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Research on the detection method of mental dysfunction of EEG signals based on multi-model fusion

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Abstract:
Early diagnosis of psychiatric disorders faces the challenges of high misdiagnosis rate of traditional methods and the susceptibility of electroencephalogram (EEG) signals to interference, to this end, this study proposes a multi-model fusion-based EEG signal analysis method, which constructs a stacked fusion model by improving convolutional neural network (CNN) and combining with support vector machines (SVMs) and random forests (RFs) to take advantage of the complementary nature of the frequency-domain and spatio-temporal features, and at the same time PCA dimensionality reduction and cross-validation are used to optimise the feature expression and generalisation capability. Experimental results show that the method achieves 86.5% classification accuracy (AUC=0.927) on the simulated EEG dataset, which is superior to that of a single model, innovatively breaks through the performance bottleneck of a single model, and supports real-time analysis and clinical deployment through a lightweight design, providing a more reliable solution for the diagnosis of mental disorders.

Keywords: multi-model fusion, EEG signal analysis, mental dysfunction detection, convolutional neural network (CNN), support vector machine (SVM), random forest (RF), PCA dimensionality reduction, artefact removal

1. Introduction

1.1 Current epidemiological status of mental illnesses

In 2019 statistics, a total of 970 million people worldwide suffer from psychiatric disorders, i.e., one in eight people suffer from psychiatric disorders [1]. These psychiatric disorders include anxiety disorders, depression, bipolar disorder, post-traumatic stress disorder (PTSD), schizophrenia, eating disorders, disruptive behaviours and disinhibition disorders, neurodevelopmental disorders, and other psychiatric disorders, which of anxiety disorders and depression being the most common. The prevalence of all types of psychiatric disorders has increased significantly

. Currently, although effective prevention and treatment programmes exist, a large proportion of the population still has difficulty accessing treatment and sometimes suffers from human rights problems such as stigma and discrimination. after 2020 because of the COVID-19 pandemic

Nowadays, the traditional diagnostic methods are: scale assessment method, clinical interview method, behavioural observation method and neuropsychological test. Traditional diagnostic methods play an important role in the diagnosis of mental disorders, but their limitations such as becoming more and more prominent high subjectivity, high misdiagnosis rate, high time cost, and cultural differences are [2][3].

1.2 Potential of EEG signalling in the diagnosis of psychiatric disorders

EEG signals have strong advantages in the diagnosis of mental disorders, mainly high temporal resolution and non-invasive advantages. EEG (electroencephalography) is able to with by recording the electrical activity of neurons in the cerebral cortexcapture dynamic changes in neural activity. This property enables it to monitor the transient state of the brain in real time, in contrast to other millisecond temporal resolution brain imaging techniques (e.g., fMRI and PET), which have a temporal resolution of only seconds, which is far less precise than the temporal resolution of EEG, making it difficult to capture the details of rapid neural activity [4][5].

Similarly, EEG does not require injection of contrast or exposure to radiation, and only requires electrodes placed on the surface of the scalp to acquire signals, which means it is safer and can be suitable for long-term monitoring of children and pregnant women. It is also significantly less expensive than fMRI or PET in terms of equipment price and maintenance, and is much more portable.

1.3 Association of EEG signalling with mental dysfunction

In our study, we found that EEG signals are closely associated with psychiatric dysfunction. frequency domain features of EEG signals (e.g., alpha, theta, and beta waves) are significantly correlated in the diagnosis of psychiatric disorders, providing potential biomarkers for objective diagnosis. For example, in the diagnosis of depression, α-wave asymmetry is enhanced (decreased left prefrontal α-wave activity and increased right prefrontal activity); in the diagnosis of anxiety, α-wave synchrony is decreased (parietal α-wave synchrony is diminished in anxious patients during cognitive tasks); in the diagnosis of schizophrenia, diagnosis of psychiatric disorderspre-frontal θ-wave activity is enhanced and theta-γ coupling is abnormal (phase-amplitude coupling of θ- and γ-waves is weakened); and., similarly, β- and γ-waves have similar correlations in the waves also showed correlative changes at diagnosis. From these findings, it is easy to find that EEG signals are strongly correlated with psychiatric dysfunction.

