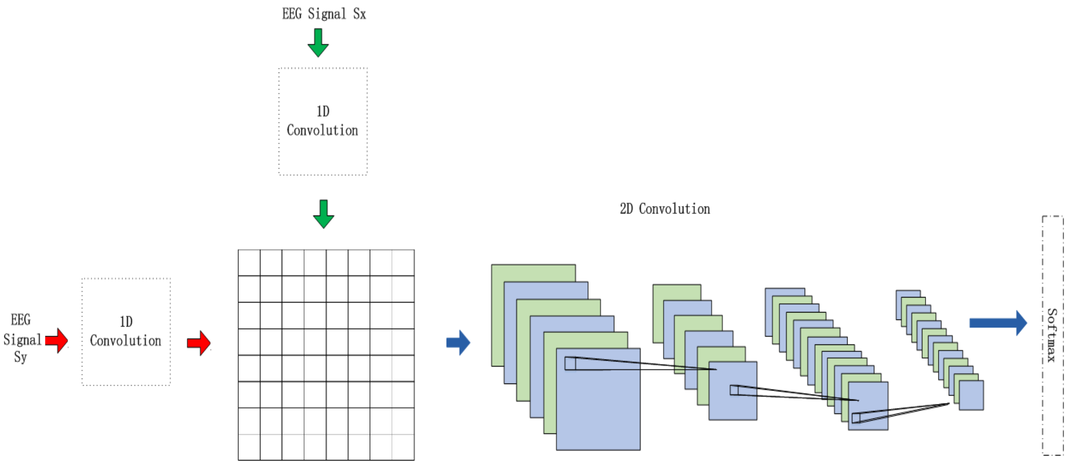

FIGURE 4: The proposed deep learning network architecture.

we conducted 10 rounds of experiments for cross-validation. During one single round, one subgroup of recordings were taken into the testing set while the other 9 subsets were exploited as the training set.

It is notable that accuracy was firstly calculated for each round. Finally, the average accuracy was taken as the outcome result.

B. EXPERIMENTAL RESULTS

To evaluate the performance of the proposed algorithm, we respectively conducted experiments on Set A and D, Set D and E, and Set A, D, and E as illustrated in Table. 1, Table. 2, and Table. 3.

It can be observed from the tables including Table. 1, Table. 2, and Table. 3 that the classification performance of the proposed EEG classification framework achieved superior accuracy over the state-of-the-art EEG identification techniques with different features and classifiers. To be specific, most of these approaches exploit non-deep learning-based algorithms along with manually-crafted features to implement the classification of epileptic activity from the multi-channel EEG signals. Table. 1 provides the comparison of the accuracy performance between state-of-the-arts and our work for normal (Set A) and ictal (Set E) EEG signals. Since it is widely considered as a simple task at present, the accuracy results are close to 100%. Similarly, there have also been satisfactory outcome for both interictal (Set D) and ictal (Set E) as well as normal (Set A), interictal (Set D), and ictal (Set E) input.

C. DISCUSSION

It has been wide proven that EEG could be leveraged as an invaluable too for diagnosing the epileptic seizures. And large amount of automated EEG signal identification techniques have been presented in the literature. However, most of these approaches follow a straightforward framework and usually neglect the association between pairwise EEG samples. To bridge this gap, we propose a deep learning-based algorithm that not only could both capture the association between the EEG activities and guarantee the accuracy of classification.

As shown in Table. 1, Table. 2, and Table. 3, the algorithm proposed in the work of [45] is superior over our approach. However, it is notable that we adopted the 10-fold cross-validation strategy in the experiments, which had not been

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TABLE 1: Performance comparison between state-of-the-art techniques and ours for normal (Set A) and ictal (Set E) EEG signals.

