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Detection of alcoholic EEG signals based on whole brain connectivity and convolution neural networks

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ABSTRACT

Alcoholism is a common complex brain disorder caused by excessive drinking of alcohol and severely affected the basic function of the brain. This paper investigates classification of the alcoholic electroencephalogram (EEG) signals through whole brain connectivity analysis and deep learning methods. The whole brain connectivity analysis is proposed and implemented using mutual information algorithm. Continuous Wavelet transform was applied to extract time–frequency domain information in each selected frequency bands from EEG signal. The 2D and 3D convolutional neural networks (CNN) were used to classify the alcoholic subjects and health control subjects. UCI Alcoholic EEG dataset is employed to evaluate the proposed method, a 96.25 ± 3.11 % accuracy, 0.9806 ± 0.0163 F1-score result in 3D-CNN model was obtained via leaving-one out training method of all the testing subjects.

1. Introduction

Alcoholism is a physical disease that is addicted to drinking, similarly to obsessive–compulsive disorder [1]. The most common negative effects of alcoholism patients are digestive system diseases which include Ulcers, esophageal bleeding, stomach cancer, acute and chronic pancreatic inflammation and nervous system disorders such as mentally handicapped, Alzheimer, stroke [2]. In addition, the excessive alcohol consumption can cause high blood pressure and gout. According to the report of World Health Organization (WHO), alcoholism is regarded as the third highest risk factor for causing diseases, and it summarized that about 3.3 million deaths every year result from the excessive alcohol consumption [3]. Long-term consumption of alcohol impairs the development of the brain that severely damage the brain's grey and white matter [4]. Similarly, in short-term, alcohol may cause issues in cognition problems and memory loss [5].

Early diagnosis of alcoholism will help individual subjects understand their condition and prevent permanent damage. Traditional alcoholism identification methods are based on questionnaires, breath test and blood tests. Pham, T.T.L., S. Callinan, and M. Livingston used questionnaires method to assess the prevalence of risky drinking among people with a range of chronic diseases [6]. However, the data used in their work is self-reported data which may exist inaccurate responses in their study. Bertholet, N., et al. stated that the breath test and blood test for identifying alcoholism are questionable as the biomarkers can only provide 66 % sensitivity in carbohydrate-deficient transferrin blood test and missed 70–80 % of cases in breath test [7]. Electroencephalogram (EEG), which records brain activities electronically from the scalp and is the most popular technique in detecting complex brain disorder, can support more accurate classification of the alcoholism brain and health control brain [8,9]. Compared with traditional methods of alcoholism identification, EEG is low-cost, non-invasive, high accuracy of detection and less reliant on trained professionals in practical applications [10]. EEG as the recorded brain activity signals has different features in time domain, frequency domain and time–frequency domain. However, traditional research methods such as Fast Fourier Transform etc are not suitable for analysing the resting-state EEG because EEG signals are considered to be non-stationary time series in this condition, and it can also be computationally expensive for high-density EEGs.

To overcome this limitation, the brain network analysis was proposed as another analogous solution. Many researchers focus on connectivity analysis of brain networks in detecting complex brain disorders such as epilepsy, Alzheimer diseases, schizophrenia etc, and alcoholism can also use connectivity analysis to extract features from EEG raw signal to do the detection work. The connectivity analysis of brain network is derived from the data of EEG and depicts the functional

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connections between different brain regions where the brain regions are regarded as nodes and the connections as edges. In EEG alcoholism detection, the nodes and edges of the graph represent the EEG channels and the connections between channels. Mumtaz et al. proposed the power coherence functional connectivity of frequency domain to detect the resting-state EEG alcoholic signal and achieved a result of 89.3 % accuracy and 88.5 % sensitivity [11]. Goksen et al. highlighted the functional connectivity measured by mutual information of time domain correlation to classify alcoholism subject and got a result of 82.33 % accuracy and 85.33 % sensitivity [12].

Machine learning methods is widely used in classification work. Comparing with the traditional statistical classification methods, the machine learning methods can provide more accuracy classification results. Nonnegative least squares (NNLS) classifier proposed by Bajaj et al. combined with time–frequency images features of short time Fourier transform (STFT) in alcoholism signal detection and achieved a result of 95.83 % accuracy [13]. Goksen et al. proposed KNN based on relative entropy features got a result of 80.33 % accuracy and 82.67 % sensitivity result [12]. Fayyaz et al. used support vector machine and long short-term memory (LSTM) with peak visualization method achieved a result of 90.97 % in accuracy [14]. Farsi also reported the LSTM algorithm of deep learning methods could directly classify the EEG alcoholism signal and achieved a result of 93 % accuracy [15]. Patidar, S., et al. used Tunable-Q wavelet transform and extracted features as centered correntropy from the decomposition level. Patidar, S., et al. proposed least squares-support vector with 10-fold cross validation method to detect EEG alcoholic signal and achieved an accuracy of 97.02 % [16]. Agarwal, S. and M. Zubair highlighted a method which combined sliding singular spectrum analysis (S-SSA), independent component analysis (ICA) and XGBoost classifier to detect alcoholic subjects and obtained an accuracy of 98.97 % [17].

