Deep Learning Methods for EEG Applications: Focusing on CNN and RNN

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Abstract. In the field of neuroscience, the electroencephalogram (EEG) study aims to discover patterns of various human brain activities in an efficient and accurate manner, which plays an important role in treating brain diseases and other fields. The emergence and development of deep learning networks bring end-to-end approaches towards processing and classifying human brain signals. In the first section of the study, two typical networks used in EEG applications—the convolutional neural network (CNN) and the recurrent neural network (RNN)—are introduced, then the study measures the performance of each network in relation to their specific characteristics in temporal and spatial domain respectively and analyzes how noise and other interference towards EEG signals affect the training of the two networks. To make an integral view of how to take advantage of both networks mentioned above for EEG applications, the paper finally introduces a general system framework using a combination of CNN and RNN. This study will bring important value to the research and application of deep learning methods for EEG applications.

Keywords: Deep Learning; Electroencephalogram; Neural Networks.

1. Introduction

To analyze and interpret signals from the brain, different methods are available, including functional near-infrared spectroscopy, functional magnetic resonance imaging, EEG and more. Among them, due to its non-invasiveness, accessibility, low cost, and great temporal resolution [1], EEG has been widely acknowledged as a standard technique for capturing human brain activity, represented as electrical signals over time. The physiological and pathological states of a person can be accurately represented by brain-derived EEG waves [2]. Even though EEG signal is a useful source of information obtained from the human's brain's activities, it is also noisy, complex, and variable. With many channels, frequency bands, time segments, and spatial locations, to lower the computational complexity and escape the restriction of dimensionality, approaches for dimensionality reduction are needed for raw EEG data [3]. Therefore, it is challenging to process and analyze EEG signal using traditional methods that rely on hand-crafted features and simple classifiers. Deep learning is a powerful technique that automatically learns detailed features from raw data and performs complex tasks such as classification, regression, generation, and more. Deep learning can handle high-dimensional and non-linear EEG data in a holistic way without requiring a manual feature extraction process or sacrificing important information. Deep learning has been used to a variety of EEG signal processing issues, including cognitive analysis, neurological illnesses, and brain-computer interface (BCI). For instance, Marleen C. Tjepkema-Cloostermans and Rafael C.V. de Carvalho [4] showed that by combining several convolutional and recurrent neural network architectures, deep neural networks are capable of reliably detecting epileptiform discharges from scalp EEG data. Navneet Tibrewal and Nikki Leeuwis [5] utilized comparison experiments to prove that employment of deep learning models on EEG signal classification for motor imagery BCI systems is promising, especially for users who struggle with BCI and cannot generate the required sensorimotor patterns for traditional methods. Until now, there have been many deep learning methods applicable to EEG signals, and each method has a different impact on classification and other tasks. Therefore, comparing different deep learning methods for specific EEG applications is helpful.

This study focuses on the characteristics of CNN and RNN used for EEG signals. After respectively reviewing this two networks' applications in the field of EEG, this study compares the performance of each deep learning network based on their own characteristics in temporal and spatial domain respectively, along with analyzing the impact brought by noise and some other interference on the training process of CNN and RNN. Finally, in order to make an integral view of how to take advantage of the two networks for EEG applications, this study proposes a general system framework for the EEG application system using a combination of CNN and RNN.

2. Deep Learning Networks

2.1. Convolutional Neural Network

Multiple layers that perform various operations on the input data, such as convolution, pooling, activation, normalization, and fully connected layers, make up a CNN. Figure 1 shows a common CNN structure used for EEG signal analysis.

