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Effects of EEG Signal to Parkinson Disease through Deep Recurrent Neural Network

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Abstract

This paper introduced a novel computer-aided diagnosis method to detect the Parkinson Disease (PD). A novel Pooling-based Deep Recurrent Neural Network (PDRNN) is used in this proposed algorithm as an efficient deep learning method. Parkinson disease gradually degrades the functionality of the brain. Because of its relevance to the abnormality of the brain, EEG (denoting the electroencephalogram) signal is used for early detection of this disease. The electroencephalogram signals of 20 Parkinson and 20 healthy cases are studied in this paper. Also, a PDRNN learning method is applied on the used dataset for tackling the demand for the traditional feature presentation step. The proposed method of this paper could obtain proper precision, sensitivity and specificity (88.31, 84.84 and 91.81 percent, respectively). In addition, our derived classification method has potential to be employed for high populations prior to be installed for clinical applications.

Keywords: Parkinson disease; Deep learning; PDRNN neural network; Computer-aided diagnosis method; EEG signal

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Introduction

In the brain, the max number of the neurons belongs to the birth time [1]. Dissimilar to other cells of the human body, the brain neurons can't be fixed. So, over the time they die and they can't be replaced [2]. Generally, Parkinson disease results by the death of the nerve cells [3]. The nerve cells generate the dopamine, which is a chemical material. This substance mainly controls the body motions. So, the quantity of the generated dopamine reduces after dying the nerve cells. Then, this situation begins to affect different communication modes of the brain [4]. This disease appears mostly in people with ages about 50 or higher. Unstable posture, muscles' stiffness, slow motions, tremor, balance losing as well as the damaged fine motor skill are some initial signs for PD [4].

Statistically, about ten million persons suffer the Parkinson disease (reported by World Health Organization) [5]. Once there are no visible motor (or non-motor) signs, it's hard to detect the PD. Hence, the intelligent detection methods can be useful for early diagnosis of the abnormal signs [6,7]. These methods are automated diagnosis systems, and they are able to objectively detect the Parkinson disease by EEG signals. Using the EEG signals, functions of cortical (or sub-cortical) segments in the brain can be simply detected. As well, other disease related to the brain such as Alzheimer and epilepsy can be identified by these signals [8-11]. Thus, the EEG signals are employed in the present work for obtaining a computer-aided system in order to diagnose the Parkinson disease.

As reported in the literature, electroencephalogram signals are complicated and non-linear inherently. So, most of the linear feature selection methods can't precisely apply on EEG signals [6]. Higher complication of these signals results in aggravation of the Parkinson disease, which is because of the non-linear elements of the electroencephalogram signals [12-15]. Therefore, utilization of the non-linear feature extraction methods will be helpful for separation of the healthy and Parkinson EEG signals.

In this way, deep neural networks as a subsection of machine learning methods are efficiently applied on various fields of pattern identification as well as the natural language processing recently [16]. Deep learning methods are a sub-group of machine learning techniques called by deep network structures. This idea was introduced for the first time as cybernetics in [17]. Nevertheless, it didn't consider as a practical concept because of 3 main limitations including: lack of an adequate dataset, lack of computational tools in case of networks with high dimensions, and lack of effective learning methods. These limitations are already tackled appearance of efficient computing methods and

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tools.

So far, these methods are successfully applied in different fields containing:

a) Computer vision like Google Goggles that employs some deep learning methods in object detection;

b) Expert systems like Alpha Go that is programmed by DeepMind [18];

c) And medical applications that use such methods to help the companies for designing new drugs [19].

Deep recurrent neural networks are very famous forms of the deep learning methods presented in literature [20,21]. Based on our studied literature, this paper applies the DPRNN model for the first time to automatically detect the Parkinson disease. A novel computer-aided method is developed in this study that classifies the used dataset into two Parkinson and healthy groups. Configuration of the suggested model is depicted in **Figure 1.** The utilized neural network is comprehensively described in the next parts.

Methodology

Proposed deep learning method

Deep learning is a class of the machine learning methods, and it can successfully hybridize the feature extraction and clustering procedures [22-25]. In the present work, the obtained characteristics from the considered dataset are utilized for construction of a robust DRNN model. Then, they are used for validation of the detection efficiency of the trained model in the testing stage. The DRNN model is efficiently applied on some applications in the literature [20,21].

