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Autonomous Estimation of Patients' Neuropsychological State Using Convolutional Neural Networks

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Abstract
The number of patients with neuropsychological problems is increasing rapidly in the world. Autonomous methods are replacing the traditional diagnosis methods in detection and classification of many mental and neurological problems. Machine learning algorithms and especially deep neural networks are able to diagnose various neurological and psychological complications automatically. In this paper, a machine learning based framework is used for autonomous estimation of patients' neuropsychological state. The proposed framework can automatically diagnose neuropsychological state of the patients and present a personalized solution for their problems. A convolutional neural networks is used for automatic profiling of patients and to classify their mental state according to their EEG signals. The proposed framework can be used to help patients to have better life experience.

Keywords: E-nurse, Convolutional neural networks, EEG, Deep neural network, Mental illness.

1. Introduction
Artificial intelligence refers to a part of computer science that simulate intelligent behavior in computer

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systems. Deep learning as a sub-field of artificial intelligence mimics the brain computational model. Deep learning architectures are inspired by the structure of the human brain and will learn any learning based problem. Deep learning utilizes complex hierarchical neural network and have many applications in face recognition, disease diagnosis and prediction among other applications. Deep learning drives the advancement in a wide range of scientific fields including medicine [1].

Data mining and machine learning methods in health care are demonstrated promising results. Predicting neurophysiological disorders are studied using health data analysis. Through effective prediction of neurophysiological and psychological disorders based o bio-signals, the related healthcare costs are decreased and quality of life is improved for patients [2]. Deep Learning methods extract features that can determine variations in EEG signals. The neurophysiological features on EEG signals are used for prediction of the state of the patient neurological system based on machine and deep learning models [3]. Medical intervention hardware systems can be used to help the patients to control their neuropsychological problems. This can be the first step in the development of a fully automated neuropsychological intervention system.

In the past few years many efforts have been made to predict seizures and assist epileptic patients. Due to the large number of epileptic patients, the purpose of these studies is to develop a device which can detect the onset of seizures before they occur. Implementation of the detection or prediction algorithms can be fully applicable on a small hardware with features such as low power consumption, portability and real time operation. These devices can act as warning devices to prevent the emergence of dangerous mental problems [4].

In this paper the software system for encoding the EEG patterns of epileptic patients using a convolutional neural network is presented. The proposed framework extracts the features of the EEG signals by a Convolutional Neural Network (CNN) layers and a fully connected classifier was employed to recognize the mental state of the patients. The optimized hardware implementation of this method is a subsystem of a decentralized network for estimation and rapid response to mental and neuropsychological problems.

The rest of the paper is structured as follows. Section2 gives a brief description of the related work which use deep neural network models. Section3 provides the dataset description as well as the proposed deep learning model. We discuss the experimental result in section4. Finally, the paper concludes in Section5.

2. Related works

The neuropsychological disorder prediction using EEG signal is of great interest to the research community in the past few years. Automatic sleep staging is an important issue in sleep disorders diagnosis. By advent of machine learning, accurate results for this application is achieved using deep learning models. In [5], authors proposed DeepSleepNet model which sleep stage scoring is performed automatically based on single channel EEG. They develop an architecture consists of two sections. The first section is utilized a CNN to extract the required features automatically from single channel EEG. The second section uses a bidirectional (Long Short Term Memory) LSTM deep neural network to learn transition rules among sleep stages from EEG. In this model, representation learning employed two CNNs. In the first layers, small and large filters were used to extract temporal and frequency information features respectively. Each CNN has four convolutional layers, two max-pooling layers and a dropout layer that were used during the training process. Then, sequence residual learning was used which consists of a bidirectional LSTM and a shortcut connection. The two step training algorithm was used: pre-training and fine-tuning. The first step is to pre-train the representation learning section with balance dataset in order to prevent overfitting and the second step is to fine-tune the model in order to encode the stage transition rules.