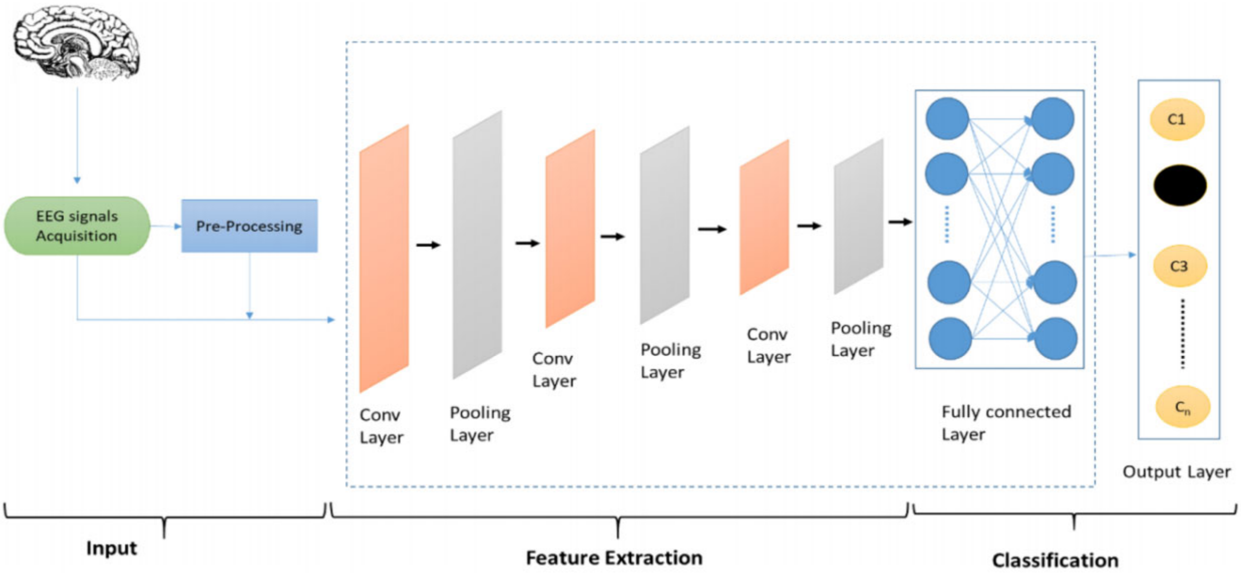

Fig. 1 A common CNN structure used for EEG signal analysis [6]

CNNs are widely used for EEG signal analysis because they can extract local and global features from the EEG signal using convolutional filters and pooling layers. Convolutional layers are trainable parameters that slide over the input data and produce feature maps that capture the EEG signal's spatial and temporal features. By using a function, such max, average, or min, to a section of the feature map, pooling layers are used to minimize the dimensionality and perplexity of the feature maps. All the neurons in one layer are connected to all the neurons in the next layer through fully connected layers, which carry out the network's final duty, such as classification or regression. CNN also has multiple hidden layers in convolutional layers, such as activation and normalization layers. Activation layers are used to introduce non-linearity to the network by applying a function, such as sigmoid, tanh, or ReLU, to each element of the feature map. Normalization layers are used to improve the network's stability and performance by adjusting the feature map's mean and variance.

In epilepsy research, CNN is often used as an effective approach for EEG signal analysis.

From the research by Mengni Zhou and Cheng Tian [7], a technique for identifying epileptic seizures using EEG signals and CNN was presented. To detect epileptic seizures, the study used a CNN method that did not use manual feature extraction, but learned directly from raw EEG signals, to classify EEG signals into three segments: ictal, preictal, and interictal. The Freiburg intracranial and the CHB-MIT scalp EEG databases were used in the study to evaluate the efficacy of time and frequency domain signals for epileptic signal detection. Additionally, the study conducted three different types of experiments—two binary classification issues and one three-class problem—to test this methodology. The findings demonstrated that for all three tests, frequency domain signals outperformed time domain signals in terms of average accuracy. The results showed that frequency domain signals could effectively classify the three segments for all patients, while time domain signals could only do so for some patients. Therefore, as to EEG signal classification, the study found that frequency domain signals were more appropriate for CNN models than time domain signals.

