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# Deep Learning Algorithms in EEG Signal Decoding Application: A Review

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**ABSTRACT** In recent years, deep learning algorithms have been developed rapidly, and they are becoming a powerful tool in biomedical engineering. Especially, there has been an increasing focus on the use of deep learning algorithms for decoding physiological or pathological status of the brain from electroencephalographic (EEG). This paper overviews current application of deep learning algorithms in various EEG decoding tasks, and introduces commonly used algorithms, typical application scenarios, important progresses and existing problems. Firstly, the basic principles of deep learning algorithms used in EEG decoding is briefly described, including convolutional neural network, deep belief network, auto-encoder and recurrent neural network. In this paper, existing applications of deep learning on EEG is discussed, including brain-computer interfaces, cognitive neuroscience and diagnosis of brain disorders. Finally, this paper outlines some key problems that will be addressed in future applications of deep learning for EEG decoding, such as parameter selection, computational complexity, and the capability of generalization.

**INDEX TERMS** Brain-computer interface, decoding, deep learning, electroencephalographic, neural networks.

## I. INTRODUCTION

Electroencephalogram (EEG) is a spontaneous and rhythmic electrical activity of the brain [1], [2]. Due to the simplicity, ease of operation and high time resolution of signals, EEG technology has played a great role in clinical and basic scientific research. For example, EEG is used as an indicator for the detection and monitoring of diseases such as epilepsy [3], [4] and sleep disorders [5], [6] in clinical practice. EEG is a brain imaging method that uses electrodes attached to surface of scalp to identify and record electrical activity signals of neuronal clusters in the cerebral cortex through precise electronic measurement technology, which can obtain brain idea and cognition. Neural electrophysiological information related to thinking and decision-making is one of the widely used brain function research methods. Compared

with other brain imaging functions, such as intra cortical neural recording, functional near-infrared spectroscopy and magnetic resonance imaging, the EEG is used in the research and development of rehabilitation equipment, such as the development of brain-computer interface (BCI) and neuro feedback technologies to achieve the recovery of patients' motor cognition and other functions [7]. In the above clinical application and scientific research of EEG, the machine learning algorithms are often used to decode EEG signals to accurately identify physiological or pathological conditions. However, shortcomings of less spatial resolution and signal-to-noise ratio (SNR) of EEG signals [8], the accuracy of machine learning decoding has greater limitations, causing many difficulties in practical applications. In, recent years rapid evolution in learning, researchers has gradually applied new and efficient machine learning algorithms to EEG decoding, and initially demonstrated its advantages over traditional machine learning. The following first introduces the

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traditional algorithms in machine learning are applied to EEG decoding, and explains advantages of deep learning based on its limitations in practical applications, and then briefly describes the basic principles of the deep learning algorithms currently applied in EEG decoding, and then introduces these. The algorithm is applied in several typical EEG decoding application scenarios, and finally the problems faced by the analysis of EEG decoding within its application, and the future development is prospected.

This paper ordered as follows. In section II, traditional machine learning algorithms to EEG Decoding EEG Decoding using Deep Learning algorithms are summarized in given in section III. In section IV, the application of deep learning algorithm in EEG Decoding is discussed, conclusion is shown in section V

## II. TRADITIONAL MACHINE LEARNING ALGORITHM APPLIED TO EEG DECODING

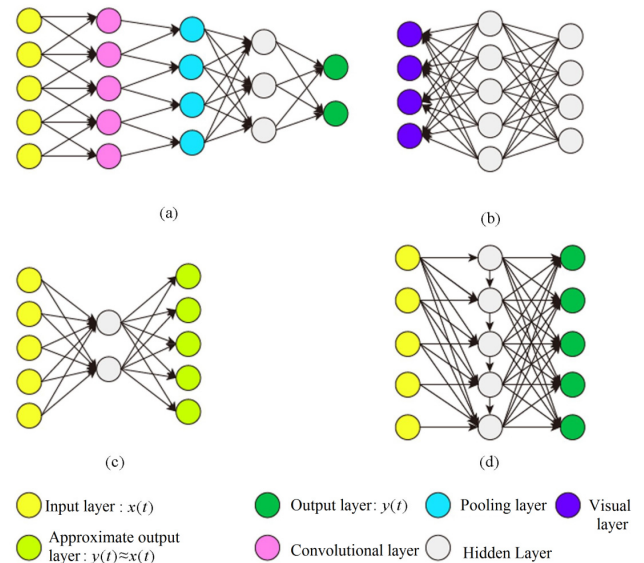
Many types of classical algorithms in machine learning, such as hidden Markov models (HMM), linear discriminant analysis (LDA), support vector machines (SVM), k-nearest neighbors (KNN) and artificial neural networks (ANA), etc., are mainly used in EEG decoding, where LDA and SVM are the most popular classifiers in BCI applications at present, because they are suitable for online and real-time EEG decoding. There are some BCI inspects that seek HMM to online grouping based on EEG imaginary movements [10]. Basis for deep learning is neural networks, where, there are only 1 or 2 hidden layers of multi-layer perceptrons (MLP). Applied to BCI decoding, it can also be applied to the recognition of epileptic seizures based on EEG [11].

The machine learning algorithms applications to EEG decoding also has some limitations. For example, in traditional EEG decoding applications, feature extraction and feature classification are performed separately, and more manual experience or Prior knowledge, but the two are difficult to obtain in many applications. In this case, feature classification and extraction are combined, and EEG signal processing is completed in one step in a purely data-driven manner. Classification is a feasible strategy this is also the main reason why deep learning algorithms have emerged in the application of EEG decoding in recent years. The following describes the deep learning algorithms that is applied in EEG decoding and their examples.