Traditional machine learning methods require manual feature extraction and model matching, while deep learning methods greatly simplifies the preprocessing process, which can automatically extract features and complete decoding at the same time. In addition, deep learning can directly deal with common events such as eye movements, artifacts, or background EEG, optimizing traditional methods, and giving full play to the end-to-end decoding characteristics of deep learning. The convolution neural network (CNN) is one of the mainstream deep learning algorithms. Most CNN models are used in the image classification work, such as the AlexNet and GoogleNet architectures. In EEG analysis, the CNN models are also used widely, in particular in the image-liked EEG data. Chen et al. combined the mutual information function connectivity and convolution neural networks (CNN) models to detect the attention-deficit/hyperactivity disorder (ADHD) based on EEG signal and obtained a 94.67 % accuracy [18]. Khan et al. applied this method to detect alcoholism EEG data, they used the partial directed coherence with a 3D-CNN model, and achieved an 87.85 % accuracy and 100 % correct classification of all testing subjects [19]. CNN also proposed by Mukhtar, H., S.M. Qaisar, and A. Zaguia to detect alcoholism in a normalized 8-second length EEG data segment directly and achieve 98 % accuracy [20].

In this paper, we proposed the brain connectivity analysis with CNN model to detect EEG alcoholic signal. MI functional connectivity can reveal the abnormal connectivity and nodes (channels) of alcoholic diseases. It can also be used to achieve a satisfying detection result. CNN is used widely in graph classification work because its perfect performance, and it can also achieve good results dealing with the image-like data. Thus, we applied the CNN models and designed a framework suitable for our experiment.

The main contributions of this study are: (1) Firstly, a deep learning enabled whole brain connectivity analysis method was applied to detect alcoholic EEG signal; (2) Design a framework of a 3D-CNN, and apply the image classification method to detect EEG signal and get an accuracy of 96.25 ± 3.11 % using leaving-one out training method for all the testing subjects; (3) Brain rhythms factor was taken into consideration in detecting the alcoholic EEG, and the gamma band (30–40 Hz) was found to be the most significant rhythm. (4) After the evaluation of all cross mutual information (CMI) connectivity values, the adjacent connectivities between the left parietal part, the left frontal part, the right temporal part, the right frontal part and the right parietal part were found to be the fuzzy locations in determining alcoholism. All the experiments in this study were carried out in a Dell workstation with dual Intel Xeon E5-2697 V3 CPUs using MATLAB 2021b.

The first section of the paper provided a brief introduction of the work. Section 2 described the details of the dataset. The pre-processing, functional connectivity analysis and classification were also introduced in this section. Section 3 reported our experimental work using the proposed method and the results obtained. The threshold selection of CMI, brain rhythms selection, statistical analysis of CMI values and machine learning method comparison were evaluated in Section 4. We also listed the previous work results to compare the proposed method in this section. Section 5 concluded the work.

2. Methodology

In this EEG based alcoholism detection study, there are four major steps. The Butterworth algorithm was applied to denoise the EEG raw data and the time–frequency domain features were extracted using continuous wavelet transform (CWT) as a pre-processing measure. After that, the extracted features were converted into image-like connectivity matrix through the CMI algorithm. The image-like data is, then, fed to the CNN model as input, and then the training data with leaving-one out training method is used to train the input and test and evaluate the results. The framework of the proposed method is described in Fig. 1:

2.1. Datasets

The data used in this study is collected from the University of California, Irvine Knowledge Discovery in Databases Archive UCI KDD [21]. Dataset SMNI_CMI_TRAIN and Dataset SMNI_CMI_TEST contain data for 10 alcoholic and 10 control subjects, with 10 runs per subject per paradigm. In these two datasets, each dataset has 600 recorded files with 256 Hz sample rate and 64 channels including the EOG signals and the reference channel ND.

2.2. Pre-processing

The sliding window technique is used in this study. A 5-second sliding window was developed and data within the moving window was considered as the input data, and the sliding window overlap was selected as 1 s. A Butterworth zero-phase filter/algorithm is used to denoise the EEG raw data. The CWT algorithm is used to extract time – frequency domain features in different frequency bands with delta band (1–4 Hz), theta band (4–8 Hz), alpha band (8–12 Hz), beta band (12–30 Hz), gamma band (30–40 Hz) and whole band (1–40 Hz). The formula of CWT with 1 Hz frequency resolution is shown as follow:

$$W_{x_i}(t,f) = \int \mathrm{x_i}(\lambda)\cdot\overline{\phi_{\mathrm{t,f}}(\mathrm{t}-\lambda)}\mathrm{d}\lambda \tag{1}$$

where $W_{x_i}(t,f)$ is the energy density in frequency f of the ith channel at time instant t, $\overline{\phi_{t,f}(t-\lambda)}$ is the complex conjugates of $\phi_{t,f}(t-\lambda)$.

