DOI: 10.54254/2753-8818/43/20240980

Parkinson's disease detection based on image analysis of EEG signals

Yitao Zhang[1,6], Han Yu[2,5,7], Chenyang Sun[3,8], Mingheng Jin[4,9]

[1]University of Electronic Science and Technology of China, Chengdu, 611731, China
[2]Southwest Jiaotong University, Chengdu, 614203, China
[3]Changshu Institute of Technology, Suzhou, 215505, China
[4]Central South University of Forestry and Technology, Changsha, 410004, China

[5]Corresponding author
[6]2020190505021@std.uestc.edu.cn
[7]el21hy@leeds.ac.uk
[8]hinode0611@gmail.com
[9]jwjcc@csuft.edu.cn

Abstract. Parkinson's disease (PD) is a common chronic neurological disease, that causes great disturbance to the patient's life and work, and when the disease develops seriously, it may even lead to the death of the patient. Until now, treating PD has been a tough nut to crack and a financial challenge for families and governments alike. In this paper, we propose to use the Resnet-50 Neural Network model to differentiate between 41 PD patients and 41 normal subjects by analyzing time-frequency domain maps of electroencephalography (EEG) signals. This method achieves classification accuracies ranging from 81% to 85% for six-channel detection and varying from 76% to 77% for single-channel detection, which opens up new avenues for the early diagnosis of Parkinson's disease, demonstrating the potential to combine EEG signals with image processing.

Keywords: electroencephalogram, Parkinson's diagnosis, deep learning, image processing.

1. Introduction

Parkinson's disease is a prevalent neurological disorder, affecting approximately 1% of individuals aged 60 and above, with its incidence increasing with advancing age. Notably, in China alone, the number of people suffering from Parkinson's approaches three million, highlighting the urgent need to address this ailment. This condition is characterized by a gradual progression that induces neurological motor dysfunctions leading to various distressing symptoms. Tremors are particularly prominent among these symptoms, often originating in the hands but occasionally starting in the feet or jaw. These tremors result in muscular rigidity, reduced motor pace, compromised equilibrium, and an elevated susceptibility to falls [1]. The etiology of Parkinson's disease lies in the deterioration of nerve cells which differ from other cellular components and lack self-repair mechanisms. This intrinsic complexity poses significant challenges for treatment and emphasizes the importance of early detection. In this context, EEG signals emerge as a crucial diagnostic parameter for Parkinson's disease.

In the current research landscape, the pursuit of identifying Parkinson's disease is primarily driven by two dominant methodologies. The first involves a direct examination of EEG signal attributes, while the second entails utilizing these signals to train computational models capable of distinguishing between Parkinson's patients and healthy individuals. Illustrating this trend, Smith K. Khare [2] utilizes unprocessed EEG signals for diagnosing Parkinson's disease, whereas Mohamed Shaban [3] directly employs EEG signals to train their model. This convergence of scientific endeavors underscores the crucial role that EEG signals play in diagnosing and classifying Parkinson's disease. It is important to note that although these conventional approaches exhibit remarkable accuracy exceeding 95%, they are burdened by intricacies and prolonged data processing procedures.

In this paper, we propose an innovative approach for diagnosing Parkinson's disease by converting EEG signals into images, which represents a novel strategy in the analysis of EEG signals. These images are then inputted into a computational model to distinguish between Parkinson's patients and healthy individuals. We utilized a subset of six channels from a publicly available dataset and employed the Resnet-50 Neural Network model. Our method achieves classification accuracies ranging from 81% to 85% for six channels detection. Although there is some disparity in accuracy compared to existing methods, our focus extends beyond numerical measures. This paper introduces novel conceptual perspectives to the diagnosis of Parkinson's disease, aiming to invigorate and broaden the landscape of diagnostic approaches.

2. Method

2.1. Source of data sets

We used the publicly available dataset reported in the Linear predictive coding distinguishes spectral EEG features of Parkinson's disease study, which is a resting-state EEG dataset of 41 Parkinson's patients and is available at https://bit.ly /3pP1pts on the public domain. A total of 41 PD patients and 41 controls from New Mexico and Iowa who shared the same demographics were included in the study [1]. The article in question has received 46 citations [1]. The dataset comprises EEG recordings of 82 participants, collected using a 64-channel EEG machine at a sampling rate of 500 samples per second. Each participant underwent one run, which included both baseline and task conditions [1]. The publicly available files for this dataset can be opened directly by MATLAB and have been extracted and filtered out of unwanted data, but there is still unwanted clutter that needs to be filtered further.

