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Review Article

ELECTROENCEPHALOGRAM CLASSIFICATION USING VARIOUS ARTIFICIAL NEURAL NETWORKS

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Abstract
Electroencephalography (EEG) is the oldest diagnostic tool used in the field of neurosciences. When a neurologist sees an EEG report, he can point out important neural defects in a person but many a times diagnoses were missed and it is just impossible for human brain to process all the data in EEG. Nowadays many deep machine learning architectures are developed to understand the information contained in EEG signals. This study reviews various literatures on classification of EEG signals using various artificial neural networks like Convoluted neural network, Recurrent Neural Network, Deep Belief neural networks and hybrids.

Keywords: Electroencephalogram, Signal Classification, Artificial Neural Networks, Convoluted Neural Network, Deep Belief Network, Multi-layer Perceptron Neural Network Long short-term Memory.

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INTRODUCTION

In the olden days, EEG was used as a tool to aid diagnoses of Seizure disorders. But now using brain computer interfaces EEGs are used to diagnose sleep disorders, worsening of dementia of Alzheimer's disease affected people, Autistic spectral disorders and many more because of its robustness, low cost and non-invasive imaging technique. The whole processes are: collecting an EEG, noise removal, feature extraction and classification of signals. EEG signals are just potentials evoked in brain at rest, sleep and performance of various tasks.

Application of Artificial Neural Networks (ANN) in the field of classification of neural network signals may help even non experts interpret the results and arrive to a diagnosis. In this review, applications of EEG signal classification using Convoluted Neural Recurrent Neural Network, Deep Belief neural networks and hybrid of such neural networks are discussed.

VARIOUS STUDIES OF APPLICATIONS OF ANNS ON CLASSIFICATION OF EEG

Use of CNN (Convoluted Neural Network) as a Classifier

CNN is a dynamic and new ANN that has been put in use recently to classify EEG signals. This part of the paer discusses on how to use CNN in various clinical and experimental settings.

Bullying is a bad experience and first step of the solution of it is identification of the problem. Diagnosis of this problem usually involves Questionnaires, discussions and Psychological testing. Baltatzis et al in 2017 propose two experiments using a video and virtual reality experiment. Brain activity was recorded using EEG in bullying scenarios and normal ones. They used Convolutional Neural Network over the raw signals among 17 subjects and had a discriminatory diagnostic accuracy of 94% [1]. Tabar et al in 2016 and Abbas et al in 2018 showed that CNN has a great discriminatory value of classifying EEG about 75 and 81% respectively [2,3].

Evoked potentials are of great interest on diagnosing neurological disorders. 66 subjects were subjected to visual oddball task in Virtual reality settings which is a P300 evoked potential. EEGs were recorded and classified using CNN in a Brain computer interface (BCI) set up which yielded an classification accuracy of 81% [4]. Vrbancic et al in 2018 used spectrograms derived from EEGs and searched for characteristic patterns which served as a basis of classification. They extracted features from that data and used a deep CNN network architecture and trained it for motor neural impairment diagnosis. When tested with controls, this approach yielded 69% accuracy among classification of subjects from controls [5].

Motor imagery (MI) is an important control paradigm in the field of brain-computer interface (BCI), which enables the recognition of personal intention. So far, numerous methods have been designed to classify EEG signal features for MI task. However, deep neural networks have been seldom applied to analyse EEG signals. Tang et al in 2016 proposed a BCI which uses deep CNN and performed feature extraction and classification of single trail EEG. They built an 5 layered CNN to classify the motor imagery where left and right hand movements of the subjects were used. They proved that Motor imagery can be classified accurately up to discrimination of 86% [6]. Another paper by Dose et al in 2018 using CNN in BCI classified motor imagery at an accuracy of 80% proving deep learning is the way of the future in this line of research [7].Wang et al in 2018 researched the difference between a CNN model and Long term-short memory deep learning method. And they succeeded in CNN obtaining a whopping 93% classification accuracy of MI [8].

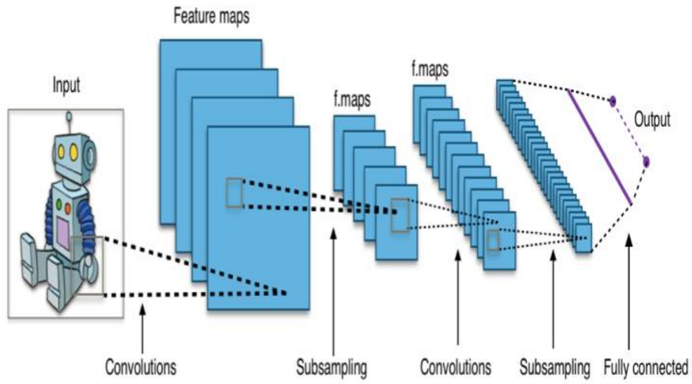

Fig. 1: Convoluted Neural Network [9]

Antoniades et al in 2016 used deep learning methods like CNN to classify interictal epileptic discharge and obtained a classification accuracy of 87.5%[10]. Salama et al in 2018 used EEG to enhance the robustness of the emotional recognition systems. They used a three dimensional CNN for classifying the issue in EEGs. Inputs were Dataset of emotion analysis and psychological (DEAP) and video data. This method outperformed other state of the art technologies of the period providing an accuracy of classification around 88% [11].