The Morlet wavelet method is selected as the mother wavelet, and the algorithm was described as follow:

$$\phi_{t,f}(\lambda) = A\cdot e^{i2\pi f(\lambda-t)\cdot e^{\frac{-(\lambda-t)^2}{2\sigma^2}}} \tag{2}$$

where $\sigma = \frac{8}{2\pi f}$ is the time spread of the wavelet.

After the denoising and CWT, the data is converted into 256*4 (delta band), 256*5 (theta band), 256*5 (alpha band), 256*19 (beta band), 256*11 (gamma band) and 256*40 (whole band) matrix respectively.

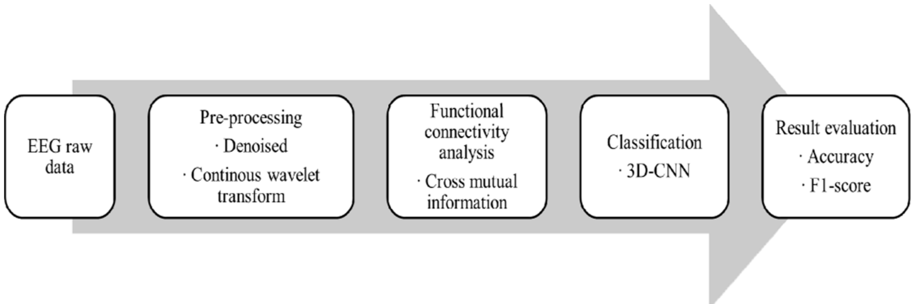

Fig. 1. The framework of CWT, CMI functional connectivity and 3D-CNN methods for seizure detection.

2.3. The cross mutual information functional brain connectivity

The cross mutual information (CMI) based on the CWT algorithm is applied to construct the functional brain matrix in time–frequency domain. The algorithm of CMI between two different channels is shown as follow:

$$MI(F_i, F_j) = H(F_i) + H(F_j) - H(F_i, F_j) \tag{3}$$

where, the $H(F_i)$ is the entropy of Channel i, which describe as:

$$H(F_i) = -\sum_{b=1}^{40} p(F_{i,b}) \log_2 p(F_{i,b}) \tag{4}$$

where F_i is the averaged power signals at the ith channel. The $p(F_{i,b})$ is the probability density function of each frequency bin. The bin is selected as 40.

$H(F_i, F_j)$ is the joint entropy of two channel's averaged power signals, given by:

$$H(F_i, F_j) = -\sum_{b=1}^{40} p(F_{i,b}, F_{j,b}) \log_2 p(F_{i,b}, F_{j,b}) \tag{5}$$

Similarly, the bin is selected as 40 and $p(F_{i,b}, F_{j,b})$ is the probability density function of averaged power signals for channel i and j.

After the calculation, the cross mutual information between channel i and j is obtained:

$$MI(F_i, F_j) = \sum_{b=1}^{40} p(F_{i,b}, F_{j,b}) \log_2 \frac{p(F_{i,b}, F_{j,b})}{p(F_{i,b}) p(F_{j,b})} \tag{6}$$

Thus, the data of six frequency bands (delta band, theta band, alpha band, beta band, gamma band and whole band) are all converted into 64*64 matrix through cross mutual information algorithm. As an example, the image-like CMI matrix of an alcoholic subject co2a0000364 in gamma band is shown in Fig. 2.