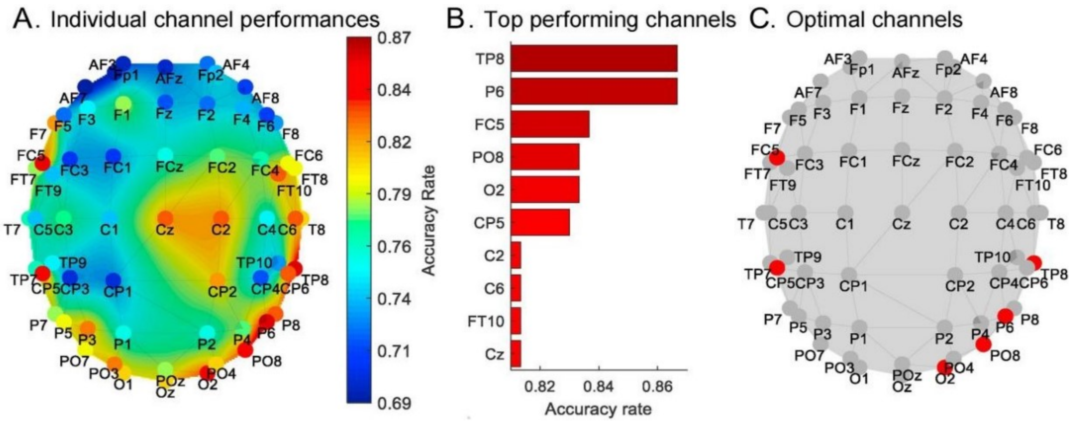


Figure 1. Channel Selection (A) Performance comparison of 62 channels. (B) Comparison of the 10 top-performing channels. (C) Channel positions of the 6 top-performing channels; red indicates selected or multi-channel classification [1].

2.2. Channel Selection

Based on the utilization of this dataset and its examination conducted by Anjum et al., it was observed that a comparison plot of the top 10 performing channels was generated from the analysis of 62 channels

[1]. For data-to-image conversion in PD disease image classification, we specifically chose the finest 6 performing channels. These selected channels include TP8, P6, FC5, PO8, O2, and CP5 as depicted in the figure below.

2.3. *Preprocessing methods with EEGLAB*

After the data and channel locations are imported for further analysis, it is necessary to conduct certain preprocessing steps in order to eliminate noise, artifacts, problematic channels, and unnecessary redundancy from the data [4]. MATLAB was used to extract EEG data. Processing software and EEGlab toolbox for filtering and analyzing EEG data with graphical results [5]. The data that underwent preprocessing consisted of a collection of 82 EEG cycles, each lasting one minute (as the individual data were not as lengthy). These cycles were synchronized with the resting state presentation and recorded from 64 EEG channels at a sampling rate of 500 Hz. The resulting dataset was saved in EEGLAB format. Preprocessing was performed in two main steps, filtering and ICA (Independent Components Analysis) denoising. A bandpass filter is applied to filter out signals in the range of 1-100 Hz. The industrial frequency interference is filtered to remove the interference components with a frequency of 50Hz. Apply notch filter to remove harmonic interference using notch filters at 49-51Hz and 99-101Hz. To mitigate interference, we employed Independent Component Analysis (ICA) technique for eliminating signals like ophthalmoscopy and electromyography. By applying ICA algorithm on filtered data, distinct independent components were isolated. Consequently, we eliminated interfering elements while identifying and removing autonomous components associated with oculo-motor function and electromyography.

After getting the pure signal, due to the different length of data, the time-frequency is close to 1 minute, we intercept 1 minute as the base time-frequency, and divide 1 minute into every fifteen minutes as a segment, and output the image of Channel time-frequency in EEGLAB, with the size of 680X536X3 (RGB), and the format of png.