Deep recurrent network with LSTM unit

Convolutional deep NNs, deep sparse autoencoder, DRNNs, and multi-layer perceptron are some ordinary configurations of deep learning methods [26]. Among these methods, DRNN is used here for detection of PD disease.

In this used deep network, several RNN layers are connected to each other for structuring a deep configuration. This deep learning method is successfully applied in some fields [20]. This paper used a state-of-art recurrent network as LSTM (denoting the Long Short Term Memory) in order to obtain the highest efficiency of the RNN network.

Structure of the DRNN is firstly presented in the present part. Afterwards, the LSTM units are applied to the structured DRNN.

DRNN architecture

The sharing states of this configuration are separated into several layers for gaining good features of deep structures. Higher efficiency of deep structures of the recurrent networks is depicted in various works [20,21].

The RNN maps the input vector (x) to the equivalent output set (y). In this graph, the learning procedure is carried out in each time-step in the range of t=1 to τ. The sharing states related to variables of each node in the l^{th} layer are updated by [26]:

$a_1(t) = b_1+W_1\times h_1(t\text{-}1) + U_1\times x(t)$……………………………………………………………(1)

$h_l(t)$ = activation-function $(a_l(t))$ $l\in[1,N]$…………………………………………….(2)

$a_l(t)= b_l+ W_l\times h_l(t\text{-}1)+U_l\times h_{(l-1)}(t)$ $l\in[1,N]$…………………………………………….(3)

$y(t)=b_N+W_N\times h_N(t\text{-}1) + U_N\times h_N(t)$………………………………………………………………(4)

L + loss-function (y(t) and y_target (t))……………………………………………………(5)

In which, x(t) denotes the input in time-step t; y(t) and $y_{target}(t)$ are the predicted and real outputs; $h_l(t)$ indicates the sharing states of layer l; $a_l(t)$ is the input of l^{th} layer that composed on 3 elements of: 1) *x(t)* or $h_{(l-1)}(t)$, 2) *b* (bias values), and 3) $h_l(t\text{-}1)$. Because of the shared features of the recurrent neural network, it will be able to learn the iterated uncertainties of the prior time-steps.

Applying the LSTM units

The LSTM is a certain configuration of recurrent networks that can tackle the non-solved long term dependencies of standard RNN configuration. In the learning process, the recurrent network aims to learn the presentation of frequently happened patterns in the past via sharing the variables across all of the time-steps. But still, the memory of the previously learned patterns can fade over the time. Dependencies of the past two input values (*x*(0) and *x*(1)) become weaker in the predicted output once it has reasonably large value.

So, long short term memory is proposed to overcome this problem via generating the paths, where the gradient is able to flow in long periods. The computing process of this unit depicts the manner of memorizing the long term patterns by LSTM units.

Dissimilar to the conventional recurrent networks, LSTM units contain a certain sharing variables vector of *S*(t) (memory variable vector), which is used for keeping the memorized data. The memory variable composed on 3 operations in all time-steps including:

1. Elimination of the useless data from *S*(t);
2. Adding new data of *i*(t) that are chosen from *x*(t) and *h*(t-1) to the memory vector;
3. Obtaining the new *h*(t) from vector of *S*(t).

As depicted in the LSTM units, just 2 operations are conducted over *h*(t) including memorizing the new data and eliminating the out-of-time data. Thus, the sharing memory is able to preserve the helpful data for a sufficient time, which leads to promote the RNN efficiency.