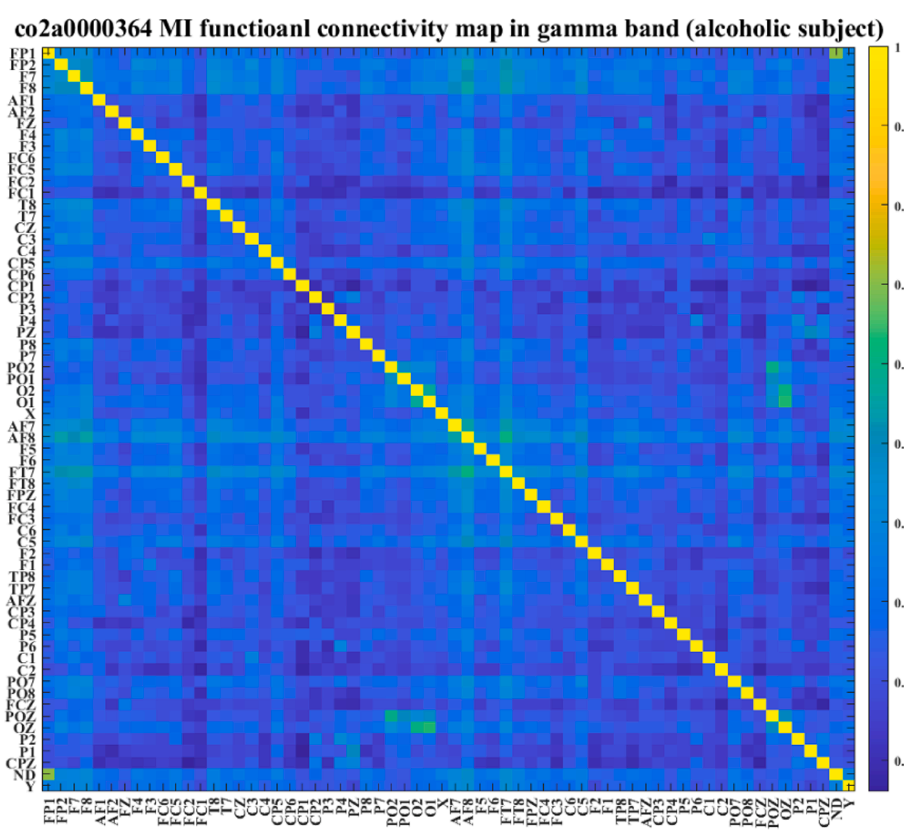

Fig. 2. Cross mutual information functional connectivity matrix of alcoholic subject co2a0000364 in gamma band.

2.4. Classification via convolutional neural networks

The functional connectivity matrix shown above is image-like data which represents the brain connection network. 20 subjects' data (10 HC subjects and 10 alcoholic subjects) from UCI alcoholic EEG dataset was used in this study. In leaving-one out training method, one subject data is used for testing and the other 19 subjects were used for training. As a result, 20 models have been trained. In addition, 20 % random training data is selected as the validation data via hold-out validation method. The input data is the 64*64 size imaged-like data constructed using the CMI algorithm. The training progress selects the learning rate as 0.01, and epochs as 400. Table 1 summarizes the architectural details of the 2D-CNN model as shown below:

The 2D-CNN model includes 6 convolution layers with batch normalization, 3 max pooling layer, 5 ReLU layers and 1 fully connected layer. The 6 convolution layers all use 64 filters with convolution kernels of 3*3, 3*3, 3*3, 3*3, 3*3, and 2*2, respectively. Batch normalization of each convolution layer is to reduce the internal covariance shift which can improve training speed and reduce the over-fitting phenomenon. The 3 Max pooling layers of this architectural is to reduce the cost of training calculation with 2*2 size and 2*2 stride. The activation function ReLU is defined as f(x) = max(0,x) which is used to activate or deactivate a node based on mapped value. The last part is the fully connected layer followed by a Softmax classifier for the identification using the concatenated outputs of the last layers.

Based on the 2D-CNN model with functional connectivity analysis, the gamma band has a better performance than other frequency bands. 3D-CNN in gamma band was designed to further improve the accuracy of the results. The CWT and CMI algorithms are used to compute the functional matrix in each Hz frequency such as (30–31 Hz, 31–32 Hz, …, 39–40 Hz). Thus, the input data size of each segment has changed into 3D imaged-like data size 64*64*10. The 3D functional matrix of the same subject in Fig. 2 is shown in Fig. 3:

In the 3D-CNN model, the learning rate is still selected as 0.01 and the epochs selected as 400 for comparison with the 2D-CNN results. In addition, the 3D-CNN architectural is designed to classify the input data shown in Fig. 3. Table 2 summarizes the architectural details of the 3D-CNN model with the hyperparameter settings in each layer.

Similar as the architectural of 2D-CNN, this model contains 6 convolution layers with batch normalization, 3 max pooling layers, The 5 ReLU layers and 1 fully connected layer as well. The difference is the hyperparameter settings of each layer. In this model, the 6 convolution layers all use 64 filters with dimensions of 3*3*3, 3*3*3, 3*3*1, 3*3*1, 3*3*1, and 2*2*1 respectively. The size of kernel in 3 max pooling layers are set as 2*2*2, 2*2*2, and 2*2*1 with stride 2*2*2, 2*2*2, and 2*2*1. Other hyperparameter setting is the same as the 2D-CNN such as the ReLU algorithm, fully connected layer and softmax classifier. The optimizer based Deep Network Designer of MATLAB 2021b of HC subject co2c0000345 is shown in Fig. 4.

Table 1
The architecture of 2D-CNN for training and test of the alcoholic detection.

