Original Article

DEEP LEARNING ON EEG FOR DETECTION OF DEPRESSION

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DOI: 10.47750/pnr.2023.14.S01.137

Abstract

In recent years, advanced neurocomputing and machine learning techniques have been used for Electroencephalogram (EEG)-based diagnosis of various neurological disorders. In this paper, a novel computer model is presented for EEG-based screening of depression using a deep neural network machine learning approach, known as Convolutional Neural Network (CNN). The proposed technique does not require a semi-manually-selected set of features to be fed into a classifier for classification. It learns automatically and adaptively from the input EEG signals to differentiate EEGs obtained from depressive and normal subjects. It was discovered in this research that the EEG signals from the right hemisphere are more distinctive in depression than those from the left hemisphere. This discovery is consistent with recent research and revelation that the depression is associated with a hyperactive right hemisphere. An exciting extension of this research would be diagnosis of different stages and severity of depression and development of a Depression Severity Index (DSI).

I. INTRODUCTION

Depression is considered by WHO as the main contributor to global disability and it poses dangerous threats to approximately all aspects of human life, in particular public and private health. This mental disorder is usually characterized by considerable changes in feelings, routines, or thoughts. With respect to the fact that early diagnosis of this illness would be of critical importance ineffective treatment, some development has occurred in the purpose of depression detection. EEG signals reflect the working status of the human brain by which are considered the most proper tools for a depression diagnosis. Deep learning algorithms have the capacity of pattern discovery and extracting features from the raw data which is fed into them. Owing to this significant characteristic of deep learning, recently, these methods have intensely utilized in the diverse field of researches, specifically medicine and healthcare.

II. STATE OF THE ART

Depression is a common mood disorder, which might cause persistent feeling of sadness, loss of interest, and impairment of memory and concentration. Depressed patients normally experience cognitive impairment and suffer long and severe emotional depression. In severe cases, some patients will experience paranoia and illusion. According to the World Health Organization statistics, >300 million individuals suffer from depression worldwide; approximately 800,000 people die due to it every year. Thus, depression is predicted to become the second most common disease after heart disease by the year 2022. Hence, the diagnosis of depression in the early curable stages is critical and might save the life of a patient.

The current methods of depression detection are human-intensive, and the results are dependent on the doctor's experience. Furthermore, depressed individuals are less likely to seek help due to fear of stigma and the nature of the disorder. As a result, a large number of depressed patients, not diagnosed accurately, do not receive optimal treatment and adequate recovery period. Therefore, finding convenient and effective methods for the detection of depression is an emerging topic for research. With the latest advances in the sensor and mobile technology, the exploration using physiological data for the diagnosis of mental disorder opens a new avenue for an objective and accurate tool for depression detection. Among all kinds of physiological data, electroencephalogram (EEG) reflects emotional human brain activity in real time.

Electroencephalography (EEG) is a commonly used neuroimaging tool. Its application ranges from clinical capacity such as sleep disorder studies, to seizure detection, to commercial circumstances such as EEG-controlled games. The EEG data is represented as a two-dimensional matrix, which consists of electric potentials on one axis and the electrode number on the other axis. This form of EEG data makes it easy to use in machine learning models. With its high temporal resolution, EEG data can provide information regarding the functional connectivity within the brain, thereby providing a topological understanding of the functioning of the human brain. This is usually carried out by transforming the electrical potentials into a Correlation Matrix. Functional connectivity is time dependent and to understand the functional aspects of the brain under conditions of executive functions and emotional states viz. depressive or anxious, it is vital to study them in terms of networks and the best way to do it, with the help of EEG signals, which have the highest temporal resolution in the field of neuroimaging techniques.

