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Applications of Deep Learning Models in Brain Signal Processing

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Abstract. Analyzing the underlying mechanisms of the brain is an ongoing challenge with extensive application prospects in the field of brain science. With the advancements achieved in computer science, researchers gained a deeper understanding of the function of brain signals via reinforcement learning and deep learning models on supercomputers. This paper focuses on deep learning methods designed for brain signal analysis, respectively discussing the applications of convolutional neural networks(CNNs), recurrent neural networks(RNNs), self-attention models and their mixtures in electroencephalogram(EEG), functional magnetic resonance imaging(fMRI), magnetoencephalogram(MEG), and functional near-infrared spectroscopy(fNIRS). The CNN models have widespread applications, especially in EEG, fMRI while RNN models have unique advantage at dealing with complex temporal data. Self-attention based large transformer models are the hotspots nowadays, general pretrained transformer models can effectively and efficiently handle most cases of brain signal analyzing tasks with enormous computing resources and achieve excellent results.

Keywords: Deep learning, brain signal analyzing, brain science, bionics

1. Introduction

The analyzing of brain signal has broad applications in the prediction and diagnosis of brain diseases, brain-computer interface(BCI) and so on, in the aspect of computing science, deeper analyzing of brain mechanism make sense in efficient and effective development of humanized LLMs. Due to the limitation of technical ethics, the mainstream methods of brain signal exporting are limited on EEG, fMRI, MEG and fNIRS. Although these methods reflect brain temporal and spatial variation of brain nervous reflex, the complexity of brain signal make it challenging to model by traditional mathematical methods. Yet now, combining chaos and complex brain signal to meaningful information via deep learning models become a hot topic with the advancements of computing devices and widespread adhibition of deep learning models.

Brain signal is formed by the activation of brain nerve cells, which keep highly packed information and complex topological structures. The analyzing of brain signal requires export brain information via hardware, commonly used techniques are EEG, fMRI, MEG and fNIRS. Those four methods are used in different application scenarios on account of different temporal and spatial resolution, cost and portability [1].

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Brain signal has the feature of high information density and dimension, non-linearity and non-derivability, which lead to traditional machine learning methods like principal component analysis, clustering analysis, support vector machine failure. At the aspect of neural computing, Hodgkin-Huxley model reflect the mechanism of those signals via octopus giant axons, interpret the character of membrane to a fifth-order differential equation circuit model, realizing non-linearity conductivity by voltage-gated ion channels, the leaky channel perform as linearity conductivity where efficiently handle with high-order differential equations by the employment of sodium and potassium ion channels [2].

During the rapid improvement of computing hardware, large amount of deep learning models have been proposed and widely used in different application environments. At the aspect of the function of modeling, deep learning models can be roughly classified to multi layer perceptron(MLP), convolutional neural networks(CNN), recurrent neural networks(RNN), graph neural network(GNN), and self attention based Transformer models which rose in recent years and used as backbones of large models. MLP models are build up by multi layers of approximate nerve cells and fully connected between layers, which is the simplified and static model of brain structure [3]. Inspired by the V1-V5 structure of visual nerves, researchers proposed CNN models, extracting image features by sliding convolutional kernel [4]. RNN models realize deeply control of the model by adding extra hidden nodes, which have superiority in processing sequential signal. To resolve the drifting convergence problem of basic RNN models, researchers proposed gated controlled RNN models like GRU, LSTM, these two models are wider used in application [5,6]. GNN models build calculation chart between nodes which is different from other models [7]. Transformer models calculate self attention marks to approximate probability distribution of feature, in that case, Transformer models have superiority advantage in feature fitting and global modeling, which is commonly used as backbones of generic large models [8,9]. In recent years, self attention models are widely employed in the fields of organic chemistry, biopharmacy, molecular protein prediction and brain signal analysis.

Deep learning models are also used in brain signal analysis. In this field, the CNN model EEGNet is a convolution-based model specially designed for EEG that accurately classifies EEG information after trained on datasets. The development of Transformers promotes the development of deep learning based brain signal analysis, with the process of pre-train and fine tuning, Transformer models can pre-trained on generic large datasets and fine tuning on specific direction, such as Transformer for fMRI(TFF), which can be transferred to sub-areas like specific analysis of mental illness after pre-trained and achieve state-of-the-art performance [10-12].

This article is focused on deep learning based brain signal analysis, discuss the advantages and limitations of different models by comparison, respectively analyze the performance of CNNs, RNNs, Transformers and their mixture models in different application scenes and input signals.