Layer	Input Size	Output Size	Trainable parameters
2D imaged-data input	64*64*1		
Convolution layer	64*64*1	62*62*64	Kernel size: 3*3 Stride: 1*1 Channel: 64
ReLU	62*62*64	62*62*64	
Max Pooling layer	62*62*64	31*31*64	Pooling Size: 2*2 Stride: 2*2
Convolution layer	31*31*64	29*29*64	Kernel size: 3*3 Stride: 1*1 Channel: 64
ReLU	29*29*64	29*29*64	
Max Pooling layer	29*29*64	14*14*64	Pooling Size: 2*2 Stride: 2*2
Convolution layer	14*14*64	12*12*64	Kernel size: 3*3 Stride: 1*1 Channel: 64
ReLU	12*12*64	12*12*64	
Max Pooling layer	12*12*64	6*6*64	Pooling Size: 2*2 Stride: 2*2
Convolution layer	6*6*64	4*4*64	Kernel size: 3*3 Stride: 1*1 Channel: 64
ReLU	4*4*64	4*4*64	
Convolution layer	4*4*64	2*2*64	Kernel size: 3*3 Stride: 1*1 Channel: 64
ReLU	2*2*64	2*2*64	
Convolution layer	2*2*64	1*1*64	Kernel size: 2*2 Stride: 1*1 Channel: 64
Fully Connected layer	1*1*64	1*1*2	
Softmax	1*1*2		

3. Experiments and results

Accuracy is a direct parameter in method evaluation which is define as follow:

$$Acc = \frac{TP + TN}{TP + TN + FP + FN} \tag{7}$$

where 'TP' is the true positive, 'TN' is the true negative, 'FP' is the false positive and 'FN' is the false negative.

In statistical analysis of binary classification, the F1-score is an accuracy measure of a test. It is calculated from the precision and recall of the test, where the precision is the number of true positive results divided by the number of all positive results, including those not identified correctly, and the recall is the number of true positive results divided by the number of all samples that should have been identified as positive. In this study, we use the leaving-one out training method that makes the true negative and false positive being zero. The formula of F1-score were shown in equation (10).

$$PRECISION = \frac{TP}{TP + FP} = \frac{TP}{TP} = 1 \tag{8}$$

$$RECALL = \frac{TP}{TP + FN} = Acc \tag{9}$$

$$F1 - score = 2*\frac{PRECISION*RECALL}{PRECISION + RECALL} = \frac{2*Acc}{1 + Acc} \tag{10}$$

where 'TP' is the true positive, 'FP' is the false positive, 'FN' is the false negative and 'Acc' is accuracy.

3.1. Results for 2D and 3D convolutional neural networks

Based on the performance in alcoholic subjects' detection on gamma band which detailly discussed in Discussion part section B, 2D and 3D CNN methods are applied to detect EEG alcoholic signal in this study. We achieved 86.25 ± 6.48 % accuracy, 0.9249 ± 0.0378 F1-score and 96.25 ± 3.11 % accuracy, 0.9806 ± 0.0163 F1-score respectively. The details are summarized in Table 3 and Table 4.

4. Discussion

4.1. Time-frequency domain functional connectivity analysis

The Mutual information measures the degree of interdependence between two variables which widely used in studies of analysing synchronicity. Joint entropy, as one of the significant parameters of mutual information, describes the distribution of the signal. The bin selection of the joint entropy changes the distribution of the data. The challenge in calculating the CMI from experimental data is to estimate $p(F_{i,b}, F_{j,b})$ from histograms. For a given number of data points, using larger sam-

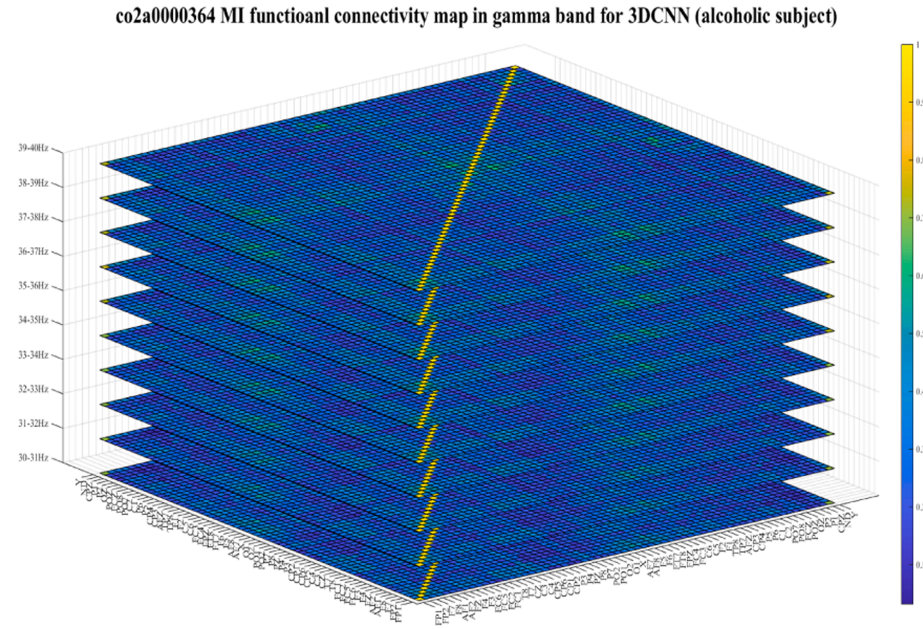

Fig. 3. 10 layers cross mutual information functional connectivity matrix of alcoholic subject in gamma band.

Table 2
The architecture of 3D-CNN for training and test of the alcoholic detection.