Driver fatigue detection is important because statistics show driver fatigue influences many accidents. Among several signal indicators, EEG data evaluate driver fatigue effectively. In [6], a novel EEG based spatial-temporal convolutional neural network is proposed for driver fatigue detection. First, temporal dependencies of each electrode is learned and spatial information are extracted. Then, the dense layers are employed for feature fusion and classification. Feature extraction is performed in three convolutional layers and a pooling layer. Two dense layer with a Softmax classifier are used after the convolutional layers.

Motor imageries (MI) are used in Brain Computer Interface (BCI) systems that read brain signal to control a computer or any device by the cognitive states of the users. EEG is a common technique to assess MI task in BCI systems because the correlation between brain signal and mental activity is high and scalp EEG as a noninvasive method shows good resolution for MI task. In [7], a classification framework based on LSTM networks is proposed. First, data normalization is performed on EEG data. Then, 1d-AX (one dimension-aggregate approximation) was employed to extract effective signal representation. In channel weighting stage, useful information is extracted by spatial filters to optimize weighting coefficients. Finally, LSTM networks process the output of the channel weighting stage and a Softmax regression layer is employed to predict the probability of each class.

Epilepsy is one of the nervous system diseases that affects around 50 million people in the world. There are many attempts to predict seizures and to develop a device that can detect the onset of seizure before it occurs. EEG signal is an important bio-signal that is broadly used for epilepsy diagnosis. One of the proposed models for seizure prediction is deep learning [8]. Features learning to distinguish between the pre-ictal and inter-ictal states is the first goal of the framework. Another goal of the proposed framework is definition of the prediction horizon to predict the states precisely and as soon as possible. A wavelet transforms on the EEG signal converts the signal from the time domain to the combination of frequency and time domains. The wavelet coefficient creates a tensor with three states: time, scale and channels. The architecture is included six convolution layers which is continued with two dense layers. Then, the max pooling layers are applied to the signal. The output layer is consisting of three neurons that is presented probability distribution on three classes. The epoch length and overlap percentage are two parameters which are used for fine tuning the model. Also pre-ictal duration is considered as a ‘l' in the training process and the model is optimized by grid search. Therefore, all of window that is located in ‘l’ minutes before the seizure onset are labeled as a pre-ictal and windows that is located after seizure is labeled ictal and other windows are labeled inter-ictal. The results are shows that the pre-ictal state occurs ten minutes before seizure onset.

Deep learning algorithms are being developed High-throughput computing and low-power consumption in comparison with machine learning algorithms. In table 1, the comparison results for hardware implementation of seizure prediction are accomplished. The main machine learning classification method is SVM and the turnout IBM chip is used in deep learning classification[9].

Table 1. The comparison results for hardware implementation of seizure prediction

Authors	Dataset	Channel	Feature Extraction	Classification	Measurement parameter	Power Consumption	Energy Efficiency	Platform	Latency
Li Feng et al [10]	Epilepsy Center at the University of Bonn, Germany The Children's Hospital Boston-MIT	1	TFD by DWT Mean absolute value & variance	Non-Linear SVM(MSMO)	Sensitivity=96.8	45 mW	112.6 Mbits/J	50 MHz Altera Cyclone II FPGA	-
Huang et al [11]	CHB-MIT	23	FFT	NL-SVM	Sensitivity=96.6	1.9 mW	170.9 µj/Class	ASIC	0.71s
Bin et al [12]	Private Data	8	-	Non-Linear SVM	-	-	1.83 µj/Class	-	2s
Wang et al [13]	Epilepsy Center at the University of Bonn, Germany	1	LDWT maximum, standard deviation	NLSVM	Accuracy=94.2	-	-	FPGA (Xilinx Virtex 5)	-
Kiral-Kornek et al [9]	Private Data of 10 patient	16	-	Deep Learning	Sensitivity=68.6	<40 mW	-	TrueNorth	-

3. Autonomous estimation of patients' neuro-psychological state

In the proposed framework an efficient CNN model is used as the software model for a later hardware implementation for neurological state prediction. The final model should ensure adequate performance and minimum time consumption.

EEG and Neuro-Psychological State

The EEG signals indicate the electrical activity of the brain by measuring the difference in electrical potential. The EEG is widely used by physicians and specialists to study brain functionality as well as diagnosis and treatment of nervous system diseases. It shown that brain activity vary based on its functional status; such as sleep, anesthesia and seizures [14].