Besides that, it was also observed by the authors that training the model with the original signal as the data resulted in considerable differences in average accuracy between the two sets of data. A plausible reason is that intracranial signals with a low amount of artifacts and a high SNR were in the Freiburg database, while the other database had more interference and noise that could affect the quality of feature extraction [8]. This study shows that CNN is rather sensitive to the quality of the signals to be processed, which can influence the accuracy to a great extent.

As to these characteristics mentioned, several possible reasons exist to further explain them.

(a)Time domain signals and frequency domain signals reflect the different dimensions and characteristics of EEG signals. Time domain signals focus on the variation of EEG amplitude over time, while frequency domain signals focus on the energy distribution of EEG at various frequencies. CNN, as a method of finding local features based on space or time, may have more sensitivity to information from frequency domain, since the information can better describe the rhythm and spectrum of EEG signals.

(b)Noise and interference cause different effects on signals in different domains. In the time domain, signals are more susceptible to noise and interference, while filtering and other methods can remove frequency domain signals. As a data-driven method, CNN may be more sensitive to noise and interference, as they can affect CNN's learning and generalization abilities.

Time and frequency domain signals have different data volume and dimension requirements. Time domain signals require more data volume and dimension to ensure information integrity, while frequency domain signals can reduce data volume and dimension through dimensionality reduction. As a deep learning method, CNN may have different requirements for data volume and dimension, as they can affect the training speed and effectiveness of CNN.

2.2. Recurrent Neural Network

According to the idea that memories and previous experiences are crucial for human cognition, unlike CNN, an RNN is a special neural network that takes into account both the input from the previous moment and a maintaining function towards the former content. As a result of nodes connecting the hidden layers, the network stores the past data and uses it to compute the current output. The hidden layer's input consists of both the output from the input layer and the output from the preceding hidden layer. Figure 2 shows a basic RNN network structure.

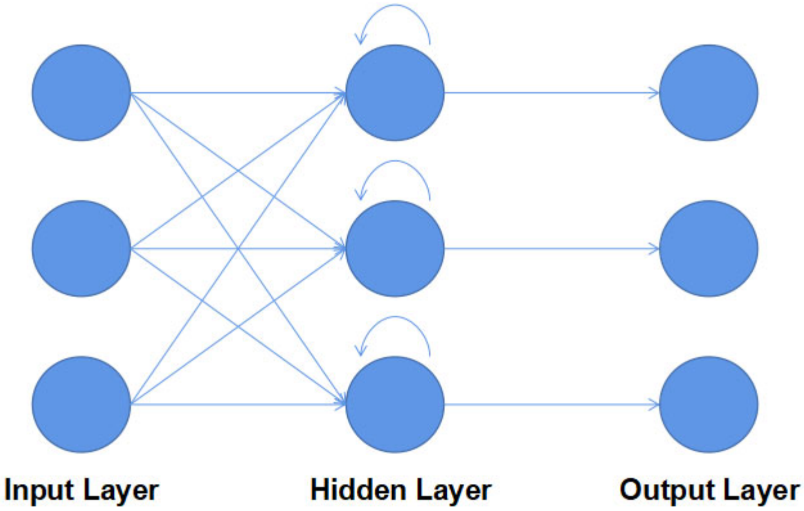

Fig. 2 A basic RNN network structure (original)

Videos, documents, and signals are examples of sequential datasets. These datasets have various properties, such as vast duration and variability, that make it difficult for a straightforward deep-learning model to interpret. [9]. RNNs are common for analyzing EEG signals because they can model the temporal dynamics of the EEG signal using recurrent units that store information from previous time steps. Recurrent units are trainable parameters that update their state based on the current and previous input. They come in a variety of forms, including the basic RNN, LSTM, and GRU. LSTM and GRU are designed to overcome the problem of vanishing or exploding gradients that affect simple RNNs by using gates to control the information flow in and out of the state [10].