2. Convolutional Neural Networks in brain signal analysis

2.1. Convolutional Neural Networks in Electroencephalogram

Convolutional Neural Networks (CNNs) achieve excellent performance in Electroencephalogram(EEG) input, taking advantage of local modeling capability. EEG information maintains the feature of multiple channels and a sequential structure, which leads to heavy feature engineering in machine learning methods, as end-to-end models, CNNs can extract features automatically.

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EEGNet is a specially designed lightweight CNN model for EEG outputs, depth-wise convolution blocks are employed for efficient training with limited data [13]. EEGNet achieves high performance in ERN, MRCP, SMR that prove the model have generalization ability. However, consider the usage of depth-wise convolution blocks, though this design enhances the lightweight ability, the fitting ability of the model is also limited by the reduce of parameter quantity.

In the area of epilepsy detection, CNN models also make revolutionary achievements. P-1D-CNN, a 1-dim CNN model designed on the basis of a spatial feature pyramid, achieve 99.1±0.9% accuracy on the dataset of University of Bonn [14]. The novelty of this method is focused on reduce 60% parameters comparing with other traditional CNN models in the area, as well as reduce the difficulty of few-shot learning via data enhancement.

CNN models also make outstanding performance in the application of motor imagery, CNN models on the basis of data enhancement in time domain and frequency domain achieve 97.61% average classification accuracy on BCI IV Dataset2a [15]. The achievement made by this method is introduce parallel CNN structure and input raw EEG image with the result of the continuous wavelet transform of the raw image into the model to complement information in time domain the frequency domain. Though the result of the model is encouraging, consider the gap between information from the two domains, the model requre specially designed module to realize feature alignment.

CNN models on EEG also make breakthroughs in the recognition of emotion. SST-CRAM modeling 4-dim EEG feature map, with the usage of PSD and DE feature, achieve accurate recognition of emotion [16]. This model achieve 98.63% recall and 98.66% precision on DEAP dataset.

CNN models can accurately capture local correlation information by local sliding kernel and gradually obtain global features as the depth of layer increases. Most CNN like brain signal analysis models have a significant advantage in local information modeling. However, when the CNNs dealing with signals containing temporal features, these models usually lack use of temporal feature due to the limitation of model structure.

2.2. Convolutional Neural Networks in fMRI

3D-CNN models make breakthrough progress in clinical diagnosis of brain tumor, this system not only grades tumors, but also recognize the hypotype of tumors. In the task of predicting childhood irritability and brain region localization, 3D-CNN models make excellent performance [17]. Researchers fuse 3D convolution blocks to ConvNext model to realize direct processing of raw information of fMRI without compression. After feature extraction, the model usage regression activation mapping to generate a significance heat map to accurately localize the problem area. The model has been applied on fMRI output of 6065 adolescents, the MSE index of the prediction is only 1.82.

3. Recurrent Neural Networks and the variant in brain signal processing

3.1. GRU, LSTM in brain signal modeling

Long Short Term Memory(LSTM) as a variant of RNN, addressing the vanishing gradient problem of traditional RNNs by introducing gating mechanism, it demonstrates unique advantages when processing brain signals with long-term dependencies. The core innovation of LSTM lies in the fact that memory units can selectively store, update and forget information, which is similar to the

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mechanism of brain processing. The Gated Recurrent Unit(GRU) is a simplified version of LSTM with higher computational efficiency.

LSTM and GRU based models make outstanding performance in recognition and classification of emotion on EEG output. On DEAP dataset, LSTM model achieve 82.11% recall and 91.07% precision [18]. In the application of brain-computer interface(BCI), LSTM models are widely used in decoding of intention of movement. Signals of motor imagery maintain prominent sequential feature, during the image of movement, brain signal experience preparing phase, executing phase and recovery phase, LSTM models can acutely capture those variations to realize classification tasks of motor imagery.

3.2. CNN-RNN mixture architecture in brain signal processing

CNN-RNN mixture architecture with the spatial feature capturing capability of CNN and the sequential modeling capability of RNN, has strong competitiveness in analyzing of multi-channel EEG and dynamic fMRI. In the task of emotion recognition, 1D CNN+LSTM structure was designed to trained and validated on DEAP dataset and achieve 90-95% of accuracy [19]. This model captures local information of EEG output by using a 1D CNN, such as energy variation in a particular frequency, while the LSTM layer due with the relationships in the temporal domain to capture the transformation of emotion in temporal domain.

In the task of motor imagery, CNN-GRU and CNN-Bi-GRU models were proposed and trained on PhysioNet dataset that achieve 99.71% accuracy on left hand motor imagery, 99.73% on right hand, 99.61% on both hands, and 99.86% on two foots [20].