EEG has an distinct advantage in diagnosing Alzheimer's disease very early than conventional diagnostic protocols. In Alzheimer's disease, EEG was used previously to focus on slowing of oscillatory brain rhythms, reduction of corresponding time-series, and the enhanced compressibility. Most of these researches have been carried out in suing single channel EEGs. Morabito et al in 2016 explored the use of deep machine learning using CNN among Alzheimer Disease and normal candidates and was able to classify mild cognitive impairment which is a feature of early dementia. They averaged a classification accuracy of 82% [12].

Qiao et al in 2017 used EEG for multi-subject emotional classification. They extracted high level features through deep learning model and transformed traditional subject-independent recognition tasks into multi-subject recognition tasks. They carried experiments using DEAP dataset and classified using CNN to obtain an accuracy of 87.3% [13]. Brain plays an important role in determining one's gait. Cortical processes associated with gait determination were poorly studied. Goh et al in 2018 designed an experiment using EEG that contained four walking conditions such as free walking, exoskeleton-assisted walking at zero, low and using unilateral exoskeleton. They used Multi-channel EEG to record signals and classified using CNN at an accuracy of 78% which is very high in this field [14].

Signal Classification Using Deep Belief Artificial Neural Network (DBN*)*

Deep Belief network is witnessing increased attention as a classification plat form. This has been applied in some classification problems like image classification, speech recognition, and natural language processing. In the below studies we can see how DBN is used to classify signals of EEGs in various settings.

Lack of feedback training makes calibration of sensory motor rhythm to be time consuming and lengthy. When Restrictive Boltzmann Machine which uses DBN as classifier was used to extract features from 9 subjects, an accuracy of 78% was achieved for a hand versus feet MI task [15]. In this study by Zheng et al, DBN was used to construct EEG based emotion recognition models for positive, neutral and negative emotions from 15 subjects. When compared with neutral emotions, other emotions showed an classification accuracy of 86.1% [16].

In this Landmark study Li et al recruited 15 pilots and conducted a 4 hour flight simulation and recorded their cognitive state data brain activity using EEG. Engagement assessment was measured and classification accuracy of 97% was achieved using this model [17]. Classification of emotions accurately posed a problem for researchers for many years. Huang et al in 2017. Emotional patches were utilised on subjects and their EEGs were subjected to signal classification using DBN. They had the highest classification accuracy in this domain of research amounting to 94.9% [18]. DEAP database was used to classify subject specific affective states emotion and EEG was recorded simultaneously. When DBN was applied as the classifier, an accuracy of 89% was obtained [19].

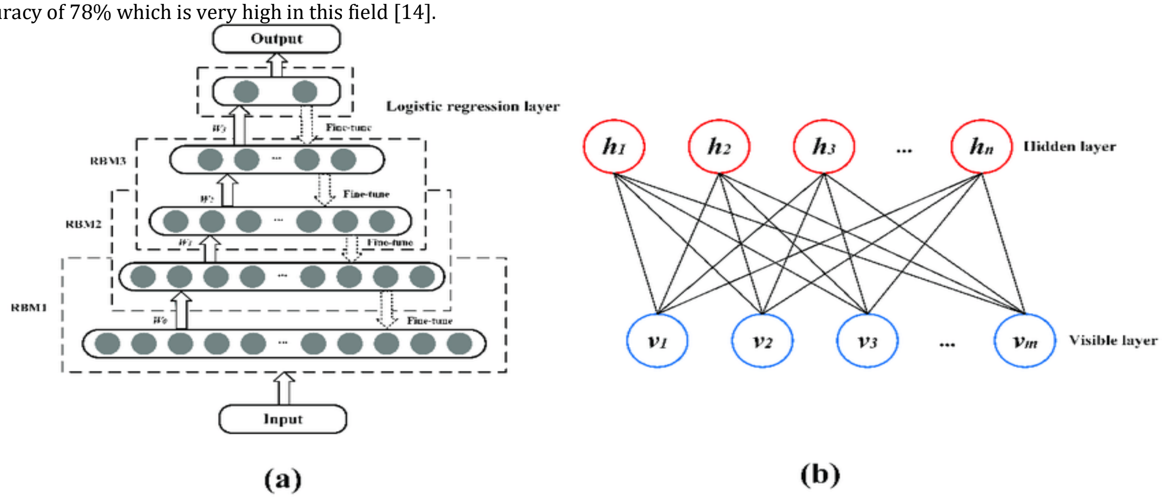

Fig. 2: DBN and Restricted Boltzmann Machine [20]