In recent years, RNN has been used to find brain anomalies that indicate schizophrenia. From the research by Rinku Supakar and Parthasarathi Satvaya [11], a method for detecting schizophrenia from EEG data using RNN-LSTM was suggested. To look into the EEG signal data and detect schizophrenia, the authors suggested a deep learning model that relies on RNN-LSTM, as deep learning can automatically learn the important features and make classifications. Three dense layers on a 100-dimensional LSTM made up the model which was proposed. The improved network could better train the models than traditional RNN because it had the ability to maintain the input data longer. An optimal feature set was obtained by using a dimensionality reduction algorithm in the study. The full and reduced feature sets achieved accuracies of 98% and 93.67% respectively. To test the model’s robustness, the measure of the combined performance and the measure of the model performance were used. The model outperformed more established machine learning methods with the entire dataset, including Random Forest, SVM, FURIA, and AdaBoost. The model also matched or exceeded the accuracy of other researchers who employed either CNN or RNN with the same data. According to the authors' work, RNN shows some characteristics different from CNN.

(a)RNN can use its recurrent structure and hidden state to capture the temporal features and dynamic changes of EEG signals, thereby improving the performance of classification or regression.

(b)RNN avoids dimensionality reduction by merging LSTM. The spatial information that it receives from the brain, however, cannot be retained by such an architecture since it only functions efficiently with vectorized input.

(c)For training, RNN needs a significant volume of EEG data of the highest caliber. Noise, artifacts, and individual differences often affect EEG data, resulting in insufficient data volume or poor quality.

(d)Having many parameters and slow training speed, RNN requires high computational resources and optimization skills, and is prone to over-fitting problems.

3. Comparison of CNN and RNN Used for EEG Applications

A CNN neural network model consists of several layers of neurons that convolutionally process the incoming data. When handling tasks for EEG applications, the data may be used by CNN to extract spatial properties, such as the brain activity patterns in different electrodes or regions. It can also apply pooling operations to reduce the data dimensionality, enhancing the model's computational efficiency and generalization ability. CNNs are suitable for handling EEG data with high spatial resolution, such as high-density electrode caps, or requiring spatial feature extraction, such as emotion recognition or brain-computer interface [12]. According to previous studies, noise can have good and bad effects on CNN. The positive impact is that noise can increase data diversity, prevent over-fitting, and improve the model's generalization ability and robustness. The negative impact is that noise may interfere with CNN's extraction of effective features, reducing the accuracy and stability of the model. The degree of impact of noise may depend on factors such as the type, level, and distribution of noise. Generally speaking, when the noise level is low, CNN can learn useful information from the noise. When the noise level is high, CNN may be affected by noise interference, leading to performance degradation.

An RNN is a neural network model that can store and process sequential information over time by having feedback connections between neurons. RNN is good at finding temporal features in the data, such as the variations of brain activity over different periods or frequency domains. RNN can also handle long-term dependencies and context information in the data, which can increase the accuracy and stability of the model. Compared to CNN, using RNN for EEG applications may cause more over-fitting issues, probably because of a larger amount of parameters. According to some research, over-fitting EEG application problems can be addressed by introducing new data layers [13]. The noise impact on RNN may depend on the source, type, and noise level.

On the one hand, the input, output, or weight of RNN can be influenced by noise, which can result in a decline in the model’s performance. On the other hand, noise may enhance the generalization ability and robustness of RNN, preventing over-fitting and gradient vanishing. RNN can utilize gating units such as LSTM or GRU to store information for a long time and effectively learn noise features through time back-propagation.

In the literature, CNN is often suggested to have a better average performance in most respects than RNN. However, both CNN and RNN may require a large amount of labelled EEG data to perform well, which may not be available or feasible in some cases.

4. A General System Framework Using a Combination of CNN and RNN

Since both CNN and RNN have some limitations when applied to EEG data analysis, some researchers have proposed hybrid models that combine CNN and RNN in different ways to overcome these limitations. This study proposes a general system framework for EEG applications using a combination of CNN and RNN.