Poverty, unemployment, tragic events of life, physical disorders, and problems with alcohol or drug consumption are considered as determining factors leading to depression. Recently, the Covid19 pandemic has advanced the cause of depression, and its consequent conditions such as imposing lockdown, going into quarantine, and practicing social distancing are considered other main reasons for experiencing depression. With regard to the fact that depression poses an unprecedented threat to public health and have some adverse effects on depressive people such as committing suicide, and also considering this matter that early diagnosis can result in providing timely and more effective treatment, devising and developing an efficient and reliable method of depression detection or even prediction would be of the high importance. Electroencephalogram (EEG) signals which naturally have nonstationary, highly complex, non-invasive, and nonlinear structure, involves human brain activities and working status. Due to this complexity, available abnormality would be difficult to detect with the naked eyes. These properties have made physiological signals are deemed to be valuable tools for depression detection. Deep learning is defined as a hierarchy structure with a series of algorithms which have some hidden neurons. These models provide computers with the ability of building complex concepts from simple statements. These learnt concepts utilize to build next layers. Furthermore, in these methods, multiple processing layers are responsible for pattern and data structure recognition.

III. LITERATURE REVIEW

The following references were taken for a comprehensive understanding of how EEG signals work when taken as a form of input for machine learning and deep learning tasks. These research publications are relatively recent and helped to form an understanding of the deep learning convolution neural network model.

TITLE	AUTHOR/YEAR	SUMMARY
A Deep Learning Approach for Mild Depression Recognition Based on Functional Connectivity Using Electroencephalography	Xiaowei Li, Rong La, Ying Wang 1 April 2020 https://doi.org/10.3389/fnins.2020.00192	Presents a novel approach to mild depression recognition using electroencephalography and suggests that the combination of a CNN and functional connectivity matrix may provide a promising objective approach for diagnosing mild depression.
Deep learning applied to electroencephalogram data in mental disorders	Mateode Bardeci, Cheng Teng Ip, SebastianOlbrich May 2021 https://doi.org/10.1016/j.biopsycho.2021.108117	This study systematically reviews clinical features, EEG-processing and Deep Learning. It also reviews model selection and testing strategy
Machine learning applications for electroencephalograph signals in epilepsy	Yang Si 29 April 2020 https://aepi.biomedcentral.com/articles/10.1186/s42494-020-00014-0	Presents advantage, challenge and future direction of ML techniques in the analysis of EEG signals
A Deep Convolution Neural Network Framework for Detecting Depression Using EEG	Ayan Seal; Rishabh Bajpai; Jagriti Agnihotri; Anis Yazidi; Enrique Herrera-Viedma; Ondrej Krejcar 25 January 2021 https://ieeexplore.ieee.org/document/9335239	This study proposes a DL-based convolutional neural network (CNN) called DeprNet for classifying the EEG data of depressed and normal subjects.
EEG-based Depression Detection Using Convolutional Neural Network with Demographic Attention Mechanism	Xiaowei Zhang; Junlei Li; Kechen Hou; Bin Hu; Jian Shen; Jing Pan; Bin Hu 27 August 2020	Presents ways that aims to decrease the computational time and improve classification accuracy, and employs features ranking and selection employing algorithm

IV. PROPOSED WORK

EEG is the preferred diagnostic tool in this research as it is non-invasive, economical, and easy to operate whereas the Magnetic Resonance Imaging (MRI) machine is expensive. Furthermore, the EEG records the brain's electrical activity over a period of time while the MRI machine captures the changes in blood flow of the brain within seconds to a minute. Thus, the EEG signals are used instead of MRI scans to identify depression patients. However, both normal and depressed EEG signals are chaotic and complex in nature with subtle differences reflecting different brain activities of the two groups that cannot be determined readily through visual observations. Therefore, a Computer-Aided Detection (CAD) system is proposed to diagnose depression from the EEG signals objectively.

