Wavelet-Based Convolutional Neural Network for Parkinson's Disease Detection in Resting-State Electroencephalography

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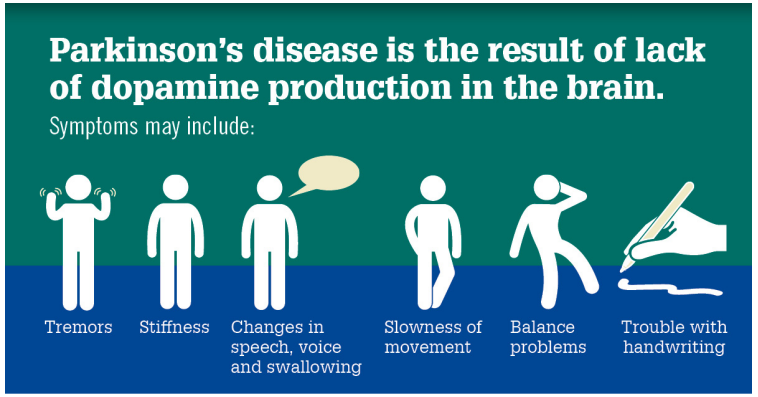
Problem Statement

- Parkinson's Disease (PD) – Second most common neurodegenerative disease after Alzheimer's disease in the United States.
- Affects elderly population (≥65 years of age).



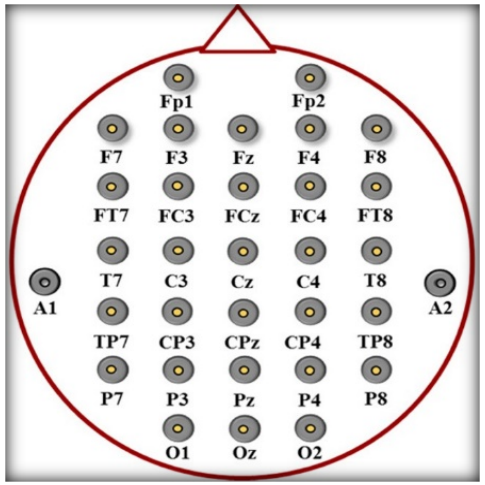
- Clinical diagnosis is subjective and takes place when almost 80% of the nerve cells are damaged.
- EEG is not a diagnostic test but previous studies show decreased beta and gamma powers [2-4], and significant phase-amplitude coupling changes in PD with respect to healthy controls (HC) [5] [6].

Related Work

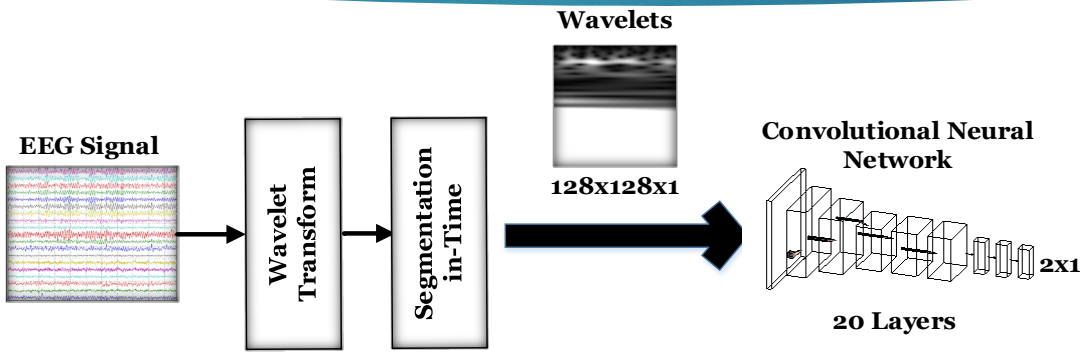
- Motivated the introduction of computer-aided diagnostic tools that provide objective and reliable detection of the disease.
- Oh et al. used 13-layer CNN to detect de novo PD subjects with an accuracy of 88.3% [10]. Shit et al. and S. Lee et al. proposed hybrid CNN-RNN models to detect PD from EEG data with an accuracy of 82.9% and 96.9% respectively [11] [12].
- Our prior work adopted an ANN-based framework applied on three spatial channels of EEG including Oz, P8, and FC2 to distinguish PD from HC with an accuracy of 98%, sensitivity of 97%, and specificity of 100% [13].