Suggested deep learning configuration

Structure of the developed model is outlined in **Figure 1.** Two phases are considered for this model containing the learning and testing phases. The stratified tenfold cross validation is presented in the training phase, in which, the used dataset is divided to

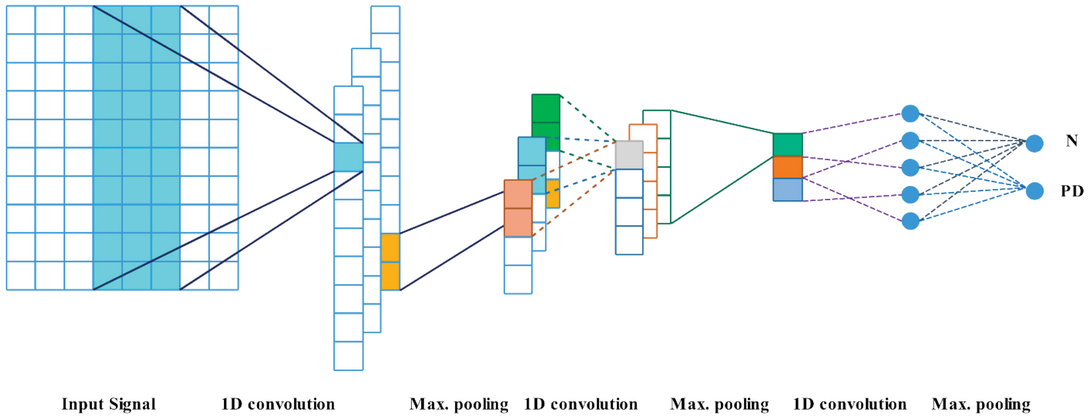

Figure 1 The designed CNN configuration.

ten sections uniformly. From these sections, nine of them are utilized for training phase, and one section is used in the testing phase. This process is repeated 10 times, in a way that, all of 10 sections are used in both stages. In addition, for evaluating the training progression in the ending of the epochs, twenty percent of the learning dataset is assigned to validate the derived model. Moreover, the SSO optimizer [27] is employed as well as some activation functions like Relu in the all layers and softmax of the end layer. Also, dropout is adjusted to 0.5 in the dropout layer.

Results and Analysis

Parkinson and healthy cases

The electroencephalogram signals for twenty Parkinson patients (ten male and ten female) are gathered from Hospital University Kebangsaan Malaysia Ethics Committee. Ages of these persons were in the range of 45-65, and their mean sickness periods were 5.75 ± 3.52 years (varying in the range of 2 to 10 years). The Hoehn and Yahr phases are in the following form [28]:

Phase 1: Two patients;

Phase 2: Eleven patients;

Phase 3: Seven patients.

The obtained MMSE (denoting the mini mental status examination) results are at the interval of the typical boundaries 25 to 30 (26.9 ± 1.51). Presence of further neurological situations or psychiatric disturbances are the exception conditions. The L-dopa drugs are used by Parkinson patients for decrement of the non-uniformity.

Furthermore, twenty healthy cases with equal age range (nine male and eleven female) without past recorded neurological (or mental) disorders are studied here. In case of the normal persons, the MMSE results are obtained in the range of 27.15 ± 1.63 years. Both of the healthy and Parkinson cases was right hand. This issue is confirmed by Edinburgh Handedness Inventory. It's as well remarked that their hearing situations are perfect.

Pre-processing phase and electroencephalogram signals

The required recordings are performed in five minutes in the steady state with 128 Hz sample rate. In this way, we utilized an emotive EPOC neuro-headset with 14 channels. It's asked from the contributors to comfortably sit in the considered silent room. Then, they informed prior to record (to don't move their body like blinking their eyes) in the recording process. Afterwards, the recorded signals divided into 2-s window length.

We employed a threshold method for eliminating the signals with level of higher than ± 100 µV (in order to eliminate the eye blinking effects). Subsequently, the frequencies are filtered using a six-order band-pass filter from Butterworth type with forward-reverse method. This filtering is performed in order to bound the frequencies at the interval of (1,49) Hz. At the last, 1588 artifact free epochs are additionally analyzed. For instance, **Figure 2** captures recorded healthy and Parkinson electroencephalograms.

Obtained results

The suggested PDRNN model is applied over all of the electroencephalogram signals. The proposed PDRNN model is implemented in Python environment and its run in a PC, Intel-Xeon 2.4GHz processor and 24GB random-access-memory.