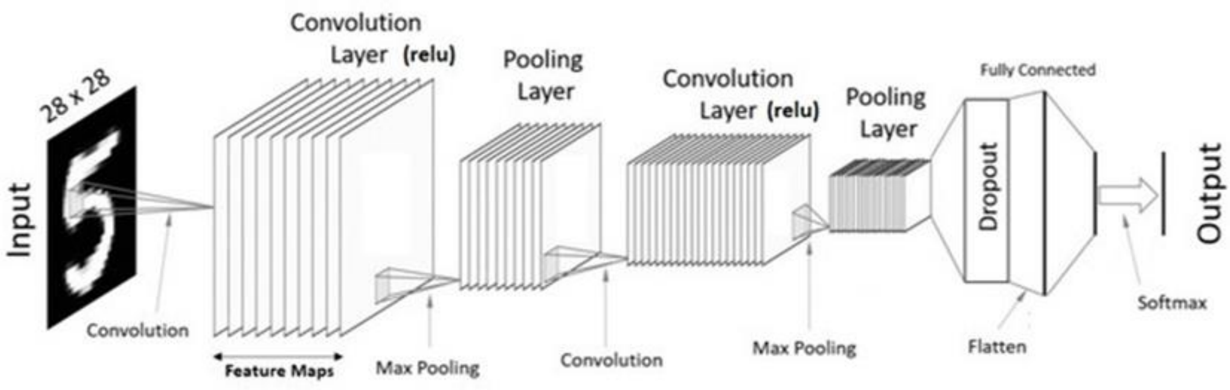
EEG data is inherently noisy because EEG electrodes also pick up unwanted electrical physiological signals, such as the electromyogram (EMG) from eye blinks and muscles on the neck. There are also concerns about the motion artifacts occurring from cable movement and electrode displacement when the subject moves. EEG signals are intrinsically noisy and suffer from channel crosstalk. In typical scalp EEG recording settings, each EEG electrode picks up signals from the area nearby, making the spatial resolution coarse (several centimeters). Unmixing the signals is not trivial because of the anisotropic volume conduction characteristics in human brain tissues, skull, scalp, and hair. Therefore, one of the standing challenges in EEG data analysis is how to formulate inputs. To simplify our project, we have chosen signal values as our type of input formulation.

At present learning, models use either the properties of the EEG signal such as amplitude, frequency, and event-related potentials as features or graph properties such as centrality measures which are nodal metrics or edge metrics such as shortest path length. Network analysis and learning models on neuroimaging data have enabled researchers to study the human brain’s functional and structural connectivity. Signal strength in the time domain is also used directly as inputs to the neural networks. Traditionally, this approach is usually associated with particular hand-engineered time domain features, such as the power spectral density features. Neural networks promise to automatically learn complicated features from large amounts of data, prompting the idea of end-to-end learning.

Existing methods included implementation of tools and techniques such as Support Vector Machine (SVM), logistic regression model, random forest, graph theory and recurrent neural networks. Our methods have a sole focus on creating a convolution neural network and inputting the dataset, of which 90% is fed into training and 10% is used for testing. The merits of this method include high accuracy, and due to the fact that the deep learning mechanism is used in the form of convolution neural network, it can automatically detect without external interference.

The demerits are mainly in the area of data preprocessing, as EEG signals are inherently noisy and suffer from channel crosstalk, and due to the intrinsic noise, it can be difficult to unmix the signals due to the antistrophic volume conduction characteristics of human signals.

V. ARCHITECTURE/ BLOCK DIAGRAM



VI. IMPLEMENTATION

A CNN has three types of layers: (i) convolution, (ii) pooling, and (iii) fully-connected. In this study, the CNN model is made up of 5 convolutional layers, 5 pooling layers, and 3 fully-connected layers.

(i) Convolutional layer:

The objective of the Convolution Operation is to extract the high-level features such as edges, from the input image. The role of the CNN is to reduce the images into a form which is easier to process, without losing features which are critical for getting a good prediction. This is important when we are to design an architecture which is not only good at learning features but also is scalable to massive datasets. The element involved in carrying out the convolution operation in the first part of a Convolutional Layer is called the Kernel/Filter. Conventionally, the first ConvLayer is responsible for capturing the low-level features such as edges, color, gradient orientation, etc. With added layers, the architecture adapts to the High-Level features as well, giving us a network, which has the wholesome understanding of images in the dataset. In this layer, the convolution is performed by sliding the kernel over the input to obtain a convolved output (feature map) using the following equation:

$$c_m = \sum_{n=0}^{N-1} f_n k_{m-n}$$

where k, f, c, and N denote signal, filter, output, and the number of data points in k, respectively. The subscript n indicates the nth element of the filter vector while m corresponds to the mth output element that is being calculated. As n runs from 0 to N-1, the sample fn is multiplied by the sample from the input signal km-n. These products are summed to produce the output. The purpose of the convolutional layer is to obtain significant features from the input EEG signal for training the algorithm.

