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EEG Signal Classification and Feature Extraction Methods Based on Deep Learning: A Review

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***Abstract*—Electroencephalography (EEG), which tracks the brain waves that contain the brain's neural activity, plays an essential role in detecting human motion and treating neurological diseases. In the Artificial Intelligence (AI) era, deep learning algorithms are widely used in human action recognition and classification. Various convolutional neural networks that process this signal are also being born. This paper provides a detailed survey of the application of deep learning to EEG signals and outlines the research process when classifying EEG signals. At the same time, this paper reviews the relevant research on the classification of human action EEG signals in recent years. Human motion signals usually use different deep learning algorithms and convolutional neural network architectures in the EEG signal analysis task. This article will discuss the advantages and challenges of each method in other studies. Finally, the paper discusses future directions for deep learning-based EEG signal classification.**

Keywords- Electroencephalography; Feature extraction; Deep learning; Convolution neural network; Classification.

I. INTRODUCTION

Deep Learning (DL) networks have recently achieved significant breakthroughs in applications such as image recognition, text classification, audio conversion, and video processing. Electroencephalography (EEG) is an imaging technique that scans the brain's electrical activity to track the brain's neural activity and acquire relevant features [1, 2]. EEG signals are generally obtained by wearing special EEG acquisition equipment, such as EEG caps, that meet the standards of the International Leading Group [3, 4]. This method of collection is non-invasive and has no risks or limitations. Compared with the intrusive collection, its safety factor is higher [5]. Compared to electromyography (EMG) (used for muscle contraction), electrocardiogram (ECG) (used for heart waves), and electrooculogram (EOG) (used to record dipole fields in the eye), EEG provides a visual representation of the brain. The electrical activity has reasonable objectivity and explanatory character. Therefore, after the EEG data are decoded, it is more suitable for studying human cognitive tasks and human action detection, such as hand movement detection [6-9], spelling, and cursor control [10, 11]. At the same time, this research can allow people to understand the detected object's potential physical and psychological state, which plays a vital role in neurological disease treatment. Such as the detection of epilepsy patients [12, 13] and the rehabilitation treatment of Parkinson's patients [14, 15].

This paper surveys the literature of the past five years and introduces methods for EEG signal classification and feature extraction based on deep learning. At the same time, the technologies of different models are compared, and the relevant advantages and disadvantages are summarized. The paper concludes by addressing future research challenges for more accurate classification.

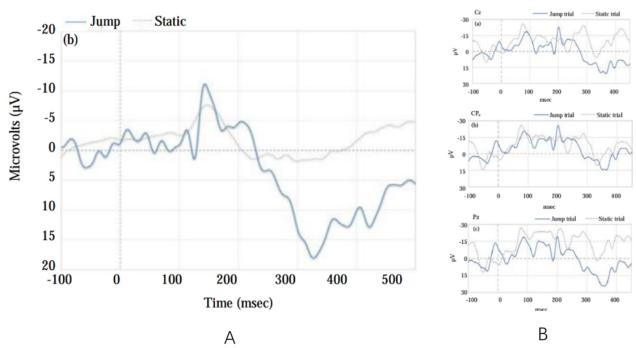

Figure 1 Some EEG features require mathematical superposition methods

II. METHOD AND ACHIEVEMENTS

The most critical part of the feature extraction and classification tasks of EEG signals is to build effective recognizers and classifiers. The recognizer needs to convert the input EEG signal accordingly for the classifier to recognize. The classifier takes the feature values as input and predicts the correct class. The essential features of EEG signals are time-domain features, frequency-domain features, features based on statistical superposition, etc.

Next, this paper will list some EEG signal feature extraction and classification models. These models have been screened in the past five years and are the mainstream models for EEG signal classification based on deep learning.