Layer	Input Size	Output Size	Trainable parameters
3D imaged-data input	64*64*10*1		
Convolution layer	64*64*10*1	62*62*8*64	Kernel size: 3*3*3 Stride: 1*1*1 Channel: 64
ReLU	62*62*8*64	62*62*8*64	
Max Pooling layer	62*62*8*64	31*31*4*64	Pooling Size: 2*2*2 Stride: 2*2*2
Convolution layer	31*31*4*64	29*29*2*64	Kernel size: 3*3*3 Stride: 1*1*1 Channel: 64
ReLU	29*29*2*64	29*29*2*64	
Max Pooling layer	29*29*2*64	14*14*1*64	Pooling Size: 2*2*2 Stride: 2*2*2
Convolution layer	14*14*1*64	12*12*1*64	Kernel size: 3*3*1 Stride: 1*1*1 Channel: 64
ReLU	12*12*1*64	12*12*1*64	
Max Pooling layer	12*12*1*64	6*6*1*64	Pooling Size: 2*2*1 Stride: 2*2*1
Convolution layer	6*6*1*64	4*4*1*64	Kernel size: 3*3*1 Stride: 1*1*1 Channel: 64
ReLU	4*4*1*64	4*4*1*64	
Convolution layer	4*4*1*64	2*2*1*64	Kernel size: 3*3*1 Stride: 1*1*1 Channel: 64
ReLU	2*2*1*64	2*2*1*64	
Convolution layer	2*2*1*64	1*1*1*64	Kernel size: 2*2*1 Stride: 1*1*1 Channel: 64
Fully Connected layer	1*1*1*64	1*1*1*2	
Softmax	1*1*1*2		

pling bins to construct the histograms produces more accurate estimates of the average probability, but then the estimate of $p(F_{i,b}, F_{j,b})$ will be over detrended, and underestimate the$MI(F_i, F_j)$. Using smaller bins is better in indicating changes in $p(F_{i,b}, F_{j,b})$ over short distances, but it produces fluctuations because of the smaller sample size, which will overestimate$MI(F_i, F_j)$. Empirically, the bin of joint entropy was selected as 40, as shown in Fig. 5:

To extract the features from both time domain and frequency domain, CWT method is applied to obtain the power spectrum of time–frequency domain. In alcoholic EEG detection, the data of gamma band (30–40 Hz) provides the best performance in detection than other frequency bands. The CWT method and CMI algorithm of brain connectivity analysis can consider both time domain and frequency domain features, which improves the performance of classification results.

4.2. Brain rhythms selection

In this study, the functional connectivity is constructed in different frequency bands, delta band (1–4 Hz), theta band (4–8 Hz), alpha band (8–12 Hz), beta band (12–30 Hz), gamma band (30–40 Hz) and whole band (1–40 Hz), to find the best brain rhythms in EEG alcoholic subject detection. Table 5 summarized the results of the accuracy and sensitivity of the classification between alcoholic subjects and health control subjects in each frequency bands.

To reduce the computational cost, the gamma band data is selection to fed into the deep learning methods.

4.3. Different classification method comparison

In this experiment of alcoholic detection via CWT, CMI and 3D-CNN models, we get a 96.25 ± 3.11 % accuracy using the gamma band. The SVM, KNN and decision tree methods with random 20 % hold-out validation of leaving-one out training method were applied to conduct the alcoholic signal detection and compared with the results of the 3D-CNN models. In 3D-CNN model, we used the 64*64*10 (40960) imaged-like data as input. But the value of CMI matrix is symmetrical, in addition, the values between the same nodes, such as (Fz to Fz), are all equal to 1. To reduce the computing costs, we used (64*64–64)/2*10 = 20160 eigenvalues as the input. The results of these three machine learning methods are summarized in Table 6.

It is evident that, from Table 6, the 3D-CNN model provides a better performance in alcoholic signal detection than the aforementioned three machine learning methods.