4.1. Hybrid Deep Learning Network

Based on the characteristics of CNN and RNN, using CNN before RNN when the goal of EEG signal categorization is to simplify and minimize the dimensionality of the input data. CNN can retain the spatial features from the original EEG signals and compress the information to be fed into the RNN part for further signal analysis. With such an sequence, RNN can focus on the temporal patterns and dependencies of the EEG signals without being overwhelmed by the noise or redundancy of the raw data. The hybrid deep learning architecture proposed in this study is shown in figure 3. The input towards the whole structure is the EEG signal segments. Then the signals from the EEG channels go through the convolutional neural networks which include multiple layers to extract the spatial features. The RNN with LSTM units obtain temporal features hidden inside the EEG signals. After processed through a combination of CNN and RNN, the EEG data will be sent to a fully connected layer which can map input features to output results. The fully connected layer can convert the feature space obtained from previous layers into the sample label space to integrate distributed feature representations into a single value. The fully connected layer can also increase the model's nonlinear expression ability, improving its complexity and robustness. Softmax function converts a single value into a final probability distribution for multi-class classification of the EEG signals.

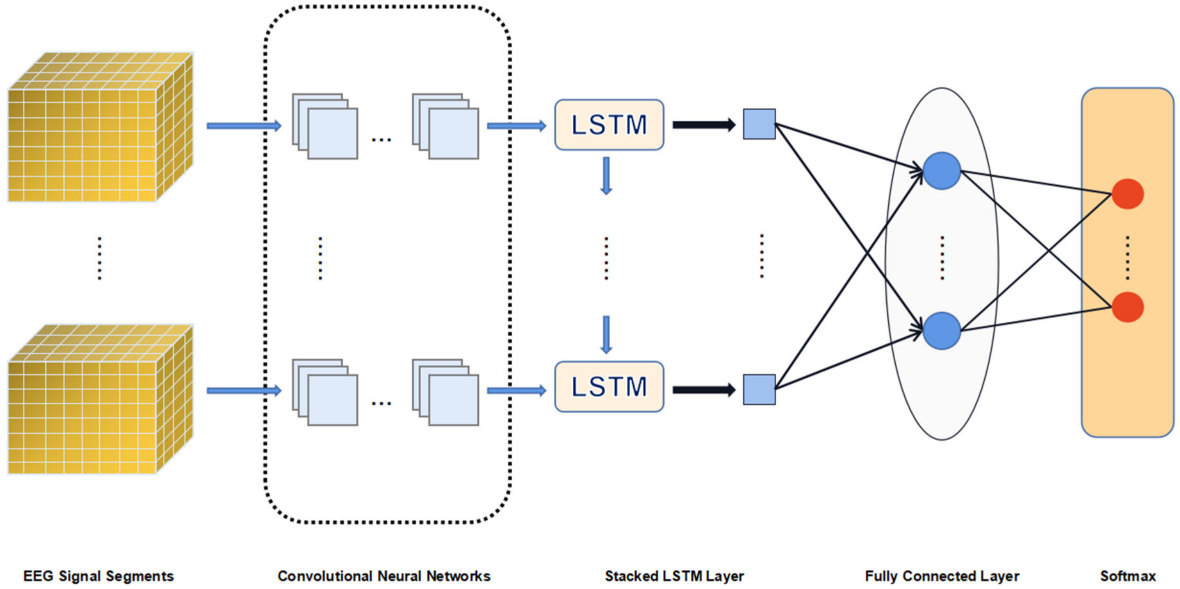

Fig. 3 A diagram of the proposed hybrid deep learning architecture (original)

4.2. System Framework for EEG Applications

Figure 4 shows a paradigm of a general system framework used for EEG applications. Apart from deep learning models, the EEG signal acquisition section consists of electrodes attached to the scalp, an amplifier which can also isolates the signal, a converter that turns analog signals into digital ones, and a module that transmits the data wirelessly. The main goals are to reduce power usage, size, and increase portability. To minimize disturbances from the outside of the scalp, notch filters and band pass filters are also applied to the signal acquisition part.