## III. EEG DECODING USING DEEP LEARNING ALGORITHM

Deep learning is machine learning paradigms that focus on deep-level learning data models [12]. It mainly uses architecture with number of deep hidden layers, and uses non-linear processing units for feature extraction and transformation. In supervision (such as classification) and/or automatically train multi-level representation of original data in unsupervised manner (such as pattern analysis). Deep learning can directly understand and train complex signal representation of original signal, and has the ability to automatically extract the advanced features required for classification. In the past

10 years, it has been widely used in different areas of research like speech recognition, computer vision and language processing [13], has been increasingly used in EEG signal decoding. At present, the depth commonly used in EEG signal decoding learning algorithm mainly includes the following types of convolutional neural network (CNN), the depth of belief networks (DBN), from the auto encoder (AE) and the recurrent neural network (RNN) are like as shown in Figure 1.



**FIGURE 1.** Different architectures for deep learning algorithm (a) CNN (b) DBN (c) AE and (d) RNN.

### A. CONVOLUTIONAL NEURAL NETWORK

The artificial neural network model i.e., CNN is very effective for image classification. The main consideration is that it uses convolution to learn local patterns in data. The typical structure of CNN mainly includes 3 hierarchical convolutional layers and pooling. The basic framework of the layer is shown in Figure 1(a). Different application scenarios of CNN require different numbers of convolutional layers. For example, a shallow structure with only one convolutional layer is applied to speech recognition [14]. A deep structure with multiple continuous convolutional layers or even more than 1,000 layers is developed into a residual network [15], which is used for classification and recognition of complex graphics (such as medical images).

The convolutional network first calculates the loss function through forward propagation. In order to train the network, the error is back propagated by calculating the gradient of the input image by deriving the weights in the convolution kernel. The convolutional neural network is used in multiple applications. Excellent, mainly through three aspects to help improve the machine learning system coefficient interaction, parameter sharing, and variable representation. In addition, the convolution method provides a method for processing variable input.

CNN not only has good decoding performance, but it is also easy to perform iterative training. It can greatly improve the decoding difficulties caused by changes in signal distribution across experimental applications. Therefore, it is favored by EEG researchers; however, CNN also exists in applications. Some problems, first of all, CNN may produce false positives, that is, excessive confidence may lead to erroneous predictions [16], [17]. This is particularly prominent in the application of computer vision. Secondly, training CNN networks may require more data, and it may take a more time to train on a simple model. Finally, the network contains many hyper parameters, such as the layers or the activation type function, this results in increase of computational complexity, and it will also bring difficulty in tuning parameters.

### B. DEEP BELIEF NETWORK

The Deep Belief Network (DBN) is a classic generative probability model composed of Restricted Boltzmann Machines (RBM). RBM is a deep probability model component that includes a visible layer and a hidden layer. The connections of DBN are limited to different layers, and there is no connection between units on the same layer. DBN is a stack of multiple RBMs, its basic framework is shown in Figure 1(b). In DBN, high-dimensional data can be passed through. The visible layer unit is input to the hidden layer of the RBM, and the hidden layer unit recognizes different types of signal characteristics according to the connection weight. The RBM connection weight in DBN is adjusted. First, it is given according to the probability drop of the energy function of the visible layer and the hidden layer. Then use layer-by-layer unsupervised learning to pre-train the weights of the network, and use global supervised learning to fine-tune. At present, DBN has been successfully applied to problems such as dimensionality reduction, image compression, digital recognition, and acoustic representation [18].

DBN not only take advantage of unsupervised learning to make full use of data that is unlabeled, and it is also applied to data with fewer samples [19]. Therefore, DBN can play a specific role in future EEG research, but it still needs to be addressed, some potential problems. First of all, as a kind of deep learning network, DBN also takes a long time to train. Second, with the increase in layer number, the memory footprint and the amount of calculation also increased, this is not expected in practical applications. Finally, the trained DBN must be as a trained model that will affect its effective transmission in cross-subject applications.

### C. AUTO-ENCODER

The auto encoder (AE) is composed of an encoder function and a decoder function. The simplest structure is a feed forward acyclic neural network similar to MLP. It has an input layer, an output layer, and a basic framework of multiple hidden layers is shown in Figure 1(c). AE is a fully connected unsupervised learning neural network. It sets the target value to the same value as the input, and can learn more in the pre-training of the classification task with good data set

representation [20]. At present, according to the AE's ability to acquire information and learn to express, there are several different AE denoising auto-encoders (DAE) model [22], sparse auto-encoders (SAE) [23], contractive auto encoder (CAE), etc., AE is usually used for dimensionality reduction, but it has been more and more widely used to generate models for learning data.

AE can effectively identify the characteristics of EEG, so AE networks are increasingly used in EEG decoding. However, if the signal is directly used as the input of AE, it is possible to lose adjacent information, which will affect the decoding quality of the signal. At the same time, the current research also shows that it is difficult to meet the needs of the application using a certain framework of AE alone, and combined with other advanced algorithms to complement each other, not only can achieve the best performance, but also can extend the network framework to other application fields and enhance its generalization ability.

### D. RECURRENT NEURAL NETWORK

Recurrent Neural Network (RNN) is used to process sequence data. In addition to the output and input layer, the simpler RNN also contains a self-connected hidden layer. Unlike MLP, it only map from input to output, it can also be mapped from all previous historical inputs to each output, its basic framework is shown in Figure 1(d). With the needs of practical applications, researchers have proposed many kinds of RNN frameworks, such as Elman network [24], Jordan network [25], time delay neural network (TDNN) [26] and echo state network (ESN) [27], etc.

RNN not only provide feed forward connection, but also feedback connection. It has strong robustness when processing time series [28]–[31] and EEG signal [32], [33]. At the same time, RNN can effectively use the input sequence, the time information, therefore, is expected to have a major role in EEG research area.