Zhao et al in 2015 applied DBN to analyse EEG data among 15 cases of Alzheimer's disease (AD) and equal number of controls. They obtained an excellent classification accuracy of 92% which makes this method a pioneering research in AD diagnosis [21]. Guilty knowledge test is a kind of test used to determine if certain information stored in brain by detecting the P300 wave. This test has been conducted in 14 subjects by Kulasingham et al in 2016 and DBN was used to classify signals and they obtained a signal classification accuracy of 87% [22]

Lie detectors are essential in cases of proving crime or excluding the innocents. DBN was used to classify EEG signals while taking deceit testing. This testing involves a mock crime scenario where relevant or irrelevant images were presented to the participants. The method provided the classification accuracy of 81% [23].

Signal Classification Using Hybrid of CNN-DBN

A novel approach to detect drowsy states in vehicle drivers was developed by Hajinoroozi et al in 2015. They used EEG from 37 drivers in 70 sessions. A combined CNN-DBN hybrid outperformed other methods providing a classification accuracy of 82.8% [24]

Signal Classification Using Hybrid of CNN-RNN (Recurrent Neural Network)

For aiding in diagnoses of neurological and psychological disorders, Automatic emotion recognition systems were developed. These record EEGs from the patient and an expert can read emotions from the EEG since he has great knowledge in domains from which signals were obtained. Li et al in 2017 combined CNN-RNN to classify features from these signals and obtained a classification accuracy of 73% [25].

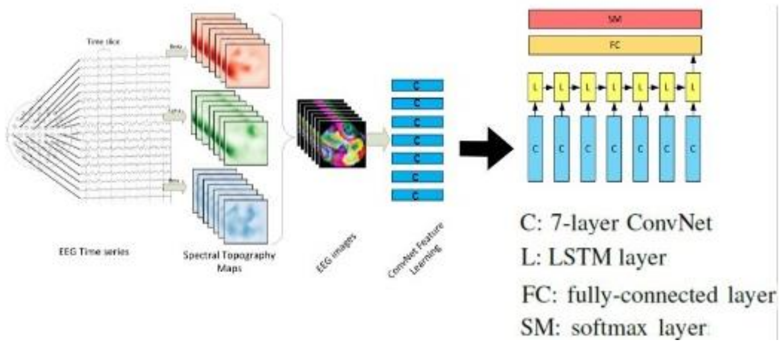

Fig. 3: CNN-RNN hybrid [26]

Many smart watches contain a single channel EEG and can analyse our sleep. This has a huge potential in human health. Bressch et al in 2018 used a single channel EEG among 29 healthy subjects. A network containing hybrid of CNN-RNN provided a classification accuracy of 80%. An important advantage of this system is that, this can be used at home for consumer usage [27].

Signal Classification Using Hybrid of RNN-MLPNN (Multi-Layer Perceptron Neural Network)

Dong et al in 2018 evaluated sleep EEG data of 62 people with 494 hours of sleep from a single EEG channel recorded at home. This is done to characterize the sleep stage progression aiding in diagnosis and monitoring of many sleep disorders. The raw signal was extracted and feature classification was done using an RNN-MLPNN hybrid. They detected sleep disorders at a high classification accuracy of 83.6% [28]

Signal Classification Using Hybrid of RNN-LSTM (Long Short-Term Memory) Network

EEG was primarily used for detection of seizures. Hussein et al in 2019 used LSTM network to first used to learn the high level representation of different EEG patterns. When classification was done using RNN, an accuracy of 100% detection achieved [29].

Emotion recognition using EEG has wide variety of applications such as automatic healthcare applications, helps autistic subjects to express emotion and in developing adaptive e-learning system. When RNN-LSTM was applied to classify EEG signals, the classification accuracy came to 87% [30].

DISCUSSION AND CONCLUSION

Neural networks when used in classification of neural signals had a long computational time and problem with vanishing gradients. This was now overcome by using large number of datasets and by using graphic processing units. This led to EEG combined with neural networks become one of the cheapest and easiest method of studying brain signals and other neural signals. Since neural networks can be trained to be learnt, even non experts of the field started using EEG for various researches.

CNN is the most discussed neural network in this paper which involves alternating layers of convolution with pooling layers. DBN composed of many number of stacked restricted Boltzmann machines with fully connected layers. RNN consists of number of recurrent layers and fully connected layers. Hybrids consists of more than one neural network for easier and accurate classification based on the needs of the researchers.

This paper tried to review studies which used hundreds of datasets of EEG and compared various classification techniques. CNN, RNN and DBN generally performed well than other ANNs. CNN performed well when spectrograms and signal values used as inputs. DBN performed well when signal values or calculated features as inputs. This paper can aid researchers on selecting best type of ANN for their specific aims.

Conflict of interest: None

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