2.4. *Model training with ResNet-50 in MATLAB*

1) Model Selection: In our research, we employed the ResNet-50 model using MATLAB. This model has been extensively utilized in medical fields to diagnose and categorize diseases, such as automating breast cancer diagnosis, detecting brain tumors, classifying tumors, and predicting skin cancer. The ResNet-50 model offers numerous benefits including its effectiveness in training deep networks with a large number of layers. It consistently achieves cutting-edge results in various tasks related to images due to its utilization of skip connections that retain valuable information from earlier layers [6]. Compared to other networks, ResNet-50 exhibits superior performance in tasks like object detection, image classification, and image segmentation. Its integration of residual blocks and skip connections makes it an efficient and robust choice for implementing deep learning techniques in computer vision [6].

The ResNet architecture adheres to two fundamental design principles. Firstly, the number of filters in each layer is determined by the size of the output element map. Secondly, to ensure consistent time complexity for every layer, if the feature graph is reduced by half, then the number of filters will be doubled [7].

2) Output of Model Blending Results: Parkinson's patients and normal subjects were divided into two groups 0, 1. 70% of their respective images were randomly selected as the training set and 30% of their respective images as the test set. In this research, we employed the ResNet-50 architecture in MATLAB to develop a straightforward MATLAB script that sequentially scans through the designated directory and reads each file individually. In this study, Channel time-frequency pictures (training set) of PD and control were analyzed. Selected models were trained using the training set to optimize the model parameters such as changing the learning rate, in-creasing the number of iterations, etc. Train the selected model using the training set and optimize the model parameters. Analyze the classification results of the model and perform necessary tuning to improve the classification performance. Analysis of classification results: Analyze the classification results of the model on the test set to understand the

DOI: 10.54254/2753-8818/43/20240980

model performance and performance. Tuning Optimization: According to the classification results, adjust the model parameters, data preprocessing steps, etc. to optimize the classification performance. The model with the best result output is validated with a training set to produce results. Repeated experiments can be performed several times to further validate and stabilize the performance of the model.

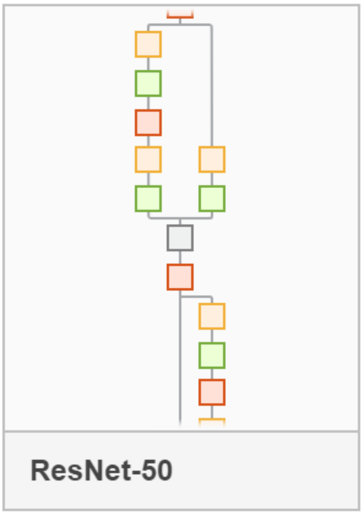


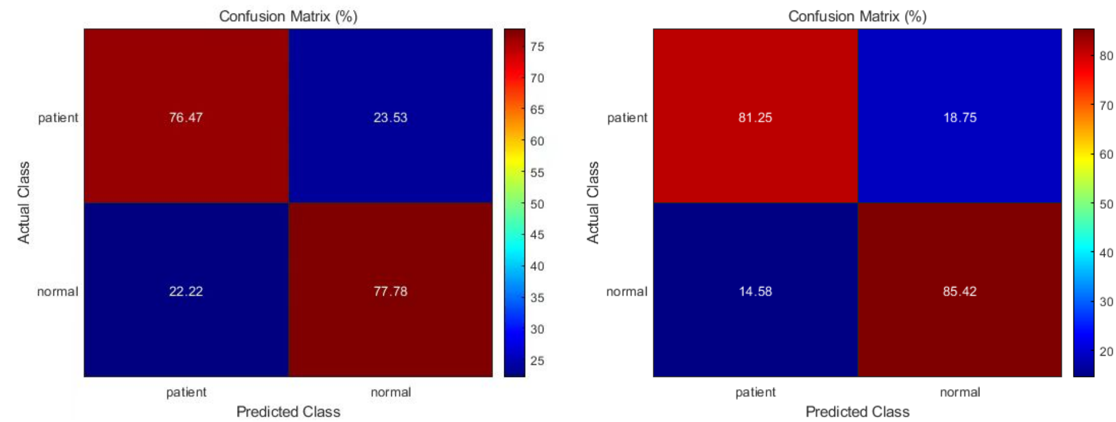
Figure 2. ResNet-50 in Matlab

3. Result

We compared the EEG signals of single-channel (TP8) and six-channel (TP8, P6, FC5, PO8, O2, CP5), and after then, we found that the test set accuracy of the single-channel (TP8) data set in PD classification was in the range of 76.5±0.5%, while the six-channel (TP8, P6, FC5, PO8, O2, CP5) could lead to an accuracy of 83±2%. This means that the data obtained by superimposing these channels can more accurately distinguish the EEG signals of PD patients from those of normal people.