## IV. APPLICATION OF DEEP LEARNING ALGORITHM IN EEG DECODING

Different deep learning models have their own advantages and limitations. Therefore, in EEG decoding, different application scenarios and needs will use different deep learning models. The following will discuss the application areas of BCI, cognitive psychology, and disease detection. The deep learning model involved in

### A. BRAIN-COMPUTER INTERFACE

Brain-computer interface (BCI) is a human-computer interaction model directly sends instructions to control external devices through the brain. It is also an important field of EEG applications in the BCI system based on the Motor Imagery (MI) paradigm. The problem is solved for many intermediate steps in traditional algorithm model, the time-space convolutional network is used to realize the end-to-end classification system of MI tasks. Schirrmester uses same strategy to achieve 92% classification on multiple public

data sets. The powerful learning ability of the deep model is demonstrated in the EEG pattern recognition. Studies have compared variation between deep and traditional learning algorithms such as CSP algorithm and Riemann method in the BCI system. It is best than conventional algorithms in terms of generalization and accuracy.

In brain-computer interface (BCI) application (see Table 1), in order to improve the signal quality and the separability of features, the following two strategies are mainly used for optimization. One is to optimize the process of feature extraction and signal processing, and the other is to choose more appropriate classifiers to improve classification accuracy. From the perspective of the first strategy, review the application of current deep learning algorithms in BCI. It is found that the deep learning algorithms that can be applied to optimize feature extraction and signal processing are only DBN and RNN, with the advantages of DBN. It is manifested that it is possible to reduce parameters and reduce computational burden through parameter sharing, and use a large amount of unlabeled data in an unsupervised

**TABLE 1. Summary of deep learning algorithms in bci application.**

Neural Networks	Application	Characteristics/features	References
AE	Imaginary movement classification	Spectrum energy	[20]
		Power Spectral Density	[21]
DBN	Finger motion detection		
	Feature extraction	Time domain Amplitude	[34]
	ERP Testing	Time Domain waveform	[35]
	Movement initiation visual evoked potential detection	Compressed Sensing Characteristics	[36]
RNN	Imaginary movement classification	FFT energy	[13]
	Image continuous visual presentation classification	Time-frequency characteristics	[37]
CNN	Imaginary motion signal filtering	Time domain amplitude	[38]
CNN	Classification of P300, ERN, MRCP, SMR	Time domain amplitude	[7]
	SSVEP classification	FFT Energy	[39]
	Detection of P300	Time Domain Amplitude	[40]
	Imaginary movement classification	Time Domain Amplitude	[41-42]
	Motion Detection	Time Domain Amplitude	[43]
	Eriksen Franker tasks and online control robots	Time domain amplitude	[44]
	Imaginary movement classification	FFT energy Diagram	[45]
Imaginary movement classification	Time-frequency characteristics	[46]	

manner. For example, Ren *et al.* [34] proposed a convolution that combines convolution architecture in DBN network to achieve parameter sharing; the convolutional deep belief network (CDBN) is applied to the EEG signal feature learning on the BCI competition data set. The results show that compared with the traditional feature extraction algorithm, the performance of the CDBN learning can be better than that of the traditional feature extraction algorithm. RNN can enhance the EEG signal in the preprocessing stage, thereby improving the performance of BCI. In addition, RNN does not make any assumptions about the nature of the noise mixed in the signal to be filtered, so it is very suitable for dealing with mixed unknown characteristic noises like EEG signals. For example, Gandhi *et al.* [38], inspired by quantum mechanics, proposed a new type of neural information processing architecture, that is, recurrent quantum neural network, when the signal is enhanced by EGN when applied to RN. In the case of noise ratio, it acts as a filter. Compared with the cross-experimental results of EEG using only the original EEG or using Savezky~Golay filtering, the use of the test-specific RQNN to filter the EEG can significantly improve the BCI performance.

From the perspective of the second strategy, choosing a suitable deep learning algorithm model is to improve classification accuracy on the one hand, and to expand cross-paradigm and cross-subject applications on the other. Looking at the current development trend of deep learning applications. Deep learning extracts the features automatically from the original signal. Therefore, it is usually selected to analyze in the time domain, different BCI paradigm (i.e., P300, error-related negativity responses (ERN), movement-related cortical potentials (MRCP) and sensory motor rhythms (SMR)) are classified, for cross-task and cross-subjects provided better help. With the continuous deepening of research and application development, methods that can be analyzed in the frequency domain or time-frequency domain have been extended. For example, Cecotti and Hubert [39] proposed a new volume, the structure of the product neural network, that is, the fast Fourier transform (FFT) is added between the two hidden layers, which makes the signal analysis transform from the time domain inside the network to the frequency domain. This strategy has an average recognition rate of 95% for five different types of steady-state visual evoked potentials (SSVEP), which outperforms other classical neural network architectures in the frequency domain. The features in the time and frequency domain are more typical and distinguishable than the features in the time domain, so transforming to the frequency domain can reduce the feature dimension and reduce the computational complexity.