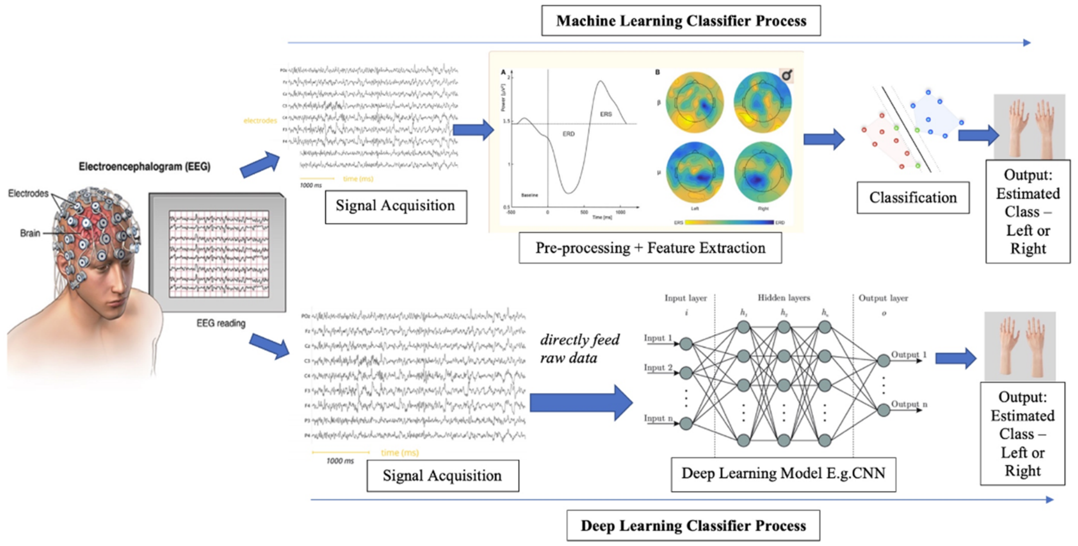

Fig. 4 A paradigm of a general system framework used for EEG applications [5]

5. Conclusion

By analyzing the structure of deep learning networks and comparing different cases, this study found that CNN and RNN exhibit different characteristics when applied to EEG signal processing and analysis. The biggest difference is mainly in the ability to represent temporal and spatial information. Having layers such as convolution and pooling makes CNN more conducive to extracting spatial information details from the original signal and performing dimensionality reduction processing. In contrast, recurrent units make RNN more sensitive to temporal signals. Besides, noise has similar influences on CNN and RNN. With a high level of noise, the performances of both networks degrades and the result of classification worsens. When the original signal is less muddy, CNN and RNN can recognize the information of the noise itself after proper training, making less affect on the result.

In some cases, introducing particular noise can improve the model's generalization ability. Based on the analysis, this study proposed a general system framework for EEG applications using a combination of CNN and RNN, placing CNN before RNN. Specifically, by using CNN, the original EEG signals' spatial characteristics are preserved, which can compress the information and feed it to the RNN part for further analysis. Moreover, to better reduce the influence of noise and other interference, RNN in this study contained LSTM units. This approach effectively combines two basic network models and can simultaneously preserve the temporal and spatial details of the processed signal, improving classification results.

However, considering the differences in EEG signals between individuals and the impact of different environments on their brain, it is necessary to make more targeted adjustments to the structure and parameters of deep learning networks for specific EEG application scenarios to meet the classification accuracy requirements. In addition, because EEG signals occur at a high frequency, factors such as the frequency response characteristics of deep learning networks also need to be considered. Future research will focus on more specific EEG applications for these unresolved issues.

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