(ii) Pooling layer: Similar to the Convolutional Layer, the Pooling layer is responsible for reducing the spatial size of the Convolved Feature. This is to decrease the computational power required to process the data through dimensionality reduction. Furthermore, it is useful for extracting dominant features which are rotational and positional invariant, thus maintaining the process of effectively training of the model.

There are two types of Pooling: Max Pooling and Average Pooling. Max Pooling returns the maximum value from the portion of the image covered by the Kernel. On the other hand, Average Pooling returns the average of all the values from the portion of the image covered by the Kernel.

Max Pooling also performs as a Noise Suppressant. It discards the noisy activations altogether and also performs de-noising along with dimensionality reduction. On the other hand, Average Pooling simply performs dimensionality reduction as a noise suppressing mechanism. Hence, we can say that Max Pooling performs a lot better than Average Pooling. This layer decreases the size of the feature map while at the same time preserving the significant features. A max-pooling operation is employed in this study, that is, only the largest value within the stride 2 window of the feature map is retained after every max-pooling operation.

(iii) Fully-connected layer: After going through the above process, we have successfully enabled the model to understand the features. Moving on, we are going to flatten the final output and feed it to a regular Neural Network for classification purposes. Adding a Fully-Connected layer is a way of learning non-linear combinations of the high-level features as represented by the output of the convolutional layer. The Fully-Connected layer is learning a possibly non-linear function in that space. Over a series of epochs, the model is able to distinguish between dominating and certain low-level features in images and classify them using the Softmax Classification technique. This layer connects every neuron within the layer to every neuron in the next layer using the following equation.

$$x_i = \sum_j w_{ji} y_j + b_i$$

where w and b denote the weights and biases, y represents the output from the previous layer, while x is the output of the current layer. Furthermore, outputs from the last fully connected layer are fed into softmax function to predict the class by determining the class probability of each EEG signals as being normal or depressive.

EEG data is inherently noisy because EEG electrodes also pick up unwanted electrical physiological signals, such as the electromyogram (EMG) from eye blinks and muscles on the neck. There are also concerns about the motion artifacts occurring from cable movement and electrode displacement when the subject moves. Most studies used frequency domain filters to limit the bandwidth of the EEG to be analyzed. This is useful when there is a certain frequency range of interest so that the rest can be safely discarded. Each record consisting of 2,000 sampling points is normalized using the Z-score normalization to overcome the amplitude scaling problem and remove the offset effect before being used for training and subsequent testing of the proposed CNN model.

The last stage of a convolutional neural network (CNN) is a classifier. It is called a dense layer, which is just an artificial neural network (ANN) classifier. And an ANN classifier needs individual features, just like any other classifier. This means it needs a feature vector.

Therefore, we need to convert the output of the convolutional part of the CNN into a 1D feature vector, to be used by the ANN part of it. This operation is called flattening. It gets the output of the convolutional layers, flattens all its structure to create a single long feature vector to be used by the dense layer for the final classification.

Training and Testing:

To avoid overfitting and improve the generalization, the dropout technique is applied to the fully-connected layers. During training for each mini-batch, some of the neurons from these layers are selected randomly and dropped. This forces the model to learn from a subset of input features and not the entire input features. The rate is set to 0.9. i.e., a probability of 90% a neuron will be kept and a probability of 10% that a neuron will be dropped out during the training. The proposed CNN model is trained using 90% of the EEG dataset. The remaining 10% of the dataset is used to test the model.

The model is tested using a ten-fold cross-validation strategy using the test dataset (10% of the EEG data). The testing of the proposed model is repeated 10 times. Then, an overall performance is computed by averaging the results from all 10 iterations.

VII. CONCLUSION

The proposed CNN model does not require the semi-manually selected extraction and selection of features for classification. Rather, the model can self-learn and pick up distinct features during the training of the algorithm.

Based on the results obtained using the proposed model with a limited number of EEG data, it can be concluded that the CNN model can be used for computer-assisted diagnosis of depression rather reliably. Moreover, this proposed algorithm can serve as a second-opinion to validate the diagnosis made by a clinician. Nonetheless, the analytical performance of the proposed model can be improved with a larger set of EEG signals.

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