## B. COGNITIVE PSYCHOLOGY

EEG can be used to evaluate and understand the changes in the brain related to mental and physiological states, such as different mental states-anxiety, depression, pain [47], etc. It can also be used as an effective tool to explore the neural mechanisms of cognitive processes ((See Table 2). In the

**TABLE 2. Summary of deep learning algorithms in clinical disease detection applications.**

Neural Networks	Application	Features/characteristics	References
AE	Seizure detection	Cross-energy matrix	[67]
DBN	Seizure detection	Time domain spike	[68]
	Abnormal waveform detection	Time domain waveform	[69]
RNN	Sleep stage classification	Energy characteristics (waveform)	[71]
	Seizure detection	Time domain amplitude	[73]
	Seizure detection	Time domain amplitude	[74]
	Seizure detection	Time domain characteristics	[75]
	Sedation testing for patients in ICU ward	Spectral characteristics	[76]
CNN	Seizure detection	Time Domain Waveform	[77-78]
	Epilepsy waveform detection	Time Domain Amplitude	[79]
	Neonatal seizure detection	Time Domain Amplitude	[80]
	Parkinson automatic detection	Time Domain Amplitude	[81]
	Classification of Dementia Stages	Power spectrum image	[82]
	Efficacy prediction for patients with autism	Time domain amplitude	[83]

EEG-based emotion recognition research, it is difficult to use traditional classifiers for application. The main reason is that the boundaries of different emotions are fuzzy. How to extract and effectively identify emotion-related features is a huge challenges problem. Therefore, researchers proposed to use deep learning to use multi-scale features to classify and recognize emotions. For example, Zheng *et al.* [52] used the differential entropy feature of EEG as the input of DBN, and integrated HMM in the network, so that accurate capture is more reliable. Emotional state switching, and two categories of emotions (positive and negative) are carried out. Compared with the classification accuracy of DBN-HMM, DBN, SVM and KNN, whether it is the DBN model or the DBN-HMM model combined with HMM, the emotion classification is improved. At the same time, DBN can perform feature selection and screen out irrelevant features to obtain better results.

In addition to emotion recognition, an important EEG application of deep learning is to identify the driver's fatigue. Chai *et al.* [53] proposed to use an autoregressive model to extract features from EEG signals, and use the extracted features as the input of sparse DBN. Compared with the results of the algorithm, sparse DBN has significantly higher classification performance. Zeng *et al.* [57] proposed to use CNN combined with residual network to predict the mental state of

drivers. The results show that the proposed method has better predictive performance. In cognitive psychology research, frequency domain features are often more discriminative than time domain features. Therefore, in future research, it is possible to transform and analyze EEG signals for different cognitive states to improve decoding performance, and reduce actual application costs.

### C. DISEASE DETECTION

In clinical applications, EEG can assist in the diagnosis of a variety of neurological and psychiatric diseases, such as Alzheimer's disease [64], epilepsy [65] and schizophrenia. It can also be used for sleep stage classification related to sleep diagnosis (see Table 2). In the detection and classification of epilepsy, Turner *et al.* [68] proposed the application of DBN to detect epileptic seizures, which can achieve a more appropriate computational complexity. And better accuracy, at the same time, in the case of using models trained on other patients' data to test new patients (the so-called "leave one method"), DBN outperforms the logistic regression algorithm using the same feature set. In addition to detecting epilepsy waveforms to assist clinical needs, deep learning algorithms can also classify patients with focal epilepsy to achieve the purpose of serving clinical surgical decisions. Taji *et al.* [70] applied three different CNN models, the classification of the EEG signals of patients with focal and non-focal epilepsy can not only use less training data to achieve the best classification performance, but also increase the calculation speed to reduce the time required for the classification process. Good classification performance provides help for the diagnosis of focal epilepsy disease.

In the research related to sleep disorders, deep learning is considered to be one of the most promising classifiers in human sleep stage classification [71]. Currently, most of the EEG decoding applications are RNN. For example, Hsu *et al.* RNN classifies human sleep stages and compares the performance of the feed forward neural network (FNN), which is widely used in biomedical classification, and the probabilistic neural network, which is mainly used to deal with classification problems. It is shown that RNN can use single-channel EEG energy features to efficiently and accurately classify sleep stages. In addition, the method combining DBN and HMM has also been successfully applied to the sleep stage classification based on EEG [72].

Based on the above research, it can be found that the application of deep learning to disease diagnosis has preliminary results. However, because most clinical data sets are small, it is still a huge challenge to the multi-center large-sample generalization ability of existing models. In addition, there are many current studies. It is offline testing rather than online application, but in actual clinical applications, it is more hoped that results can be given in time to assist clinical diagnosis. Therefore, more online research is needed in the future to verify that these deep learning methods have sufficient computational efficiency to satisfy Real-time application.

## V. CONCLUSION

Although deep learning has achieved some success in EEG decoding, its application still faces many challenges. In addition to the decoding difficulties caused by the high dimensionality and low signal-to-noise ratio of EEG signals, there are also complex practical application scenarios and the limitations of the algorithm itself have caused difficulties in research and development.

- 1) There is still a need of many-sample labeled EEG information sets, which uses the effect of existing deep learning algorithms not fully reflected. The effectiveness of deep learning greatly depends on High-quality labeled data. In existing research, especially in clinical research, EEG data with complete and accurate labeling is still scarce, and the sample size is small. In future research, in addition to collecting and sorting large samples of EEG data, it is still new machine learning algorithms such as transfer learning need to be applied to make up for the shortcomings of small sample size.
- 2) In the multi-center and longitudinal data, the generalization ability and repeatability of the existing model still lack rigorous verification. The EEG data is greatly affected by equipment and experimental personnel, so different laboratories/hospitals and the main test collection, the EEG data presents different characteristics. Moreover, EEG data has great intra and inter-individual variability. However, most existing developed models is based on data collected from same center and at the same time point. It needs to be tested on multi-center longitudinal data to ensure that the model has good generalization ability and repeatability.
- 3) The complexity of deep learning models is still high, and real-time decoding is difficult. Deep learning can continuously adjust the model according to the application. Although the depth, complexity and activation function of the model can enhance the classification model performance, however it causes defects such as increased training time, decreased training speed, and difficulty in real-time execution. These problems will increase the resources of EEG signal decoding and limit its practical application (Such as BCI).
- 4) The interpretability of deep learning in EEG research needs to be strengthened. In psychology and medical research based on EEG, classification accuracy is not the most important goal. Through machine learning models, it is necessary to obtain information about psychological or disease states. Predictive EEG characteristics to reveal neural mechanisms are an important goal of such research. Therefore, deep learning models need to increase interpretability, so that they are come a powerful tool for studying neural mechanisms.
- 5) Existing deep learning model lacks the application of unlabeled EEG data. In existing research, most of the EEG data sets used are labeled data. Therefore, deep learning models are mostly supervised learning. However, there is still a large amount of EEG data that is

unlabeled or inaccurate labeling (especially in medical research). Therefore, unsupervised or semi-supervised deep learning methods also need to be continuously developed to be applied to EEG data with missing or inaccurate labeling, such as disease classification type.