The precision, sensitivity and specificity are considered as assessment metrics. Based on the obtained results, best detection efficiency is observed in 1*E*-4 training rate. The suggested DPRNN network gives the precision, sensitivity and specificity of 88.31, 84.84 and 91.81 percent, respectively. Efficiencies of the proposed model in presence and absence of dropout layer are captured respectively in **Figure 3** and **Figure 4.** It's remarkable that it's possible to occur over-fitting in the model without the dropout layer. As can be seen from **Figure 3,** there is no a considerable difference between precision of the learning and testing datasets in presence of the dropout layer. While, as shown in **Figure 4**, precisions of the testing and learning datasets are considerably different.

The confusion matrix of the obtained results is illustrated in **Figure 5**. According to this figure, 11.28 percent of the healthy cases are

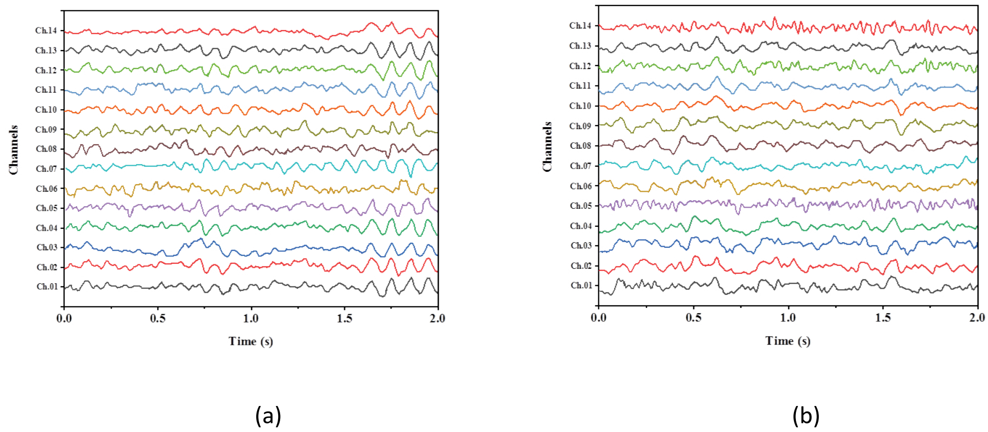

Figure 2 Samples of Healthy and Parkinson EEG signals.

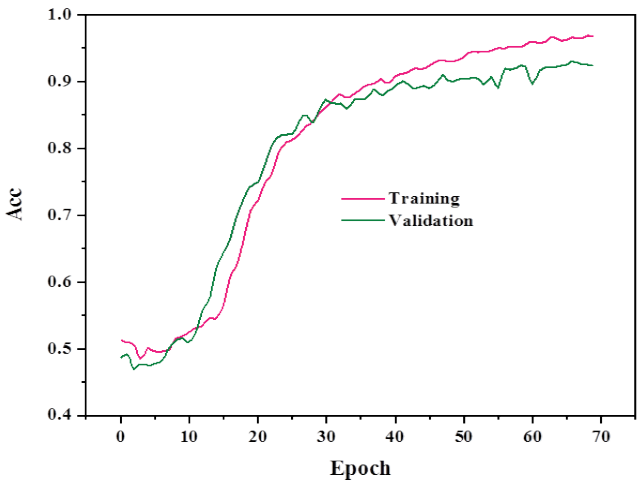

Figure 3 Accuracy profiles of various epochs.

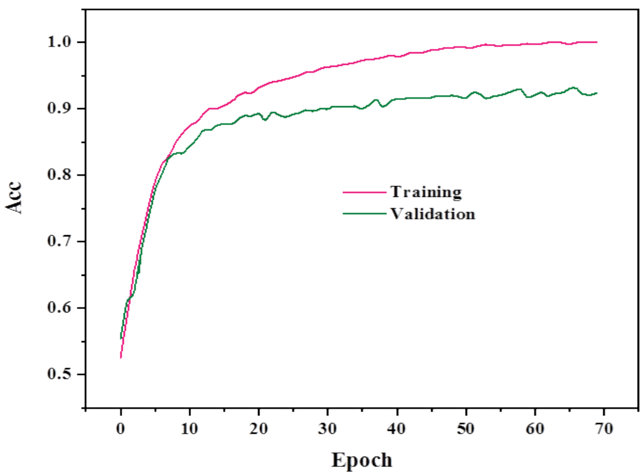

Figure 4 Accuracy profiles of various epochs in absence of the dropout layer.

wrongly categorized in Parkinson class. Also, 11.49 percent of Parkinson cases are classified wrongly in the healthy class.