Compared with individual CNN or RNN models, the CNN-RNN hybrid framework can effectively utilize the detail feature extraction ability from CNN and the time series signal modeling capability from RNN. Though those models achieve eye-catching results, since those models employ two different modules to extract features separately, it usually require greater computing support with extra feature alignment.

4. Transformer in brain signal analysis

4.1. Applications of the Transformer in multi-modal brain signal analysis

The Transformer architecture, with its unique advantage of a self-attention mechanism in capturing long-term dependencies, can process sequential data in parallel and model global dependencies through the self-attention mechanism. Researchers developed Transformer based models for brain signal processing [21], the input data of the model is a combination of MEG and fMRI output, the model is designed to estimate the cortical source response with high spatial and temporal resolution. Traditional methods for source direction require processing MEG and fMRI information respectively and fuse by specially designed algorithms, which are jointly trained in Transformer models directly. Take the advantage of this advancement, Transformers can deeply discover inner connections of different inputs and automatically align features.

In fMRI analysis, Transformer for fMRI(TFF) illustrate potential of Transformers in brain signal analysis with single modality [22]. This model adopts the pre-training and fine-tuning method commonly used for large models that firstly unsupervisedly train on fMRI datasets to reconstruct 3D information, and then fine-tune on specific tasks. This training strategy takes full advantage of an enormous amount of fMRI data without labels, avoiding the difficulty of handcraft labeling for large amount of data for pre-training, the pre-training stage remarkably enhances the performance and

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generalization ability of the model in sub-tasks. Whether in the tasks of age and gender prediction or diagnosing of schizophrenia, the TFF architecture achieves SOTA performance.

4.2. Transformer mixture structures in brain signal analysis

Although Transformer models achieve surprisingly good results in various tasks with the employment of a huge quantity of parameters and enormous training data, there are still some sore points exist such as distraction and the ignoring of attention in local relationships and computing requirements. The integration of Transformer with other deep learning models has given rise to many innovative architectures, and these hybrid models have made breakthroughs in brain signal analysis. In multi-modal Brain Tumor Segmentation, Transformer-based Brain Tumor Segmentation) demonstrates the power of the CNN-Transformer hybrid architecture [23]. This architecture effectively fuses 3D-CNN blocks into Transformer models to segment multi-modality MRI brain tumor images. Traditional 3D CNNs are less efficient when dealing with large-scale features, while the global receptive field of the Transformer can capture the overall structural information of tumors. By inserting 3D CNN blocks into Transformer, the model achieves joint modeling of local details and global structure. TransBTS achieves SOTA performance on the BraTS2020 dataset. The combination of 3D CNN and Transformer in the prediction of cerebral hemorrhage has created a new direction. The hybrid model proposed by researchers effectively predicts the treatment methods for patients with cerebral hemorrhage by using CT images and clinical data at admission.

5. Conclusion

This paper analyzes the analysis and application of different deep learning models for various types of brain signals, as well as the latest progress, and demonstrates the application of CNN, RNN, Transformer and their hybrid models in processing brain signals. Whether in the analysis of brain signal meaning, the diagnosis and treatment of mental disorders, emotion recognition, or brain-computer interfaces and other directions, deep learning has played an important promoting role.

However, at present, large models still have a generational gap in technology compared with the human brain, mainly reflected in significant design flaws in the energy efficiency, memory mechanism, fitting ability, learning mode and dynamic topological ability of artificial intelligence. At its core, modern artificial intelligence is an extension of computer applications under the Feng architecture and a one-sided and violent approach to the brain's thinking patterns. Affected by semiconductor technology, it is difficult to achieve efficient STDP learning through synapses like nerve cells do. Due to the limitations of the memory wall, the model must adopt a hierarchical architecture for batch processing to achieve efficient computing on the computer. Although algorithms are sharing the dividends of hardware breakthroughs, algorithms and hardware complement each other. A new generation of brain-inspired computing chips is being developed in cutting-edge laboratories. Analyzing complex brain signals with artificial intelligence technology is the key to designing AI with computing principles and behavioral patterns that are more "human-like", and it is also the core of the third-generation AI spiketed neural network (SNN), which is still in the conceptual stage. In the future, as the energy efficiency ratio of modern large models approaches its limit for AI technology, analyzing the principles of brain signals and applying them to AI development is likely to be an important technical node on the road to exploring intelligence. And more powerful, more effective and more in line with human behavioral standards and needs, artificial intelligence will also have a broader and deeper impact on scientific research work and life.

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