In summary, the current application of deep learning in EEG decoding is mainly based on the network architecture of CNN, DBN, AE, and RNN. It is based on several classic paradigm classifications of BCI, classification and prediction of cognitive states such as emotional fatigue, and clinical seizure detection. There have been many successful applications in sleep classification, but existing research still has many problems, such as lack of multi-center verification, high complexity, etc. In order to overcome the limitations and problems of deep learning in EEG decoding, data collection and sorting are required. The joint efforts of the improvement of deep learning algorithms and the progress of brain science mechanisms.

In the future research work, it is necessary to continuously develop robust and efficient deep learning algorithms to meet the needs of real-time online applications, and is suitable for multi-center, large sample Multi-source longitudinal data sets. In addition, a single type of deep learning algorithm may not meet the needs of the application. Therefore, in addition to optimizing the architecture of the model, several different models can also be integrated, using integrated learning and reinforcement learning. The idea is to comprehensively use the advantages of different models to achieve higher performance.

## REFERENCES

- [1] J. C. Henry, "Electroencephalography: Basic principles, clinical applications, and related fields," *Neurology*, vol. 67, no. 11, p.2092, 2006.
- [2] G. Buzsáki and A. Draguhn, "Neuronal oscillations in cortical networks," *Science*, vol. 304, no. 5679, pp. 1926–1929, Jun. 2004.
- [3] S. Ghosh-Dastidar, H. Adeli, and N. Dadmehr, "Mixed-band wavelet-chaos-neural network methodology for epilepsy and epileptic seizure detection," *IEEE Trans. Biomed. Eng.*, vol. 54, no. 9, pp. 1545–1551, Sep. 2007.
- [4] H. Adeli, Z. Zhou, and N. Dadmehr, "Analysis of EEG records in an epileptic patient using wavelet transform," *J. Neurosci. Methods*, vol. 123, no. 1, pp. 69–87, Feb. 2003.
- [5] S. Charbonnier, L. Zoubek, S. Lesecq, and F. Chapotot, "Self-evaluated automatic classifier as a decision-support tool for sleep/wake staging," *Comput. Biol. Med.*, vol. 41, no. 6, pp. 380–389, Jun. 2011.
- [6] R. K. Sinha, "EEG power spectrum and neural network based sleep-hypnogram analysis for a model of heat stress," *J. Clin. Monitor. Comput.*, vol. 22, no. 4, p. 261, 2008.
- [7] V. J. Lawhern, A. J. Solon, N. R. Waytowich, S. M Gordon, C. P. Hung, and B. J. Lance, "EEGNet: A compact convolutional neural network for EEG-based brain–computer interfaces," *J. Neural Eng.*, vol. 15, no. 5, 2018, Art. no. 056013.
- [8] B. W. McMenamin, A. J. Shackman, L. L. Greischar, and R. J. Davidson, "Electromyogenic artifacts and electroencephalographic inferences revisited," *NeuroImage*, vol. 54, no. 1, pp. 4–9, Jan. 2011.
- [9] F. Lotte, M. Congedo, A. Lécuyer, F. Lamarche, and B. Arnaldi, "A review of classification algorithms for EEG-based brain–computer interfaces," *J. Neural Eng.*, vol. 4, no. 2, pp. R1–R13, Jun. 2007.
- [10] B. Obermaier, C. Guger, C. Neuper, and G. Pfurtscheller, "Hidden Markov models for online classification of single trial EEG data," *Pattern Recognit. Lett.*, vol. 22, no. 12, pp. 1299–1309, Oct. 2001.