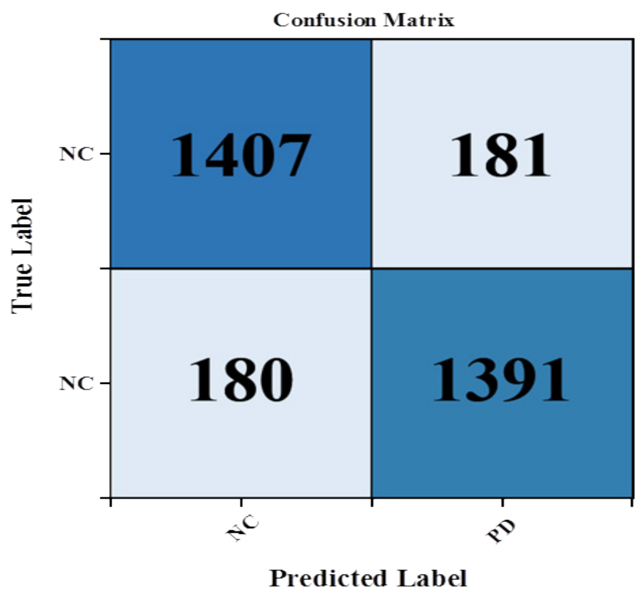

Figure 5 Confusion matrix of suggested approach.

Analysis

Multitude non-invasive methods are recently suggested in literature for detection of the Parkinson disease by voice [29-31], and gait [32]. Also, various computer-aided methods are proposed for obtaining proper models in order to separate the healthy and Parkinson cases. For example, a feature reduction approach is proposed in [29] to remove the undesired data from the Parkinson voice signals. They could obtain about 96.07% mean detection precision using the PCA (Principal Component Analysis) reduction method and FKNN classification algorithm. Subsequently, [30] promoted the precision by applying a population-based optimization method on the FKNN classification method. This proposed method is used for classification of the healthy and Parkinson voices. In [31] a hybrid method is suggested based on an ELM (extreme learning machine) method for classifying the Parkinson and healthy voices, which could

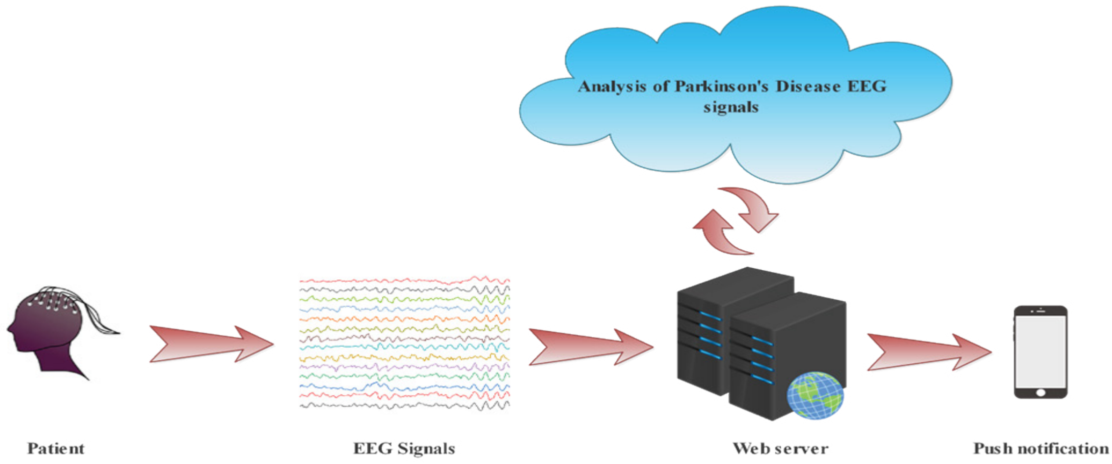

Figure 6 Web-based computer aided configuration for detection of the Parkinson disease.