Research on EEG paves the way for the detection of many neurological disorders in the human nervous system. In addition, these signals are also used for treatment of medical problems of nervous system including detection of epileptic seizures, identifying the source of seizures, monitoring cognitive interactions, monitoring anesthesia depth, coma and brain death, monitoring brain growth and mental disorders [15].

Convolutional Neural Network

Convolutional neural networks as a feed forward deep learning method is popular for feature extraction from image data and attracted big attention in recent years. In general, a CNN consists of convolutional layers, pooling layers and fully connected layers [16]. In convolutional layer, kernels matrix slide across the input and convolved with them as follows:

$$y_{ij}^{l} = \sum_{a=1}^{m} \sum_{b=1}^{m} w_{ab}^{l} * x_{(i+a)(j+b)}^{l-1} \qquad (1)$$

The stride controls the size of the convolution across the input. An activation map from the input is calculated using convolutional filters. After the convolutional layer (linear operation), nonlinear function such as sigmoid, tanh and ReLU is applied to the result of convolutional layers.
The next layer in a convolutional neural network is pooling layer that computes maximum or average output from the neighborhood and reduces the dimensionality of a layer and cuts down the amount of parameters for simpler outputs. If the max operator is used, the max pooling is defined as:

$$S_i = \underset{i \in R_j}{\text{Max}}\, h_i \qquad (2)$$

And if the average operator is used average pooling is defined as:

$$S_i = \frac{1}{n} \sum_{j \in R_j}^{n} h_j \qquad (3)$$

Where *h* is quantity of element in the sub-region R_j from the feature map and *n* is the number of elements in the sub-region.
The neurons in the fully connected layers as a final layer of the network have full connectivity with previous and next layers. Each neuron adds the weights from its inputs and a bias together as follows [17]:

$$\text{f(x)} = \varphi(b + \textstyle\sum_{i=1}^{n} x_i\ w_i\ ) \qquad (4)$$

Dataset

The data used in this paper was presented by the American Epilepsy Society [18]. The dataset contain EEG data from five dogs and two human patients with totaling 48 seizures and at around 627.7 h inter-ictal recordings. Intracranial EEG dogs' data were recorded using an ambulatory monitoring system and were sampled from 16 electrodes at 400 Hz. The datasets from patients with epilepsy undergoing intracranial EEG were 15 electrodes for patient1 and 24 electrodes for patient2 are sampled at 5000 Hz. Details on the raw EEG dataset are summarized in Table 2. Since the characteristics of canine epilepsy are similar to focal human epilepsy and EEG signals of canine and human for focal onset is undisguisable, the canine epilepsy very good model for human epilepsy [19].

TABLE 2. CHARACTERISTICS OF THE EEG DATASET [18]

	Dog 1	**Dog 2**	**Dog 3**	**Dog 4**	**Dog 5**	**Patient 1**	**Patient 2**
Segments labeled pre-ictal	24	42	72	97	30	18	18
Segments labeled inter-ictal	480	500	1440	804	450	50	42
Ratio inter-ictal / pre-ictal	20	12	20	8	15	3	2
Sampling frequency [Hz]	400	400	400	400	400	5000	5000
Channels	16	16	16	16	15	15	24

Pre-ictal and inter-ictal EEG data were split into 10 min segments. Pre-ictal segments occur between 5 to 65 min before a seizure. In order to avoid any potential contamination between inter-ictal, pre-ictal, and post-ictal EEG signals inter-ictal segments were restricted to be at least one week before or after any seizures and at least four hours before or after any seizures for dogs and patients, respectively.

Network Architecture

The proposed CNN network can be applied for epileptic seizure prediction hardware. The architecture of the mental state prediction CNN model is presented in Figure 1.