- [11] A. H. Osman and A. A. Alzahrani, "New approach for automated epileptic disease diagnosis using an integrated self-organization map and radial basis function neural network algorithm," *IEEE Access*, vol. 7, pp. 4741–4747, 2019.
- [12] R. B. Palm, "Prediction as a candidate for learning deep hierarchical models of data," Tech. Univ. Denmark, Lyngby, Denmark, Tech. Rep., 2012, vol. 5.
- [13] N. Lu, T. Li, X. Ren, and H. Miao, "A deep learning scheme for motor imagery classification based on restricted Boltzmann machines," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 25, no. 6, pp. 566–576, Jun. 2017.
- [14] O. Abdel-Hamid, A.-R. Mohamed, H. Jiang, L. Deng, G. Penn, and D. Yu, "Convolutional neural networks for speech recognition," *IEEE/ACM Trans. Audio, Speech Language Process.*, vol. 22, no. 10, pp. 1533–1545, Oct. 2015.
- [15] L.-C. Chen, G. Papandreou, I. Kokkinos, K. Murphy, and A. L. Yuille, "DeepLab: Semantic image segmentation with deep convolutional nets, atrous convolution, and fully connected CRFs," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 40, no. 4, pp. 834–848, Apr. 2017.
- [16] E. D. Cubuk, B. Zoph, S. S. Schoenholz, and Q. V. Le, "Intriguing properties of adversarial examples," 2017, *arXiv:1711.02846*. [Online]. Available: <http://arxiv.org/abs/1711.02846>
- [17] Y. Guo, Y. Liu, A. Oerlemans, S. Lao, S. Wu, and M. S. Lew, "Deep learning for visual understanding: A review," *Neurocomputing*, vol. 187, pp. 27–48, Apr. 2016.
- [18] T. Kuremoto, S. Kimura, K. Kobayashi, and M. Obayashi, "Time series forecasting using a deep belief network with restricted Boltzmann machines," *Neurocomputing*, vol. 137, pp. 47–56, Aug. 2014.
- [19] I. Goodfellow, *Deep Learning*, vol. 1. Cambridge, MA, USA: MIT Press, 2016.
- [20] J. Li, Z. Struzik, L. Zhang, and A. Cichocki, "Feature learning from incomplete EEG with denoising autoencoder," *Neurocomputing*, vol. 165, pp. 23–31, Oct. 2015.
- [21] Z. Wang, "Deep feature learning using target priors with applications in ECoG signal decoding for BCI," in *Proc. 23rd Int. Joint Conf. Artif. Intell.*, 2013.
- [22] P. Vincent, "Stacked denoising autoencoders: Learning useful representations in a deep network with a local denoising criterion," *J. Mach. Learn. Res.*, vol. 11, no. 12, pp. 3371–3408, 2010.
- [23] P. C. Bjork, "The master algorithm: How the quest for the ultimate learning machine will remake our world," *Perspect. Sci. Christian Faith*, vol. 68, no. 3, pp. 214–216, 2016.
- [24] J. L. Elman, "Finding structure in time," *Cognit. Sci.*, vol. 14, no. 2, pp. 179–211, Mar. 1990.
- [25] L. G. B. Ruiz, M. P. Cuéllar, M. D. Calvo-Flores, and M. D. C. P. Jiménez, "An application of non-linear autoregressive neural networks to predict energy consumption in public buildings," *Energies*, vol. 9, no. 9, p. 684, 2016.
- [26] K. J. Lang, A. H. Waibel, and G. E. Hinton, "A time-delay neural network architecture for isolated word recognition," *Neural Netw.*, vol. 3, no. 1, pp. 23–43, 1990.
- [27] W. Maass, T. Natschläger, and H. Markram, "Real-time computing without stable states: A new framework for neural computation based on perturbations," *Neural Comput.*, vol. 14, no. 11, pp. 2531–2560, 2002.
- [28] X.-D. Li, J. K. L. Ho, and T. W. S. Chow, "Approximation of dynamical time-variant systems by continuous-time recurrent neural networks," *IEEE Trans. Circuits Syst. II, Exp. Briefs*, vol. 52, no. 10, pp. 656–660, Oct. 2005.
- [29] L. A. Feldkamp and G. V. Puskorius, "A signal processing framework based on dynamic neural networks with application to problems in adaptation, filtering, and classification," *Proc. IEEE*, vol. 86, no. 11, pp. 2259–2277, Nov. 1998.
- [30] M. Hásken and P. Stage, "Recurrent neural networks for time series classification," *Neurocomputing*, vol. 50, pp. 223–235, Jan. 2003.
- [31] L. Jin, P. N. Nikiforuk, and M. M. Gupta, "Approximation of discrete-time state-space trajectories using dynamic recurrent neural networks," *IEEE Trans. Autom. Control*, vol. 40, no. 7, pp. 1266–1270, Jul. 1995.
- [32] A. M. Schäfer and H. G. Zimmermann, "Recurrent neural networks are universal approximators," in *Proc. Int. Conf. Artif. Neural Netw.* Berlin, Germany: Springer, 2006, pp. 632–640.
- [33] N. F. Güler, E. D. Übeyli, and I. Güler, "Recurrent neural networks employing Lyapunov exponents for EEG signals classification," *Expert Syst. Appl.*, vol. 29, no. 3, pp. 506–514, Oct. 2005.
- [34] Y. Ren and Y. Wu, "Convolutional deep belief networks for feature extraction of EEG signal," in *Proc. Int. Joint Conf. Neural Netw. (IJCNN)*, Jul. 2014, pp. 2850–2853.