A. EEGNet

Brain-computer interfaces (BCIs) use the neural activity as control signals and can communicate directly with a computer. The neural signal is usually selected from various well-studied electroencephalogram (EEG) signals. In performing a detection task for a given BCI paradigm, feature extractors and classifiers typically need to be specially customized according to the characteristics of the actual EEG. Otherwise, it is difficult to limit the scope of their application to the signal under study. In previous studies on BCI, a BCI design can usually only solve a single-track BCI task and cannot be used for other BCI classifications. Therefore, the design and restrictions of architecture are traditionally extensive, and it isn't easy to promote. Based on the above difficulties, someone proposed EEGNet, a compact convolutional neural network. This model mainly encapsulates the feature extraction architecture of BCI. In the experimental session, they classified the collected data according to the experiments, including experiments within the same subject and experiments across multiple issues, and then compared EEGNet with the current state-of-the-art methods of several BCI paradigms: P300 visually evoked potentials, error-related negative responses (ERN), motor-related cortical potentials (MRCP), and sensorimotor rhythms (SMR). Due to the collection of EEG data sets, the data sets are usually small, and it is challenging to feed huge data for results. Experiments show that when the data set size is minimal, EEGNet can better obtain paradigm features, and its performance is not weaker than traditional models. This study also shows that EEGNet can be generalized to ERP and oscillation-based BCI. Afterward, they offer different ways to visualize the content of the trained EEGNet model, which helps a lot in obtaining interpretable features. It can be concluded that EEGNet is a powerful and efficient general-purpose BCI model that can learn corresponding interpretable features in a series of different BCI tasks. It also can be shown that the results are not affected to artifacts or sources of noise in the data [16].

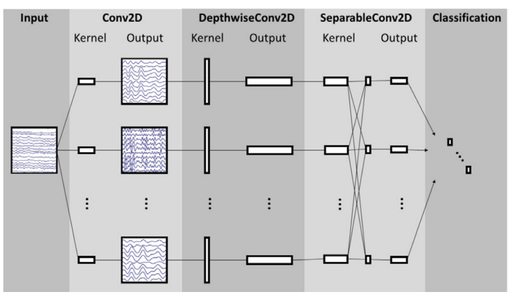

Figure 2 EEGNet Model Structure

B. LSDD-EEGNet

Depression is a mood disorder that negatively impacts people and is a significant health burden worldwide. But effective and low-cost depression detection remains a great challenge. EEG is one of the essential indicators for depression assessment so it can be used in the research of depression rehabilitation treatment. An efficient end-to-end framework named LSDD-EEGNet was proposed for EEG-based depression detection. It has two salient features in depression recognition: First, it considers the advantages of the Convolutional Neural Network (CNN) in feature extraction and the Long Short-Term Memory (LSTM) for time series signals. This model combines the two as the extractor of LSDD-EEGNet to extract EEG features. Second, a domain discriminator is used to modify the data representation space and eliminate the difference between training and testing datasets, which has achieved good results in classification experiments. In the experimental example, they evaluate the performance of the proposed deep framework for depression detection through the data of 80 volunteers. Of these 80 volunteers, 40 were EEG signals from depressed patients (DP), while the other half were EEG signals from healthy controls (HC). Compared with other typical models, LSDD-EEGNet achieves high performance on agent-independent evaluation. At the same time, the results show that LSDD-EEGNet is a promising method for depression detection [17].

C. TSGL-EEGNet

In addition to being applied to various classification tasks, extensive attempts have also been made in the brain-computer interface (BCI) field. Although the accuracy of detection tasks of deep learning-based motor imagery (MI) systems has been greatly improved compared with some traditional algorithms, clearly interpreting deep learning models remains a considerable challenge. To solve the above problems, they compared the EEGNet model. Experimental results show that the 1D convolution of EEGNet can be explained by a special Discrete Wavelet Transform (DWT). In contrast, the depthwise convolution of EEGNet is like the Common Spatial Pattern (CSP) algorithm. Therefore, they use the algorithm Temporal Constrained Sparse Group Lasso (TCSGL) to improve EEGNet to enhance its performance and propose a new model TSGL-EEGNet. The model is tested on the BCIC.IV.2a and BCIC.III.IIIa datasets, which are 4-category MI tasks. The test results show that the proposed model achieves an average classification accuracy of 78.96% and a kappa index of about 0.7194 on the dataset BCIC.IV.2a. This metric is higher than the results of previous models such as EEGNet, C2CM, FBCSP, MB3DCNN, and SS-MEMDBF, especially in insensitive classification topics. At the same time, the model also achieved an average classification accuracy of 85.30% and a kappa index of about 0.8040 on the BCIC.III.IIIa, which is higher than the experimental results of EEGNet, MFTFS, and other models. Finally, they use average validation and stacking to enhance the model further. In the BCIC.IV.2a and BCI C.III.IIIa datasets, the average accuracy of 4 classification tasks reached 81.34% and 88.89%, while the kappa index reached 0.7511 and 0.8519, respectively [18].