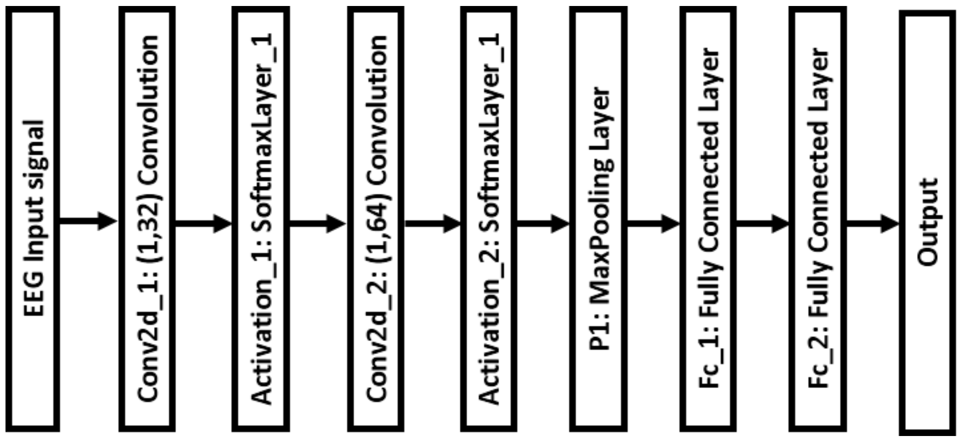

Fig 1. CNN architecture

Primarily, Band-pass filters have been used to transmit frequencies between 0.1 to 180 Hz. The signals transform by Fourier filter is divided into 1-minute segments. Then we use two convolutional layers for feature extraction. The first convolutional layer has (1, 32) filter size and (5, 5) kernel length. The second convolutional layer is has (1, 64) filter size and the same kernel length compared to the previous convolutional layer. Each convolutional layer uses batch normalization, a RELU activation function and Adam optimizer. After feature extraction by the convolutional layer, the local features are obtained using the pooling layer. In classification section, two fully connected layers are implemented with a hyperbolic tangent function and Softmax function, respectively. Finally, the output layer with 2 output neurons (normal and pre-ictal classes) are connected to the last fully connected layer.

4. Experimental Setup and Results

All implementation and development is performed using MATLAB programming software. In particular, we applied the deep learning Toolbox for classification algorithms as well as feature engineering. The EEG data from EEG dataset that are recorded intracranial, are used to verify binary classification. Data classification is performed in two classes, pre-ictal and inter-ictal as positive and negative class.

The performance is evaluated by computation of classification accuracy. The accuracy is defined as:

$$Accuracy = \frac{TP+TN}{(TP+TN+FP+FN)} \quad (5)$$

where TP, FP, TN and FN are True positive, False positive, True negative and False negative respectively. In this paper we proposed a framework seizure prediction using CNN without handcrafted feature extraction. Since the final goal is the hardware implementation of the CNN based model, the complexity of the system should be reduced as much as possible while maintaining classification accuracy in acceptable ranges. According to the experimental result, the accuracy can be improve with more EEG data. Table 3 summarized results of recent seizure prediction approaches and this work. The comparison between the works in predicting the onset of seizure isn't appropriate because different datasets are used and same parameter has not been measured. The accuracy of the proposed model will be improved in the later stages of the research.

TABLE 3. SUMMARY OF RECENT SEIZURE PREDICTION APPROACHES

Authors	Year	Dataset	Feature	Classification	Performance
Petrosian et al[20]	2000	Private Data	Wavelet transform	RNN	Time Prediction = 2 min
Mirowski et al[21]	2009	MIT	Bivariate features	CNN	Sensitivity=71 %
Khan et al [8]	2017	MSSM, MIT	Wavelet transform	CNN	Sensitivity= 87.8%
Tsiouris et al [22]	2018	MIT	Statistical features, Zero crossings, Wavelet transform, Power spectral Cross-correlation, Graph theory	LSTM	Sensitivity=99%
This work	2019	Kaggle	Fourier Transform	CNN	Accuracy=84.7 % Time Prediction=97 s

5. Conclusion

In this paper a deep neural network based for autonomous neuropsychological state prediction is presented. The proposed technique uses the CNN architecture to semantically label the EEG signals. A series of simulations are performed for seizure prediction using the proposed model. The experimental results show that the presented framework have acceptable accuracy and speed for neuropsychological state prediction.

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