obtain a mean precision of 99.49 percent. Besides, [32] applied a Fourier transform based feature selection method for separation of the healthy and Parkinson gait signals. This proposed method resulted in 91.2 percent precision. Nevertheless, there is just a few numbers of the works who used the EEG signals for detection of the Parkinson disease. Different computer-aided methods are presented in literature for separation of the healthy and Parkinson EEG signals. As an instance, an experimental study is performed in [6] for separation of the healthy and Parkinson cases by EEG signal. It's shown in this reference that, the entropy levels of the Parkinson EEG signal is considerably greater compared to the healthy cases. So, the EEG signals related to Parkinson cases have higher complexity. Also, [7] proposed the HOS (denoting the Higher Order Statistics) method to obtain the features and divide the healthy and Parkinson EEG signals. Based on their obtained results, the HOS method could explicitly present the hidden non-linear features of the Parkinson EEG signals for classifying aims.

However, a deep RNN configuration is suggested in the present work for PD diagnosis. This proposed network contains multitude layers to efficiently separate the Parkinson disease and healthy cases by electroencephalogram signals. In addition, there is no requirement for manually obtained features in the proposed method. This advantage of the proposed method considerably reduces the procedure of experimenting and leads to optimally obtain the main features for classifying aims.

Furthermore, a web based detection method is suggested for additionally promoting the performance of the automated detection method which can be investigated in the next works. Process of this web based automated method is captured in **Figure 6**. Internet of detect is utilized in this mechanism for detection of the Parkinson disease. The gathered electroencephalogram signals are recorded in the local memory in the clinic and they are forwarded via the cloud (where our DRNN-based model is developed). Then, obtained results are sent back straightly to the patients through messages. So, by installing this system, workload of the experts can be considerably decreased.

The main novelties of the suggested method are summarized as follows:

a) This paper developed a deep RNN architecture equipped with LSTM cells for automatically detection of the Parkinson disease by electroencephalogram signals.

b) In this suggested model it is not needed to extract, select and classify the features.

c) As well, a stratified tenfold cross validation method is used for authentication of the model.

d) Based on our best knowledge, it's the first time to apply our proposed deep learning method to diagnose the Parkinson disease by electroencephalogram signals.

e) The proposed method can present a proper efficiency even with a low number of healthy and Parkinson cases, which shows good robustness of the suggested model.

Nevertheless, our suggested methods have some drawbacks that are briefly represented as:

a) A low number of cases (twenty healthy and twenty Parkinson cases) are used for developing the proposed PDRNN model.

b) The proposed PDRNN models have high computing costs in comparison with traditional machine learning methods.

Conclusion and Discussion

This paper suggested a novel computer-aided method based on a deep RNN network for detection of the Parkinson disease by EEG signals. Based on our best knowledge, it's the first time that this deep learning method is applied for detection of the Parkinson disease by EEG signals. Although just a low number of cases were utilized in the present work, the proposed model could achieve proper efficiency. This model could give 88.31, 84.84 and 91.81 percent precision, sensitivity and specificity, respectively. Respect to the high efficiency of the proposed model, it can be used as a reliable tool for detection of the Parkinson disease in the clinics. A high number of the cases can be used to develop the proposed model in the future works for early detection of the Parkinson disease.

References

1 Stiles J, Terry LJ (2010) The basics of brain development. Neuropsychol Review 20: 327-348.

2 Silver J, Martin ES, Phillip GP (2015) Central nervous system regenerative failure: Role of oligodendrocytes, astrocytes, and microglia. Cold Spring Harb Perspect Biol 7: a020602.

3 Surmeier DJ (2010) What causes the death of dopaminergic neurons in Parkinson's disease?. Prog Brain Res 183: 59-77.

4 Lih Oh S, Hagiwara Y, Raghavendra U (2018) A deep learning approach for Parkinson's disease diagnosis from EEG signals. Neural Comput Appl 32: 1-7.

5 https://www.who.int/mental_health/neurology/neurological_disorders_report_web.pdf

6 Chun-Xiao H (2013) Investigation of EEG abnormalities in the early stage of Parkinson's disease. Cogn Neurodyn 7: 351-359.

7 Yuvaraj R, Acharya UR, Yuki H (2018) A novel Parkinson's Disease Diagnosis Index using higher-order spectra features in EEG signals. Neural Comput Appl 30: 1225-1235.