D. Q-EEGNet

The Moving Image Brain-Machine Interface (MIBMI) guarantees communication access between the human brain and machines by analyzing brain activity recorded using Electroencephalography (EEG). However, due to the high requirements of MIBMI for reliability, timeliness (delay), and privacy, it is not suitable to put the calculation of collected data into the cloud operation and return it when performing related signal processing. When used in a natural environment, installing the trained MIBMI into a wearable device is usually necessary. These devices are usually battery-powered and have a low average power consumption so that the device can be used effectively for a long time. In recent research, many complex algorithms for classifying EEG have emerged. Although MIBMI processing based on deep learning models can achieve high accuracy, these models tend to easily exceed the limits of devices due to their memory and computational requirements. They present the algorithm and implementation optimizations for EEGNet. First, they quantize weights and activations to 8-bit for hyperparameter configuration, an operation with negligible loss of accuracy of no more than

0.4% at level 4 MI. And demonstrated an energy-efficient hardware-aware implementation on a chip (SoC) on the Mr. Wolf PULP system, utilizing its custom RISC-V ISA extensions and 8-core computing cluster. The above optimization steps can achieve a 64x overall speedup and 85% reduction in memory footprint compared to the single-core layer-by-layer baseline implementation. At the same time, it takes only 5.82 milliseconds to implement a single task and only consumes 0.627mJ for each inference. With 21.0 GMAC/s/W, it is up to 256 times more energy efficient than the EEGNet [19].

E. S-EEGNet

Traditional models are difficult to capture the characteristics of EEG signals. Because EEG signals are more comprehensively from the time and space dimensions. It usually requires the average of time and space dimensions or compound extraction features. Therefore, a single feature extraction will specifically impact the accuracy of EEG classification. To solve the issue, they improve classification accuracy through end-to-end learning of EEG temporal and spatial dimensions. In this model, they propose a novel EEG classification network, Separable EEG Network, based on Hilbert-Huang Transform (HHT) and Separable Convolutional Neural Networks with Bilinear Interpolation (S-EEGNet). In this model, HHT first converts the EEG signal into a time-frequency representation so that EEG can get a better description in the time domain. Then, feature maps are extracted by combining the depth and point-wise elements of the network. Next, they need to use the separable structure of the CNN to add displacement variables to the convolutional layers of the separable CNN through bilinear interpolation, allowing the sampling grid to deform freely. To demonstrate the accuracy, they tested the model on three different types of EEG public datasets. One is a motor imagery signal dataset, and the other is a different emotion classification dataset. The results showed an accuracy rate of 77.9% in the motor imagery classification task. The accuracy of sentiment classification tasks reached 89.91% and 88.31%. Compared with the traditional model based on the same data set, the classification accuracy of S-EEGNet increased by 3.6%, 1.2%, and 1.3%, respectively [20].

F. NeuroGrasp

Designing MI-driven BCI systems relevant to achieving natural hand-grasping tasks is challenging due to the high complexity of BCIs. However, in the past, many related studies have successfully decoded the movement intention of various large body parts. However, MI decoding high-level and fine-grained motor behaviors, such as grasping, is crucial to extend the generality of MI-based BCIs further. Therefore, in this study, they proposed the NeuroGrasp model. NeuroGrasp is a two-stage DL framework that decodes and classifies multi-handed grasping tasks from EEG signals under the MI paradigm. The method effectively uses the learning of EEG and EMG, enabling EEG-based reasoning during the test phase. EMG guidance during model training helped the BCI more accurately predict the hand grasp type of motion based on the EEG signal. NeuroGrasp not only improves the performance of offline classification, but the online classification performance is also stable. They recruited 12 subjects who met the experimental requirements in the classification test task. They conducted data collection for four types of grasping tasks. Results show that the model achieves an average offline classification accuracy of 68% (±9%) in the data classification task. It performs a classification accuracy of 86% (±4%) for the two-grasp tasks. Furthermore, we achieve average online classification accuracies of 65% (±9%) and 79% (±9%) across six high-performance subjects. Therefore, this model can be concluded that the method can show stable classification performance whether it is evaluated online or offline [21].