However, compared to other studies based on data stream analysis, the accuracy of our model based on image analysis has decreased. For example, Md Fahim Anjum was able to classify the EEG of Parkinson's patients and normal subjects by the LEAPD method with an accuracy of up to 85.3 ± 0.1%.[2] The main reason for the low accuracy in classifying EEG signals from Parkinson's disease and normal individuals is the loss of data when converting EEG signals into time-frequency domain images.

We processed and filtered the EEG dataset containing 41 PD patients and 41 normal subjects and obtained about 500 images in the time-frequency domain, of which 450 images were used as the training set and 50 as the test set. We put these 450 time-frequency domain images into the resnet-50 model, and it took an hour and a half to complete the training set portion of the study. After training is complete, we can immediately obtain test results for the test set, i.e., the model is very fast in making Parkinson's disease judgements on samples that have never been encountered before.



(a) (b)

Figure 3. Confusion matrix obtained by Resnet with (a) Single-channel, and (b) Six-channels.

4. Discussion

In this research endeavor, we have developed and evaluated a novel image processing methodology aimed at the discernment of PD. Our meticulously designed approach focuses on computational efficiency by utilizing EEG time-frequency images in conjunction with the powerful Resnet-50 model to differentiate between individuals affected by PD and demographically matched control subjects. Furthermore, we conducted a comparative analysis, comparing the classification efficacy of a single channel (TP8) with that of a more comprehensive array consisting of six channels (TP8, P6, FC5, PO8, O2, CP5) after rigorous preprocessing and conversion procedures. The empirical findings unequivocally demonstrate significantly higher accuracy achieved through the utilization of the six-channel configuration compared to the singular channel approach. However, it is important to acknowledge that our image-based classification technique falls short in precision when compared to previous seminal work [1].

Our devised framework, proficient in distinguishing PD patients from control subjects, represents a multifaceted advancement across various domains. In comparison to the method-ology proposed by Chaturvedi et al. [8], which achieved an accuracy rate of 78%, our innovative six-channel approach demonstrates commendable performance with an accuracy of 83%. It is worth noting that while certain studies, such as Vanneste et al.'s [9] achieving 94.34% accuracy and Yuvaraj et al.'s [10] reaching an impressive 99.62%, have reported exceptional classification outcomes, these achievements were accomplished on larger and more extensive datasets characterized by dissimilarities in class distribution and age groups. Moreover, our contribution lies in the inventive transformation of EEG signals into visually interpretable time-frequency domain representations. This transformation, combined with state-of-the-art image processing methodologies and advanced classification techniques, embodies a pioneering advancement in the analysis of EEG signals. Beyond its technical merits, our work opens up novel avenues for the diagnostic application of EEG-based methodologies in the field of mental health disorders. Furthermore, the significance of our design extends to real-world scenarios by offering promising prospects for real-time applications. Notably, our approach can achieve robust accuracy within a mere second when inputting images from all six channels, underscoring its potential practicality and effectiveness.

However, within the bounds of this approach, certain limitations warrant consideration. Firstly, our analysis against [1] reveals a marginal 2% decrease in accuracy compared to our method, which achieves an accuracy of 83% on the same dataset. This decrement can be attributed to the conversion of EEG signals into images, resulting in information loss and reduced granularity due to the decreased number of pixels compared to temporal sampling points. Consequently, this poses challenges for precise classification. Secondly, despite having access to 64 channels per individual, we have only utilized six discerning EEG channels for PD detection. To enhance our future investigations, we plan to explore

DOI: 10.54254/2753-8818/43/20240980

additional avenues relevant to cerebral disorders. By incorporating multi-channel fusion methodologies into our model architecture, we aim to capture inter-channel correlations and extract valuable insights across channels in order to improve overall classification efficacy. Furthermore, it is important to acknowledge that our current design solely focuses on PD detection and does not encompass other movement disorders such as multiple-systems atrophy or mental afflictions like epilepsy. It is crucial that we expand our scope beyond PD detection and consider these dimensions for exploration and analysis. Moreover, our approach has been validated and fine-tuned through rigorous examination involving a cohort of 41 PD patients and 41 controls. Looking ahead, we anticipate scaling up our dataset size in order to demonstrate increased accuracy and broader applicability.