- [35] J. Li, Z. L. Yu, Z. Gu, W. Wu, Y. Li, and L. Jin, "A hybrid network for ERP detection and analysis based on restricted Boltzmann machine," *IEEE Trans. Rehabil. Eng.*, vol. 26, no. 3, pp. 563–572, Mar. 2018.
- [36] T. Ma, H. Li, H. Yang, X. Lv, P. Li, T. Liu, D. Yao, and P. Xu, "The extraction of motion-onset VEP BCI features based on deep learning and compressed sensing," *J. Neurosci. Methods*, vol. 275, pp. 80–92, Jan. 2017.
- [37] S. Ahmed, L. Mauricio Merino, Z. Mao, J. Meng, K. Robbins, and Y. Huang, "A deep learning method for classification of images RSVP events with EEG data," in *Proc. IEEE Global Conf. Signal Inf. Process.*, Dec. 2013, pp. 33–36.
- [38] V. Gandhi, G. Prasad, D. Coyle, L. Behera, and T. M. McGinnity, "Quantum neural network-based EEG filtering for a brain-computer interface," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 25, no. 2, pp. 278–288, Feb. 2014.
- [39] H. Cecotti, "A time-frequency convolutional neural network for the offline classification of steady-state visual evoked potential responses," *Pattern Recognit. Lett.*, vol. 32, no. 8, pp. 1145–1153, Jun. 2011.
- [40] H. Cecotti and A. Graser, "Convolutional neural networks for P300 detection with application to brain-computer interfaces," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 33, no. 3, pp. 433–445, Mar. 2011.
- [41] Z. Tang, C. Li, and S. Sun, "Single-trial EEG classification of motor imagery using deep convolutional neural networks," *Optik*, vol. 130, pp. 11–18, Feb. 2017.
- [42] K. G. Hartmann, R. T. Schirrmester, and T. Ball, "Hierarchical internal representation of spectral features in deep convolutional networks trained for EEG decoding," in *Proc. 6th Int. Conf. Brain-Comput. Interface (BCI)*, Jan. 2018, pp. 1–6.
- [43] E. Nurse, B. S. Mashford, A. J. Yepes, I. Kiral-Kornek, S. Harrer, and D. R. Freestone, "Decoding EEG and LFP signals using deep learning: Heading TrueNorth," in *Proc. ACM Int. Conf. Comput. Frontiers*, May 2016, pp. 259–266.
- [44] M. Volker, R. T. Schirrmester, L. D. J. Fiederer, W. Burgard, and T. Ball, "Deep transfer learning for error decoding from non-invasive EEG," in *Proc. 6th Int. Conf. Brain-Comput. Interface (BCI)*, Jan. 2018, pp. 1–6.
- [45] W. Abbas and N. A. Khan, "DeepMI: Deep learning for multiclass motor imagery classification," in *Proc. 40th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (EMBC)*, Jul. 2018, pp. 219–222.
- [46] B. Xu, L. Zhang, A. Song, C. Wu, W. Li, D. Zhang, G. Xu, H. Li, and H. Zeng, "Wavelet transform time-frequency image and convolutional network-based motor imagery EEG classification," *IEEE Access*, vol. 7, pp. 6084–6093, 2019.
- [47] W. Peng, "Changes of spontaneous oscillatory activity to tonic heat pain," *PLoS One*, vol. 9, no. 3, 2014, Art. no. 91052.
- [48] W. Liu, W.-L. Zheng, and B.-L. Lu, "Multimodal emotion recognition using multimodal deep learning," 2016, *arXiv:1602.08225*. [Online]. Available: <http://arxiv.org/abs/1602.08225>
- [49] S. Jirayucharoensak, S. Pan-Ngum, and P. Israsena, "EEG-based emotion recognition using deep learning network with principal component based covariate shift adaptation," *Sci. World J.*, vol. 2014, Sep. 2014, Art. no. 627892.
- [50] X. Chai, Q. Wang, Y. Zhao, X. Liu, O. Bai, and Y. Li, "Unsupervised domain adaptation techniques based on auto-encoder for non-stationary EEG-based emotion recognition," *Comput. Biol. Med.*, vol. 79, pp. 205–214, Dec. 2016.
- [51] E. Q. Wu, X. Y. Peng, C. Z. Zhang, J. X. Lin, and R. S. F. Sheng, "Pilots' fatigue status recognition using deep contractive autoencoder network," *IEEE Trans. Instrum. Meas.*, vol. 68, no. 10, pp. 3907–3919, Oct. 2019.
- [52] W.-L. Zheng, J.-Y. Zhu, Y. Peng, and B.-L. Lu, "EEG-based emotion classification using deep belief networks," in *Proc. IEEE Int. Conf. Multimedia Expo (ICME)*, Jul. 2014, pp. 1–6.
- [53] R. Chai, S. H. Ling, P. P. San, G. R. Naik, T. N. Nguyen, Y. Tran, A. Craig, and H. T. Nguyen, "Improving eeg-based driver fatigue classification using sparse-deep belief networks," *Front. Neurosci.*, vol. 11, p. 103, Mar. 2017.
- [54] A. Saha, A. Konar, A. Chatterjee, A. Ralescu, and A. K. Nagar, "EEG analysis for olfactory perceptual-ability measurement using a recurrent neural classifier," *IEEE Trans. Human-Mach. Syst.*, vol. 44, no. 6, pp. 717–730, Dec. 2014.
- [55] P. Bashivan, I. Rish, M. Yeasin, and N. Codella, "Learning representations from EEG with deep recurrent-convolutional neural networks," 2015, *arXiv:1511.06448*. [Online]. Available: <http://arxiv.org/abs/1511.06448>
- [56] M. Hajinoroozi, Z. Mao, T.-P. Jung, C.-T. Lin, and Y. Huang, "EEG-based prediction of driver's cognitive performance by deep convolutional neural network," *Signal Process., Image Commun.*, vol. 47, pp. 549–555, May 2016.