4.4. Statistical significance of CMI connectivity in whole brain connectivity

Finding the connectivity location can aid in detecting the location of

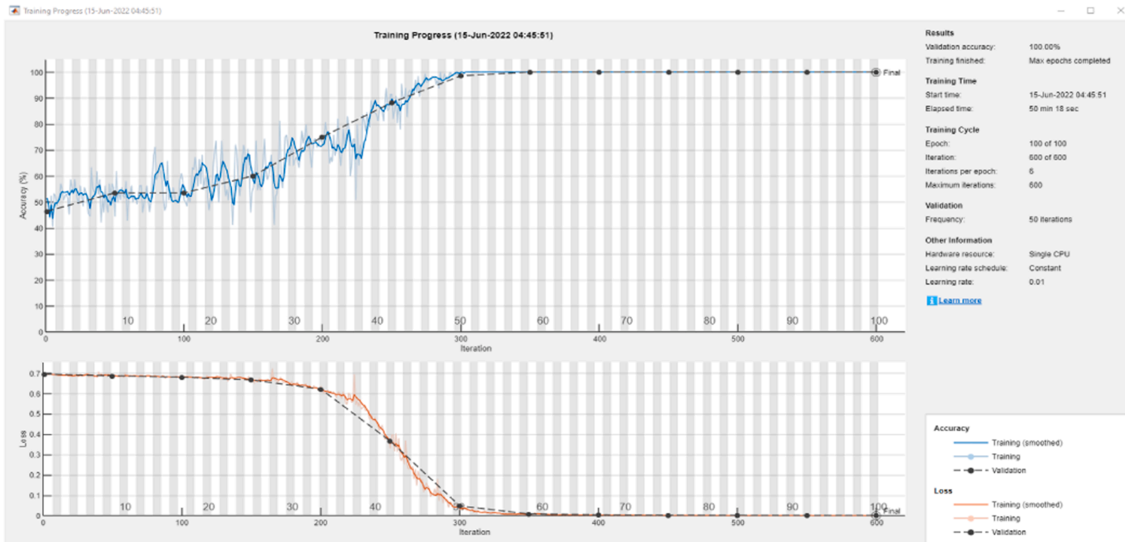

Fig. 4. The optimizer for 3D-CNN model of HC subject co2C0000345.

Table 3
Classification performance of 2D-CNN test.

Subject No.	CMI matrices	Samples identified as		Acc (%)
		ALC	HC	
Co2a0000364	56	48	8	85.71
Co2a0000365	56	50	6	89.29
Co2a0000368	56	49	7	87.50
Co2a0000369	56	44	12	78.57
Co2a0000370	56	47	9	83.93
Co2a0000371	56	48	8	85.71
Co2a0000372	56	49	7	87.50
Co2a0000375	56	52	4	92.86
Co2a0000377	56	56	0	100.00
Co2a0000378	56	40	16	71.43
Co2c0000337	56	5	51	91.07
Co2c0000338	56	12	44	78.57
Co2c0000339	56	11	45	80.36
Co2c0000340	56	8	48	85.71
Co2c0000341	56	6	50	89.29
Co2c0000342	56	7	49	87.50
Co2c0000344	56	7	49	87.50
Co2c0000345	56	3	53	94.64
Co2c0000346	56	12	44	78.57
Co2c0000347	56	6	50	89.29
Mean ± Std				86.25 ± 6.48

'*ALC*' is the alcoholic subject, '*HC*' is the healthy control subject, and '*Acc*' is accuracy.

Table 4
Classification performance of 3D-CNN test.

Subject No.	CMI matrices	Samples identified as		Acc (%)
		ALC	HC	
Co2a0000364	56	55	1	98.21
Co2a0000365	56	51	5	91.07
Co2a0000368	56	55	1	98.21
Co2a0000369	56	55	1	98.21
Co2a0000370	56	56	0	100.00
Co2a0000371	56	55	1	98.21
Co2a0000372	56	55	1	98.21
Co2a0000375	56	56	0	100.00
Co2a0000377	56	56	0	100.00
Co2a0000378	56	51	5	91.07
Co2c0000337	56	5	51	91.07
Co2c0000338	56	0	56	100.0
Co2c0000339	56	3	53	94.64
Co2c0000340	56	4	52	92.86
Co2c0000341	56	3	53	94.64
Co2c0000342	56	3	53	94.64
Co2c0000344	56	3	53	94.64
Co2c0000345	56	2	54	96.43
Co2c0000346	56	3	53	94.64
Co2c0000347	56	1	55	98.21
Mean ± Std				96.25 ± 3.11

'*ALC*' is the alcoholic subject, '*HC*' is the healthy control subject, and '*Acc*' is accuracy.

symptoms in alcoholism patients. We calculated all CMI connectivity values and listed the top 7 channels ($\geq$0.05) with the major difference in CMI mean values between HC subjects and alcoholic subjects in Table 7:

We found that the major difference happened to the connectivity between the left parietal part, the left frontal part, the right temporal part, the right frontal part and the right parietal part. In addition, the most difference connectivities are between adjacent channels. The HC subjects' CMI values in this location are obviously more remarkable than the alcoholic subjects.

4.5. Performance comparison with previous work

Table 8 summarizes the performance of the proposed method and other peer works in alcoholic signal detection. The proposed method achieved a result of 96.25 ± 3.11 % in accuracy through function connectivity analysis and 3D-CNN deep learning model.

The proposed method achieved a satisfying result of 96.25 ± 3.11 % in accuracy. In addition, this method can also determine fuzzy locations of the abnormal connectivity area caused by alcoholic diseases. Furthermore, the sliding window technique applied can capture the dynamics of alcoholism [11,25–27]. However, this study still has several limitations. Firstly, there is more work to be done to implement real-time detection, as the proposed method cannot calculate a sliding window size smaller than 10 s. Secondly, the alcoholic diseases' location is fuzzy, this method cannot detect the alcoholic diseases in specific regions of interest in the brain at the moment.