5. Conclusion

Within the confines of this paper, we present an innovative diagnostic approach specifically designed for Parkinson's patients by transforming EEG signals into image-based representations for analytical examination. The Resnet-50 Neural Network is chosen as the underlying model to support this endeavor. Despite the limited number of channels and small sample size used in this study, our method achieves classification accuracies ranging from 81% to 85% for six-channel detection and varying from 76% to 77% for single-channel detection. These accuracy results are influenced by the inherent constraints imposed by the restricted number of channels and relatively small dataset. However, beyond its numerical precision, this technique paves a new path in early Parkinson's diagnosis, showcasing the potential of merging EEG signals with image processing and hinting at novel dimensions of diagnostic innovation. As advancements in image processing and analysis techniques continue to evolve rapidly, we anticipate that the trajectory of accuracy for this method will ascend further. Looking towards the future, we aspire to extend the application of this technique to encompass a broader range of neurological disorders.

Acknowledgment

Yitao Zhang, Han Yu, Chenyang Sun, and Mingheng Jin contributed equally to this work and should be considered co-first authors.

This work was supported by Professor Neal Bangerter throughout our research. Additionally, the teaching assistants Taylor and Jason, assistance and guidance were indispensable for our study.

We would also like to express my sincere appreciation to Md Fahim Anjum and colleagues for providing the publicly available dataset used in this study, which was sourced from https://bit.ly/3pP1pts.

References

[1] M. F. Anjum, S. Dasgupta, R. Mudumbai, A. Singh, J. F. Cavanagh, and N. S. Narayanan, "Linear predictive coding distinguishes spectral eeg features of parkinson's disease," Parkinsonism & Related Disorders, vol. 79, pp. 79–85, 2020.

[2] S. K. Khare and V. Bajaj, "A cacdss for automatic detection of parkinson's disease using eeg signals," in 2021 International Conference on Control, Automation, Power and Signal Processing (CAPS), 2021, pp. 1–5.

[3] M. Shaban, "Automated screening of parkinson's dis-ease using deep learning based electroencephalography," in 2021 10th International IEEE/EMBS Conference on Neural Engineering (NER), 2021, pp. 158–161.

[4] A. Ehtemami, S. Bernadin, and S. Foo, "Analyzing and clustering of baseline and non-baseline eeg signal using matlab toolboxes," in 2019 SoutheastCon, 2019, pp. 1–5.

[5] H. Do, V. Truong, K. George, and B. Shirke, "Eeg-based biometrics utilizing image recognition for patient identification," in 2019 IEEE 10th Annual Ubiquitous Computing, Electronics & Mobile Communication Con-ference (UEMCON), 2019, pp. 0591–0595.

[6] W. ML, "Understanding resnet-50 in depth: Architecture, skip connections, and advantages over other networks - wisdom ml," Mar 2023. [Online]. Available: https:

//wisdomml.in/understanding-resnet-50-in-depth-archi tecture-skip-connections-and-advantages-over-other-net works/

[7] Datagen, "Resnet-50: The basics and a quick tutorial," Aug 2023. [Online]. Available: https://datagen.tech/gui des/computer-vision/resnet-50/

[8] M. Chaturvedi, F. Hatz, U. Gschwandtner, J. G. Bogaarts, A. Meyer, P. Fuhr, and V. Roth, "Quantitative eeg (qeeg) measures differentiate parkinson's disease (pd) patients from healthy controls (hc)," Frontiers in Aging Neuro-science, vol. 9, Jan 2017.

[9] S. Vanneste, J.-J. Song, and D. De Ridder, "Thalamocor-tical dysrhythmia detected by machine learning," Nature Communications, vol. 9, no. 1, Mar 2018.

[10] R. Yuvaraj, U. Rajendra Acharya, and Y. Hagiwara, "A novel parkinson's disease diagnosis index using higher-order spectra features in eeg signals," Neural Computing and Applications, vol. 30, pp. 1225–1235, 2018.