8 Lima CAM, André C, Sandro C (2009) Automatic EEG signal classification for epilepsy diagnosis with relevance vector machines. Expert Syst Appl 36: 10054-10059.

9 Leuchter AF (2009) Effectiveness of a quantitative electroencephalographic biomarker for predicting differential response or remission with escitalopram and bupropion in major depressive disorder. Psychiatry Res 169: 132-138.

10 Gandal MJ (2012) Gamma synchrony: Towards a translational biomarker for the treatment-resistant symptoms of schizophrenia. Neuropharmacol 62: 1504-1518.

11 Hampel H (2010) Biomarkers for Alzheimer's disease: Academic, industry and regulatory perspectives. Nat Rev Drug Discov 9: 560.

12 Chua KC (2009) Analysis of epileptic EEG signals using higher order spectra. J Med Eng Technol 33: 42-50.

13 Acharya UR, Eric Chern-Pin C, Chua KC, Min LC, Tamura T (2010) Analysis and automatic identification of sleep stages using higher order spectra. Int J Neural Syst 20: 509-521.

14 Roshan Joy M, Acharya UR, Mandana KM, Ray AK (2013) Cardiac decision making using higher order spectra. Biomed Signal Process Control 8: 193-203.

15 Yuvaraj R (2014) Optimal set of EEG features for emotional state classification and trajectory visualization in Parkinson's disease. Int J Psychophysiol 94: 482-495.

16 Krizhevsky A, Sutskever I, Geoffrey EH (2012) Imagenet classification with deep convolutional neural networks. Adv Neural Inf Process Syst.

17 McCulloch WS, Walter Pitts (1990) A logical calculus of the ideas immanent in nervous activity. Bull Math Biol 52: 99-115.

18 David S, Huang A, Christopher M, Arthur G (2016) Mastering the game of Go with deep neural networks and tree search. Nature 529: 484-489.

19 Lusci A, Gianluca Pi, Pierre B (2013) Deep architectures and deep learning in chemoinformatics: the prediction of aqueous solubility for drug-like molecules. J Chem Inf Model 53: 1563-1575.

20 Graves A, Abdel-rahman M, Geoffrey H (2013) Speech recognition with deep recurrent neural networks. arXiv.

21 Pascanu R (2013) How to construct deep recurrent neural networks. arXiv preprint arXiv.

22 Acharya UR (2017) Automated detection of arrhythmias using different intervals of tachycardia ECG segments with convolutional neural network. Inf Sci 405: 81-90.

23 Acharya UR (2017) Automated detection of coronary artery disease using different durations of ECG segments with convolutional neural network. Knowledge-Based Systems 132: 62-71.

24 Jen Hong T (2017) Segmentation of optic disc, fovea and retinal vasculature using a single convolutional neural network. J Comput Sci 20: 70-79.

25 Shu Lih O (2018) A deep learning approach for Parkinson's disease diagnosis from EEG signals. Neural Computing and Applications 1-7.

26 http://www. iro. umontreal. ca/bengioy/dlbook

27 Abedinia O, Nima A, Ali G (2016) A new metaheuristic algorithm based on shark smell optimization. Complexity 21: 97-116.

28 Hoehn MM, Melvin DY (1967) Parkinsonism: onset, progression, and mortality. Neurology 17: 427-427.

29 Hui-Ling C, Chang-Cheng H, Xin-Gang Y, Su-Jing W, et al. (2013) An efficient diagnosis system for detection of Parkinson's disease using fuzzy k-nearest neighbor approach. Expert systems with applications 40: 263-271.

30 Wan-Li Z, Zhi-Yan W, Tong L, Hui-Ling C (2013) Effective detection of Parkinson's disease using an adaptive fuzzy k-nearest neighbor approach. Biomedical Signal Processing and Control 8: 364-373.

31 Chao M, Ouyang J, Hui-Ling C, Xue-Hua Z (2014) An efficient diagnosis system for Parkinson's disease using kernel-based extreme learning machine with subtractive clustering features weighting approach. Comput Math Methods Med 2014.

32 Mohammad RSD (2013) Chi-square distance kernel of the gaits for the diagnosis of Parkinson's disease. Biomedical Signal Processing and Control 8: 66-70.