- [57] H. Zeng, C. Yang, G. Dai, F. Qin, J. Zhang, and W. Kong, "EEG classification of driver mental states by deep learning," *Cogn. Neurodyn.*, vol. 12, pp. 597–606, Dec. 2018.
- [58] M. Lee, S.-K. Yeom, B. Baird, O. Gosseries, J. O. Niemenen, G. Tononi, and S.-W. Lee, "Spatio-temporal analysis of EEG signal during consciousness using convolutional neural network," in *Proc. 6th Int. Conf. Brain-Comput. Interface (BCI)*, Jan. 2018, pp. 1–3.
- [59] H. Mei and X. Xu, "EEG-based emotion classification using convolutional neural network," in *Proc. Int. Conf. Secur., Pattern Anal., Cybern. (SPAC)*, Dec. 2017, pp. 130–135.
- [60] S. Tripathi, "Using deep and convolutional neural networks for accurate emotion classification on DEAP dataset," in *Proc. 31st AAAI Conf. Artif. Intell.*, 2017, pp. 4746–4752.
- [61] S. Stober, D. J. Cameron, and J. A. Grahn, "Using convolutional neural networks to recognize rhythm stimuli from electroencephalography recordings," in *Proc. Adv. Neural Inf. Process. Syst.*, 2014, pp. 1449–1457.
- [62] P. Zhang, X. Wang, W. Zhang, and J. Chen, "Learning spatial-spectral-temporal EEG features with recurrent 3D convolutional neural networks for cross-task mental workload assessment," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 27, no. 1, pp. 31–42, Jan. 2019.
- [63] Z. Gao, X. Wang, Y. Yang, C. Mu, Q. Cai, W. Dang, and S. Zuo, "EEG-based spatio-temporal convolutional neural network for driver fatigue evaluation," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 30, no. 9, pp. 2755–2763, Sep. 2019.
- [64] D. Al-Jumeily, "A novel method of early diagnosis of Alzheimer's disease based on EEG signals," *Sci. World J.*, vol. 2015, Jan. 2015, Art. no. 931387.
- [65] K. Samiee, P. Kovács, and M. Gabbouj, "Epileptic seizure classification of EEG time-series using rational discrete short-time Fourier transform," *IEEE Trans. Biomed. Eng.*, vol. 62, no. 2, pp. 541–552, Feb. 2015.
- [66] M. Shim, H.-J. Hwang, D.-W. Kim, S.-H. Lee, and C.-H. Im, "Machine-learning-based diagnosis of schizophrenia using combined sensor-level and source-level EEG features," *Schizophrenia Res.*, vol. 176, nos. 2–3, pp. 314–319, 2016.
- [67] Y. Qi, Y. Wang, J. Zhang, J. Zhu, and X. Zheng, "Robust deep network with maximum correntropy criterion for seizure detection," *BioMed Res. Int.*, vol. 2014, Jul. 2014, Art. no. 703816.
- [68] J. T. Turner, "Deep belief networks used on high resolution multichannel electroencephalography data for seizure detection," in *Proc. AAAI*, 2014, pp. 75–81.
- [69] D. F. Wulsin, J. R. Gupta, R. Mani, J. A. Blanco, and B. Litt, "Modeling electroencephalography waveforms with semi-supervised deep belief nets: Fast classification and anomaly measurement," *J. Neural Eng.*, vol. 8, no. 3, 2011, Art. no. 036015.
- [70] A. M. Taqi, F. Al-Azzo, M. Mariofanna, and J. M. Al-Saadi, "Classification and discrimination of focal and non-focal EEG signals based on deep neural network," in *Proc. Int. Conf. Current Res. Comput. Sci. Inf. Technol. (ICCIIT)*, Apr. 2017, pp. 86–92.
- [71] Y.-L. Hsu, Y.-T. Yang, J.-S. Wang, and C.-Y. Hsu, "Automatic sleep stage recurrent neural classifier using energy features of EEG signals," *Neurocomputing*, vol. 104, pp. 105–114, Mar. 2013.
- [72] M. Långkvist, L. Karlsson, and A. Loutfi, "Sleep stage classification using unsupervised feature learning," *Adv. Artif. Neural Syst.*, vol. 2012, pp. 1–9, Jul. 2012.
- [73] H. Rajaguru and S. K. Prabhakar, "A unique approach to epilepsy classification from EEG signals using dimensionality reduction and neural networks," *Circuits Syst.*, vol. 7, no. 8, p. 1455, 2016.
- [74] D. Ahmedt-Aristizabal, C. Fookes, K. Nguyen, and S. Sridharan, "Deep classification of epileptic signals," in *Proc. 40th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (EMBC)*, Jul. 2018, pp. 332–335.
- [75] R. Hussein, H. Palangi, R. K. Ward, and Z. J. Wang, "Optimized deep neural network architecture for robust detection of epileptic seizures using eeg signals," *Clin. Neurophysiol.*, vol. 130, no. 1, pp. 25–37, 2019.
- [76] H. Sun, S. B. Nagaraj, O. Akeju, P. L. Purdon, and B. M. Westover, "Brain monitoring of sedation in the intensive care unit using a recurrent neural network," in *Proc. 40th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (EMBC)*, Jul. 2018, pp. 1–4.
- [77] A. Page, C. Shea, and T. Mohsenin, "Wearable seizure detection using convolutional neural networks with transfer learning," in *Proc. IEEE Int. Symp. Circuits Syst. (ISCAS)*, May 2016, pp. 1086–1089.
- [78] U. R. Acharya, S. L. Oh, Y. Hagiwara, J. H. Tan, and H. Adeli, "Deep convolutional neural network for the automated detection and diagnosis of seizure using EEG signals," *Comput. Biol. Med.*, vol. 100, pp. 270–278, Sep. 2017.
- [79] J. Thomas, L. Comoretto, J. Jin, J. Dauwels, S. S. Cash, and M. B. Westover, "EEG Classification via convolutional neural network-based interictal epileptiform event detection," in *Proc. 40th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (EMBC)*, Jul. 2018, pp. 3148–3151.
- [80] A. OrShea, G. Lightbody, G. Boylan, and A. Temko, "Investigating the impact of CNN depth on neonatal seizure detection performance," in *Proc. 40th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (EMBC)*, Jul. 2018, pp. 5862–5865.
- [81] S. Chambon, "A deep learning architecture to detect events in EEG signals during sleep," in *Proc. IEEE 28th Int. Workshop Mach. Learn. Signal Process. (MLSP)*, Sep. 2018, pp. 1–6.
- [82] C. Ieracitano, N. Mammone, A. Bramanti, A. Hussain, and F. Morabit, "A convolutional neural network approach for classification of dementia stages based on 2D-spectral representation of EEG recordings," *Neuro-computing*, vol. 323, pp. 96–107, Jan. 2019.
- [83] Y. Li, "Targeting EEG/LFP synchrony with neural nets," in *Proc. Adv. Neural Inf. Process. Syst.*, 2017, pp. 4620–4630.



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