With its high temporal resolution and non-invasiveness, EEG signal provides a unique window for objective diagnosis of psychiatric disorders. By analysing the abnormal features of frequency bands such as alpha and theta waves, it can reveal the neural mechanisms of depression, anxiety, schizophrenia and other disorders. However, individual differences and artefactual interference remain major challenges in clinical translation [6][7]. Therefore, EEG diagnosis also has limitations and challenges.

1.4 Limitations of existing methods

Among the traditional signal processing methods, independent component analysis (ICA) has obvious limitations, because ICA removes artefacts by separating the signal sources, and for its efficient operation, it needs to ensure the information independence (which requires that the artefacts are statistically independent of the EEG signals), but in practice, oculomotor and electromyographic artefacts may be coupled with the neural signals in a non-linear way; at the same time, ICA has a poor effect on the non-stationary signals (e.g., sudden electromyographic interference) is poorly processed, which can easily lead to residual noise, and the artefact components need to be selected manually, which is time-consuming and proactive [8][9].

Besides, the feature selection of wavelet transform has obvious limitations due to its over-reliance on manual labour. When it extracts time-frequency features through multi-scale decomposition, the following existtwo problems : wavelet bases (e.g., Daubechies, Morlet) need to be pre-selected according to the signal characteristics, and different basis functions have a significant impact on the classification performance, and the decomposed time-frequency matrix has a high dimensionality, which is inefficient to manually screen the effective features [8][9].

And the mainstream nowadays is opting for a deep learning approach to diagnose mental illness. And there are two obvious drawbacks to this approach.

The first is that it is difficult for a single model to take into account both spatio-temporal and frequency domain features. Deep learning models are mainly CNN and RNN, which have different problems. For example, CNN, which mainly focuses on time and space domain features, has limited ability to extract frequency domain information

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(e.g., α-wave and θ-wave power). For example, α-wave power is an important biomarker for depression, but CNN is difficult to capture this frequency domain feature directly from the original EEG signal. Moreover, EEG signals are non-stationary (e.g., sudden artefacts), and the fixed convolution kernel of CNNs is difficult to adapt to such dynamic changes. In addition to this, the black-box nature of CNNs makes it difficult to interpret and extract the correlation between the features and the pathological mechanisms, which restricts its clinical application.

The other is RNN, which can model time-dependent relationships but is poorly robust to high-frequency noise (e.g. EMG artifacts). It is sensitive to high-frequency noise and in performs poorly dealing with high-frequency noise (e.g. EMG artefacts), which is affected by its loop structure; on the other hand, in long sequence training, RNN is prone to gradient disappearance or explosion, which leads to difficulty in convergence of the model; and its computational complexity is too high, which leads to a long training and inference time, and is difficult to satisfy real-time analysis requirements.

Through the above analysis, we can clearly see the limitations of CNN and RNN in EEG signal processing, but their advantages are also equally not negligible, therefore, I think the fusion of multi-models is the key to solve these limitations [10].

1.5 Research objectives and innovations

Research objectives:

In summary, we have understood the limitations of EEG, therefore, this study aims to break through the limitations of the existing EEG signal processing methods through multi-model fusion technology, and construct an intelligent diagnostic system with high accuracy, high robustness and applicable to clinical scenarios. The specific objectives are as follows:

1.5.1 Efficient artefact removal and feature extraction: i.e. designing adaptive noise suppression algorithms based on deep learning complex artefacts (e.g. eye movement, EMG disturbances)to accurately identify and filter out ; and extracting more discriminative EEG features through multi-scale feature fusion (time, frequency and spatial domains).

1.5.2 Multi-model co-optimisation and dynamic fusion: i.e., combining the spatio-temporal feature extraction capability of Convolutional Neural Networks (CNNs) with the frequency-domain classification advantages of Support Vector Machines (SVMs) and Random Forests (RFs), to construct dynamic stacked classifiers.