5. Conclusion

In this paper, the whole brain connectivity analysis is applied and implemented using mutual information algorithm. The functional connectivity maps between the whole brain regions are estimated using CWT and CMI algorithms. The 2D and 3D convolutional neural networks are applied to classify the alcoholic subjects and health control subjects.

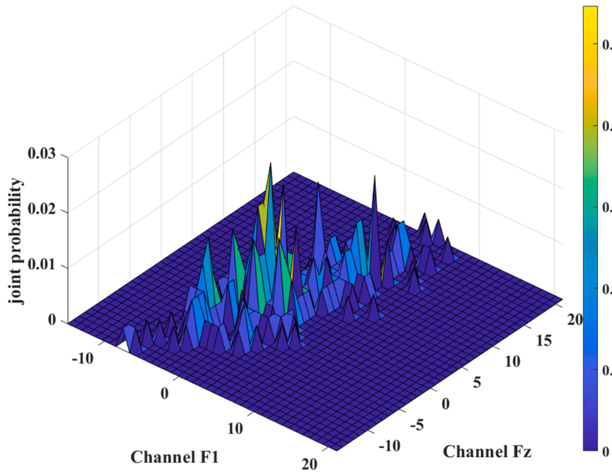

Fig. 5. Joint entropy of channel F1 and channel Fz.

Table 5
Results of 2D-CNN in different brain rhythms.

Frequency bands	Acc (%)
Delta band (1–4 Hz)	52.02 ± 7.98
Theta band (4–8 Hz)	55.66 ± 6.73
Alpha band (8–12 Hz)	62.50 ± 6.34
Beta band (12–30 Hz)	75.84 ± 7.65
Gamma band (30–40 Hz)	86.25 ± 6.48
Whole band (1–40 Hz)	72.54 ± 7.56

'*Acc*' is accuracy.

Table 6
Results of 3 machine learning methods.

Machine learning methods	Validation Acc (%)	Acc (%)
Decision tree	94.93 ± 0.88	88.93 ± 6.15
SVM	99.72 ± 0.32	95.18 ± 5.41
KNN	99.82 ± 0.36	91.67 ± 6.03
Proposed Method 3D-CNN	99.77 ± 0.29	96.25 ± 3.11

'*Acc*' is accuracy.

Table 7
The mean value of CMI values.

CMI location (Channel to Channel)	CMI values in HC subjects	CMI values in alcoholic subjects
FP2-AF2	0.2534 ± 0.0337	0.1850 ± 0.0313
*P*4-P8	0.2314 ± 0.0332	0.1811 ± 0.0357
P8-PO2	0.2213 ± 0.0318	0.1682 ± 0.0296
F7-F5	0.2392 ± 0.0449	0.1848 ± 0.0236
T7-C5	0.2080 ± 0.0256	0.1555 ± 0.0279
P5-P7	0.2983 ± 0.0310	0.2309 ± 0.0390
*P*6-P8	0.2845 ± 0.0295	0.2286 ± 0.0274

'ALC' is the alcoholic subject, 'HC' is the healthy control subject.

In particular, the 2D-CNN model achieved results of 86.25 ± 6.48 % in accuracy and 0.9249 ± 0.0378 F1-score of gamma band data which have better performance than other frequency bands. Based on the 2D-CNN results, a 3D-CNN was proposed to improve the detection results further and 96.25 ± 3.11 % accuracy and 0.9806 ± 0.0163 F1-score of all the testing subjects. Furthermore, we analysed the CMI values in the whole connectivity and found the most significant channels that can detect the fuzzy brain connectivities location of symptoms in alcoholism patients.

Table 8
Comparison of the proposed method and previous works in EEG alcoholism detection.

References	Channels	Features	Classifier	Acc (%)
Mumtaz et al. (2017) [11]	19	Coherence functional connectivity	Logistic regression	89.3
Goksen et al. (2017) [12]	19	Mutual information functional connectivity	KNN	82.33
Patidar, S., et al. (2017) [16]	64	Tunable-Q wavelet transform, centered correntropy	LS-SVM	97.02
Malar et al. (2020) [22]	64	Wavelet decomposition	Extreme learning machine	87.6
Farsi et al. (2020) [15]	64	EEG signal	LSTM	93
Agarwal, S. and M. Zubair (2021) [17]	64	S-SSA, ICA	XGBoost classifier	98.97
Mukhtar, H., S.M. Qaisar, and A. Zaguia (2021) [20]	64	Normalized EEG signal	CNN	98
Khan et al. (2021) [19]	6	Effective connectivity (DMN)	3D-CNN	87.85 ± 4.64
Kumari, N et al. (2022) [23]	19	Raw EEG signal	CNN	92.7
Li, H. and Wu, Lei (2022) [24]	64	Discrete Wavelet Transformation	CNN, Bi-LSTM	99.32
Proposed method	64	Cross mutual information functional connectivity	3D-CNN	96.25 ± 3.11

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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