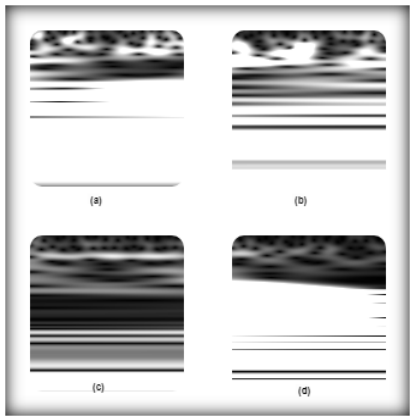
Dataset Description

- Created in the Aron lab at the University of California at San Diego.
- Available on OpenNeuro with the latest version of 1.0.4 published in January 2021.
- Fifteen right-handed PD patients (eight females, mean age 62.6 ± 8.3 years old), and sixteen matched HC (nine females, 63.5 ± 9.6 years).
- All PD patients have either mild or moderate PD.
- Recorded at a sampling rate of 512 S/s using thirty-two standard electrodes.



Proposed Approach





Scalogram representing the EEG Wavelets recorded at Fp1 for (a)(b) HC and (c)(d) PD

Layer	Layer Size	No. of Layers	No. of Feature Maps
Input Image	128×128	1	-
Convolutional with ReLU	11×11	4	32
Maximum Pooling	2x2	1	32
Convolutional with ReLU	9×9	4	64
Maximum Pooling	2x2	1	64
Convolutional with ReLU	7×7	4	128
Maximum Pooling	2×2	1	128
Fully Connected with ReLU	128, 64, 32, 16	4	-
Fully Connected with SoftMax	2	1	-

Experimental Results

- A total of 12,260 images were labelled as HC while 12,004 were related to PD.
- A batch size, learning rate, decay rate, and momentum of 50, 5×10^{-5}, 0.1, and 0.9 were selected as the hyperparameters of the model.
- Both 4-fold and 10-fold cross-validation methods were used to evaluate the performance of the model.

Channel	Fp1	FC1	CP5	Fz
Training Accuracy	100%	100%	100%	100%
Validation Accuracy	98.6%	99.7%	99.9%	98.9%
Sensitivity	98.9%	99.8%	99.9%	99.1%
Specificity	98.3%	99.6%	99.9%	98.8%
Weighted Kappa	0.97	0.99	0.99	0.98
AUC	0.99	0.99	0.99	0.99

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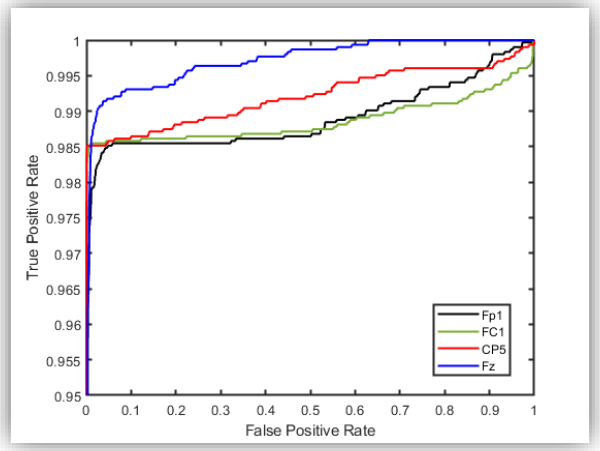

Conclusions

- We have developed a deep-learning mechanism that exploits the wavelet domain of resting-state EEG signals to detect PD.
- It was observed that subjects with PD exhibit uniform dark regions corresponding to the low-scale wavelet components as compared with HC.
- The significant deviations between the HC and PD cohorts in the Wavelet domain triggered the success of the 20-layer CNN feature Extractor and Classifier.
- The CNN structure was able to efficiently distinguish between subjects with PD and HC at a very high 4-fold as well as 10-fold cross-validation accuracy, sensitivity and specificity of up to 99.9% outperforming the recent state-of-the-art deep learning architectures [10-13]

Method	Proposed	[10]	[11]	[12]	[13]
Accuracy	99.9%	88%	83%	93%	98%

Limitations

- The proposed approach can not support the pre-clinical diagnosis of the disease since it has been trained and validated on recorded EEG for patients with a confirmed clinical diagnosis of PD.
- Due to the limited number of subjects per each disease stage, we were not able to validate the approach to further classify the subjects based on the progression of the disease.