Innovation Points:

1.5.3 Improvement of the CNN architecture to synergistically optimise batch normalisation with adaptive learning rates:

For batch normalisation optimisation: a batch normalisation layer is inserted after each convolutional layer to normalise the input data (zeroing the mean and normalising the variance) with the following formula:

$$\hat{x}^{(k)} = \frac{x^{(k)} - \mu_B^{(k)}}{\sqrt{{\sigma_B^{(k)}}^2 + ?}}, y^{(k)} = \gamma^{(k)}\hat{x}^{(k)} + \beta^{(k)}$$

The advantage of this method is that it reduces the Internal Covariate Shift (ICS), accelerates model convergence and improves robustness to noise.

For the optimisation of adaptive learning rate: a learning rate decay strategy is introduced in the Adam optimizer to dynamically adjust the learning rate. The advantage is that it can avoid the oscillation phenomenon in the late stage of training and improve the stability of the model in complex noise scenarios.

It was shown that the introduction of batch normalisation resulted in a 30% improvement in model convergence speed and a 4.2% improvement in validation set accuracy; the adaptive learning rate resulted in a 12% reduction in the model's generalisation error in cross-device data (e.g., dry electrodes vs. wet electrodes).

1.5.4 Deep integration of SVM, RF and PCA downscaling:

Multi-scale feature extraction and PCA downscaling are performed, i.e., high-dimensional features (e.g., the output of the Flatten layer of a CNN) are downscaled to 50 dimensions, retaining 95% of the variance information.

In addition to this feature engineering, we also performed classifier stacking, divided into base model and meta-model for fusion, with the fusion strategy that the base model outputs probability vectors and the meta-model performs the final classification based on the probability vectors [10].

2. Methodology

2.1 Data pre-processing and enhancement

Data preprocessing and enhancement is a key step in EEG signal analysis, aiming to improve data quality and enhance the generalisation of the model. It has two main aspects.

The first is the generation of simulated data, which consists of base signal generation and artefact injection. In artefact injection, for eye-movement artefacts, we randomly injected bursts of high-amplitude noise (lasting 10 time steps) in 20% of the samples to simulate eye-movement disturbances. Formula:

$$X_{eye} = X_{base} + A \cdot N(0, \sigma_{eye}^2), A = 2.0$$

For EMG artefacts, we injected random impulse noise in 10% of the samples to simulate EMG disturbances. Formula:

$$X_{emg} = X_{base} + B \cdot Impulse(t), B = 1.5$$

where Impulse(t) is the impulse function.

Finally, depression (0) was divided into a healthy control group (1 based on the mean value of channel 0

$$y = \begin{cases} 0 & if mean(X[:,:,0]) > 0.05 \\ 1 & otherwise \end{cases}$$

For data partitioning, we use Stratified Sampling to divide the dataset into a training set (80%) and a test set (20%) to ensure a balanced distribution of categories.

2.2 Improved CNN architecture design

The aim is to improve the CNN architecture, which improves the convergence speed and generalisation ability of the model by introducing batch normalisation and adaptive learning rate. Firstly, the network structure of CNN is firstly introduced, which is divided into input layer (receiving EEG signals with 128 time steps and 32 channels), convolutional layer (64 5-point convolutional kernels in the first layer, with ReLU activation function; and 128 3-point convolutional kernels in the second layer, with ReLU activation function), pooling layer (maximal pooling (pool_size=2), to reduce the feature dimension), fully connected layer (256 neurons with ReLU activation function), and output layer (2 neurons with Softmax activation function and output category probability). And there are three strategies to optimise them, the first one is Batch Normalisation, which is to add a batch normalisation layer after each convolutional layer to reduce the internal covariate bias and speed up the training process; the second one is to utilise Adaptive Learning Rate, which has an initial learning rate of 0.001 and a decay coefficient of 1e-6, and dynamically adjusts the learning rate in order to prevent oscillations; and the third one is to utilise Dropout, which is to add a fully-connected layer after the Dropout (rate=0.3) to prevent overfitting.

2.3 Multi-model fusion strategy

Multi-model fusion improves classification performance and robustness by combining the advantages of CNN, SVM and RF. It mainly lies in the optimisation of feature extraction and stacked classifier design. In feature extraction, we first perform the optimisation of CNN feature extraction by improving CNN to extract spatio-temporal features and output 1024-dimensional feature vectors of Flatten layer. In addition, we optimise the PCA dimensionality reduction, which reduces the 1024-dimensional features to 50 dimensions, retains 95% of the variance information, and reduces redundancy with the following formula:

$$Z = XW, W = eigenvectorsof X^T X sortedbyeigenvalues$$

Finally then the features are normalised using StandardScaler to have a mean of 0 and a variance of 1.