G. TinySleepNet

The quality of human sleep is related to whether the EEG signal is standard. However, most existing models are overdesigned to consist of many layers, leading to overfitting the model. They need to be trained on large datasets to prevent overfitting problems. Some studies introduce additional steps and operations in the processing flow. But most sleep datasets contain a limited amount of class-imbalanced data. Based on the above reasons, it is tough to process sleep data sets, and applying them to general scenarios isn't easy. Therefore, they proposed an efficient deep learning model called TinySleepNet, a classification model based on raw single-channel EEG. Experimental results demonstrate that the proposed method is effective for end-to-end model training and automatic sleep stage scoring. Compared with the existing model, the model contains fewer training parameters and hyperparameters, so the model only needs less training data and computing resources, and the performance has been improved. The training technique also incorporates data augmentation processing, which can make the model's movement on the time axis more robust and prevent the model from remembering the order of sleep stages. This operation can effectively enhance the versatility of automatic sleep scoring. Evaluations of seven public sleep datasets found that these datasets performed well in terms of recording channels, and environments, and all obtained different interpretable features. TinySleepNet performs better, showing that the approach generalizes well to the most extensive datasets. The model also has greater possibilities for the research of general automatic sleep stage scoring mechanisms [22].

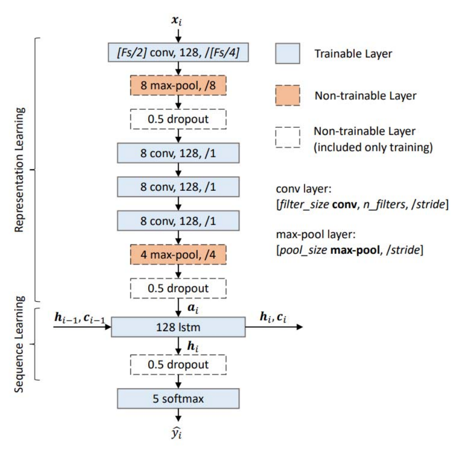

Figure 3 TinySleepNet Model Structure

III. Comparison and Discussion

The leading technologies and improvement effects of the above models are shown in Table 1.

Table 1 Model Comparison

Num.	**Models**		
	Model Name	***Applications***	***Results***
1	EEGNet	Depthwise and separable convolutions	AUC in Average: 90.54%
2	LSDD-EEGNet	LSTM and domain discriminator	ACC.:94.69% SPE.:97.55% SEN.:90.96% PRE.:94.39% F-S.:92.64%
3	TSGL-EEGNet	TCSGL	ACC.:78.96% (BCI IV 2a) ACC.:85.30% (BCI III 3a)
4	Q-EEGNet	Quantize weights and activations	64x overall speedup
5	S-EEGNet	Separable Convolutions and HHT transform	ACC.:77.90% (MI) ACC.:88.31% (Emotion)
6	NeuroGrasp	Two-stage deep learning framework	ACC.:86% (Offline) ACC.:79% (Online)
7	TinySleepNet	Representation Learning	ACC.87.5% MF1:83.2% K:0.82

The main classification methods of EEG are divided into four categories: linear method, neural network method, nearest neighbor method, and nonlinear Bayesian classification method. Most of the EEG classification are revolved around EEGNet, a compact neural network. At the same time, for different fields and paradigms, some specialized enhancement techniques are used to improve classification accuracy. The EEG signal research is very accurate and highly reliable.

IV. Conclusions

This paper introduces the classification method of EEG signal and feature extraction based on deep learning. At the same time, the mainstream models in the past five years are described in detail. With the development of Deep Learning, more excellent EEG classification frameworks will appear, the speed of classification tasks will be faster, and the results will be more accurate. However, the larger dataset required to learn various patterns is a challenge for deep learning methods. Multi-channel and real-time EEG signals can be incorporated into deep learning architectures for more applications.

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