Future Work

- We plan to develop an AI framework based upon a sleep EEG dataset acquired for subjects who were later diagnosed with PD as well as visualize the features detected by this AI framework.
- This may provide further insights on critical and unique early EEG biomarkers of the disease since it has been shown in the literature that prodromal PD (i.e., early stage PD) subjects usually present with sleep disorders and reduction in rapid eye movement (REM) sleep [16].
- Having access to larger and more diverse datasets will allow a successful and reliable application of AI for PD screening and staging.

References

[1] Dauer, W., and Przedborski, S., Parkinson's disease: mechanisms, and models. *Neuron,* Vol. 39, no. 6, pp. 889-909, 2003.

[2] Pezard, L., Jech, R., and Ruzicka, E., Investigation of non-linear properties of multichannel EEG in the early stages of Parkinson's disease. *Clinical Neurophysiology*, Vol. 165, no. 1, pp. 38-45, 2001.

[3] Bosboom, J., Stoffers, D, Stam, C., Dijk, B., et al., Resting state oscillatory brain dynamics in Parkinson's disease: an MEG study. *Clinical Neurophysiology*, Vol. 117, no. 11, pp. 2521-2531, 2006.

[4] Soikkeli, R, Partanen, J., Soininen, H., Pääkkönen, A., and Riekkinen, P., Slowing of EEG in Parkinson's disease. *Electroencephalography, and Clinical Neurophysiology*, Vol. 79, no. 3, pp. 159-165, 1991.

[5] Hemptinne, C., Ryapolova-Webb, E., Air, E., Garcia, P., et al., Exaggerated phase-amplitude coupling in the primary motor cortex in Parkinson disease. *Proceedings of National Academy of Sciences of the United States of America*, Vol. 110, pp. 4780–4785, 2013.

[6] Swann, N., Hemptinne, C., Aron, A., Ostrem, J., et al., Elevated synchrony in Parkinson disease detected with electroencephalography. *Annals of Neurology,* Vol. 78, pp.742–750, 2015.

[7] Vanegas, M., Ghilardi, M., Kelly, S. and Blangero, A., Machine Learning for EEG-Based Biomarkers in Parkinson's Disease. *IEEE International Conference on Bioinformatics and Biomedicine*, Madrid, Spain, 2018.

[8] Wagh, N., and Varatharajah, Y., EEG-GCNN: Augmenting Electroencephalogram-Based Neurological Disease Diagnosis Using a Domain-Guided Graph Convolutional Neural Network. *Machine Learning Research,* Vol. 136, pp. 367-378, 2020.

References

[9] Koch, M., Geraedts, V., et al., Automated Machine Learning for EEG-Based Classification of Parkinson's Disease Patients, *IEEE International Conference on Big Data*, Los Angeles, USA, 2019.

[10] Oh, S., Hagiwara, Y., Raghavendra, U., et al., A deep learning approach for Parkinson's disease diagnosis from EEG signals. *Neural Computing and Applications*, Vol. 32, pp. 10927-10933, 2020.

[11] Shi, X., Wang, T., et al., Hybrid Convolutional Recurrent Neural Networks Outperform CNN and RNN in Task-State EEG Detection for Parkinson's Disease. *Asia-Pacific Signal and Information Processing Association Annual Summit and Conference*, Lanzhou, China, 2019.

[12] Lee, S., Hussein, R., and McKeown, M., A Deep Convolutional-Recurrent Neural Network Architecture for Parkinson's Disease EEG Classification. *IEEE Global Conference on Signal and Information Processing*, Ottawa, Canada, 2019.

[13] Shaban, M., Automated Screening of Parkinson's Disease Using Deep Learning Based Electroencephalography. *International IEEE EMBS Conference on Neural Engineering*, Virtual, 2021.

[14] Rockhill, A., Jackson, N., et al., UC San Diego Resting State EEG Data from Patients with Parkinson's Disease, 2020. [Online]. Available: https://openneuro.org/datasets/ds002778/versions/1.0.4

[15] Shaban, M., Salim, R., Abu Khalifeh, H., et al., A Deep-Learning Framework for the Detection of Oil Spills from SAR Data. *Sensors,* MDPI, Vol. 21, no. 7, 2021.

[16] Chahine, L., Amara, A., and Videnovic, A., A systematic review of the literature on disorders of sleep and wakefulness in Parkinson's disease from 2005 to 2015. *Sleep Medicine Reviews,* Vol. 35, pp. 33-50, 2017.

Thank You!