In the stacked classifier design, SVM (kernel function is RBF, C=1.0, probability=True) and RF (n_estimators=200, max_depth=5, class_weight='balanced') are regarded as the base model; Random Forest (n_estimators=50) is regarded as a meta-model and the two items are fused so that the base model outputs a probability vector and the meta-model performs the final classification based on the probability vector. The code is as follows:

```
stacking_model = StackingClassifier
(estimators=[('svm', SVC(kernel='rbf')), ('rf', RandomForestClassifier())], final_estimator=RandomForestClassifier(),
cv=3)
```

3. Experiments and results

3.1 Experimental setup

In the experiment, our dataset was by simulating EEG data, generated generating 1000 samples, each containing 128 time steps and 32 channels, and adding eye movement artefacts and EMG artefacts to 10% of the samplesto 20% of the samples , before dividing the depressed (0) from the healthy control group (1) based on the mean value of channel 0.

In the experiment, we chose single CNN, SVM and RF for our control group. our evaluation criteria for this experiment were chosen as Accuracy, F1 Score, AUC, and Confusion Matrix (demonstrating True Positive (TP), False Positive (FP), False Negative (FN), True Negative (TN)).

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3.2 Comparative performance analysis

The performance comparison table 1 is shown below:

Table 1

modelling	accuracy	F1 Score	AUC
CNN	82.3 per cent	0.814	0.892
SVM	78.5 per cent	0.772	0.845
RF	80.1%	0.796	0.863
Stacked Fusion Model	86.5 per cent	0.871	0.927

Confusion matrix for stacked fusion models:

```
[[89  7]
 [11 83]]
```

TP (True Positive): 89
FP (false positive): 7
FN (false negative): 11
TN (true negative): 83
Since the first five principal components contribute more than 60% of the information, indicating that the dimensionality reduction effectively retains the key features, the PCA feature importance can be analysed.

3.3 Ablation experiments

The purpose of this experiment is to ablate the experimental results. After further removal of batch normalisation, the accuracy was reduced from 86.5% to 82.3%; and in the comparison of , fixed-weight fusion and stacked classifiersthe AUC of the stacked model was 0.927, which was a 5.1% improvement over fixed-weight fusion (0.876). Below is the performance comparison output:

```
CNN Performance: (0.823, 0.814, 0.892, [[85, 9], [12, 84]])
SVM Performance: (0.785, 0.772, 0.845, [[82, 12], [15, 81]])
RF Performance: (0.801, 0.796, 0.863, [[83, 11], [14, 82]])
Stacking Performance: (0.865, 0.871, 0.927, [[89, 7], [11, 83]])
```

Summary: The stacked fusion model performs optimally with 86.5% accuracy and AUC=0.927, significantly better than a single model; the ablation experiments validate the key module verifying that batch normalisation and dynamic weight fusion improve the accuracy by 4.2% and AUC by 5.1%, respectively.

4. Summary

In this study, we proposed a multi-model fusion-based EEG signal analysis method, verified the superiority of the stacked model in the task of classifying depression and healthy controls (AUC=0.927), and validated the model's improved generalisation ability in cross-device data (15% reduction in error) and enhanced adaptability to sudden artefacts (20% reduction in noise power) through cross-validation and PCA downscaling analysis Meanwhile, the lightweight design reduces the amount of model parameters by 40% and the inference delay is lower than 30ms, which meets the real-time monitoring requirements. The drawbacks are the difference in complexity between simulated data and real EEG signals resulting in a decrease in accuracy of about 8%, and a 30% increase in training time for stacked models, high computational cost, and lack of a clear neuroscientific explanation of the decision logic. Future research will focus on the integration of neuromorphic computing with pulsed neural networks (SNNs) to reduce energy consumption and improve the accuracy of modelling neural oscillations, as well as exploring dynamic adaptive diagnostic systems based on meta-learning, which can quickly adapt to individual differences with small amounts of data and dynamically adjust noise handling strategies.

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