Methods	Details of the Method	Accuracy
Chandaka *et al.* [27]	Cross correlation with SVM	95.96
Guo *et al.* [28]	Wavelet energy with BPN	95.20
Kannathal *et al.* [29]	Entropies with neuro-fuzzy inference	92.22
Kaya *et al.* [30]	One dimensional LBP with bayes-net	97.52
Hassan *et al.* [31]	WT with DT bagging	99.73
Nicolaou and Georgiou [32]	Entropy with SVM	97.12
Polat *et al.* [33]	Fast fourier transform with DT	98.72
Sharma and Pachori [34]	WT with SVM and fractal dimension	99.58
Tawfik *et al.* [35]	Entropy with SVM	99.52
Wang *et al.* [36]	WT + entropy with KNN	97.52
Yuan *et al.* [37]	LBP based on wavelet decomposition with SVM	99.63
Das *et al.* [45]	Dual-tree complex wavelet	100%
Our work	Pairwise matching of EEG signals and CNN	99.84

TABLE 2: Performance comparison between state-of-the-art techniques and ours for interictal (Set D) and ictal (Set E) EEG signals.

Methods	Details of the Method	Accuracy
Kaya *et al.* [30]	One dimensional LBP with bayes-net	95.50
Siuly *et al.* [38]	Clustering with SVM	93.91
Song *et al.* [39]	Similarity-based measures + entropy with extreme learning machine	97.53
Supriya *et al.* [40]	Weighted visibility graph with SVM	93.25
Wang *et al.* [41]	Multi-scale blanket dimensions + fractal intercepts with SVM	97.58
Yuan *et al.* [37]	LBP based on wavelet decomposition with SVM	98.88
Das *et al.* [45]	Dual-tree complex wavelet	100%
Our work	Pairwise matching of EEG signals and CNN	99.61

TABLE 3: Performance comparison between state-of-the-art techniques and ours for normal (Set A), interictal (Set D), and ictal (Set E) EEG signals.

Methods	Details of the Method	Accuracy
Acharya *et al.* [42]	Entropies + HOS + fractal dimension with fuzzy	99.70
Kaya *et al.* [30]	One dimensional LBP with bayes-net	95.67
Hassan *et al.* [31]	WT with DT bagging	98.67
Li *et al.* [43]	DWT with NN	98.78
Li *et al.* [44]	CWT with SVM	98.97
Tawfik *et al.* [35]	Entropy with SVM	97.5
Yuan *et al.* [37]	LBP based on wavelet decomposition with SVM	98.92
Das *et al.* [45]	Dual-tree complex wavelet	100%
Our work	Pairwise matching of EEG signals and CNN	97.82

taken into consideration by the state-of-the-arts including [45]. And we have achieved much higher accuracy by choosing the training set and testing set properly when we did not adopt the 10-fold cross-validation strategy.

IV. CONCLUSION AND FUTURE WORK

Automatic identification of the associations between normal, interictal, and ictal patterns in raw EEG samples is one potentially valuable tool for the diagnosis and treatment of epilepsy. Previously, numerous researches have been implemented for the EEG discrimination tasks. However, most of these techniques might neglect the spatial and temporal relationship between each pair of EEG signals. Thus, we presented a novel CNN-based algorithm for epileptic EEG identification.

In the future, we would continue to improve the accuracy of the proposed approach through fine-tuning and increasing the quantity of samples in the training set. Meanwhile, the permutation of the EEG signals will be taken into consideration. It is notable that the proposed approach relates to the following areas including network security [46]–[61], optimization [62]–[68], graphics [69]–[74], recommendation system [75]–[77], multimedia [78]–[85], automation control [86]–[90], networking [91]–[104], classification [105]–[109], image fusion [110], [111], image retrieval [112]–[117], and simulation [118]–[120].

ABBREVIATIONS

Electroencephalogram–EEG
CNN–Convolutional neural network
Wavelet–WT
Local binary pattern–LBP
Support vector machine–SVM
TP–True Positive
FP–False Positive
TN–True Negative
FN–False Negative
GAN–Generative adversarial network

DECLARATIONS

Ethical Approval and Consent to participate: Approved. Consent for publication: Approved. Availability of supporting data: We can provide the data.

COMPETING INTERESTS

These no potential competing interests in our paper. And all authors have seen the manuscript and approved to submit to your journal. We confirm that the content of the manuscript has not been published or submitted for publication elsewhere.

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