Gait Disorders in Parkinson's disease Using EEG Signal with Different Deep Learning Methods: A Survey

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Abstract

Parkinson's disease (PD) is the second most hazardous neurological disease, it deteriorates the people lifestyle. Diagnosis of Parkinson's disease is a complex task due to the inaccuracy of clinical evaluation measurements. Therefore, efficient schemes are needed to act automated evaluation for early detection of Parkinson Disease and to increase the life span. Gait-based medical detection provides positive indications for the presence of Parkinson Disease. Recently, computer vision-based analysis has more demand and effectual in Parkinson Disease investigation. Gait Disorders in PD with the help of EEG Signal can be divided into three steps: first data acquisition next image pre-processing and finally the pre-processed images are given to deep learning methods for classify and detect the Parkinson's disease. Here, detailed statistical analysis is provided in this review which was conducted by extracting information from 50 papers published between the years 2018 to 2021. Finally, this survey is helpful for researchers in the field of Gait Disorders in Parkinson's disease Using EEG signal. 5877

Keywords Computer vision, Classification, Deep learning, Gait disorders, Preprocessing, Parkinson's disease.

DOINumber:10.14704/nq.2022.20.8.NQ44614 **NeuroQuantology2022;20(8):5877-5886**

INTRODUCTION

Parkinson's disease (PD) is a progressive neurodegenerativedisease. It is caused by the loss of dopaminergic neurons. According to the statistics from Parkinson's foundation (PF), around one million people are afflicted with Parkinson's disease in 2020 USA[1]. The PD diagnosis is largely based on the clinical motor symptoms, including gait, tremor, rigidity, postural instability and bradykinesia. Even though, at present, surgical therapy and drugs are considered to be the clinical treatments to mitigate the symptoms, there is no cure for PD. However, early prognosis of PD will help to plan for appropriate therapy/medication so that the disease progression can be alleviated. Currently, in the clinical setting, the diagnosis and severity rating of PD is based on the visual observation and unified Parkinson's disease rating scale (UPDRS) score prepared by the clinicians. Since the visual observation is subjective, it may result in biased assessment. Hence,

recently, there has been a paradigm shift towards utilizing machine learning (ML) algorithms to uncover the hidden patterns in the physiological signals, which can help the clinicians in their daily diagnosis of PD. One of the significant reasons for using ML algorithms in bioinformatics is their ability to handle large volume of data and discover biomarkers, resulting in not only accurate prediction but also reduced time for diagnosis Some of the physiological signals used for PD diagnosis are speech, handwriting, tremor and gait. Speech signal manifests the non-motor symptoms of PD.
Gait impairments are a typical feature of PD, this is the foremost reason of functional dependency, falls and mortality [1]. PD gait disorders are persistent that producing short stride length or involving freezing of gait (FOG) [2]. Even though, gait inconsistencies in PD are often referred to as condensed dopamine innigro-striatal pathway, dopaminergic therapy has inadequate effect on gait [3]. Non-pharmacological interventions, like cueing is employed toameliorate gait impairments, lessen falls risk [4]. Visual cues are utilized toenhancethe gait, with theories suggesting visual9 and attentional10 mechanismshelps togait enhancement [5]. The basic neurological mechanisms associated with gait impairment in PD are difficult to fully identify gait control, but rely on the involvement of multiple cortical and sub-cortical centers[6].

DATASET DESCRIPTIONS

It represents the task of collecting useful information by various sources. The system performance based onsuperiority of data captured. The incorporation of devices / technologies with operational capacities plays a significant role in the processing of data collection.The application of modality is found in certain areas, but it has revealed its comprehensive contribution to analysis and collection of gait data of PD affected people.

2.1 PD gait database

Thisisgathered in the Unit of Tel-Aviv Sourasky Medical Center at Gait &Neurodynamics Laboratory, Movement Disorders. It saves 93 PD subjects along 73 control subjects.

2.2 Vertical Ground Reaction Force (VGRF) dataset

Vertical Ground Reaction Force dataset involves gait information from 93 patients with idiopathic PD and 73 healthy controls (average age of 66.3, 55% male). With the information in the VGRF, examine the key record as a functioning of time with location, obtain measures that reflect the center of pressure as a functioning of time, alsocompute stride or swing time for every step changing time.
The gait acquisition task is attained once, other crucial step of diagnostic mode called pre-processing. At several cases, the data receivedthrough modality that is not directly performed, it is pre-processed to upgrade the data as per theparticular task. Pre-processing includes a set of algorithms that is employed todevelop the data quality by performing some operations, like noise reduction, segmentation,and contrast adjustment. At the initial stages, the pre-processing leads to feasible outcomes in the later stages The following segment presents a brief description of certain gait data pre-processing strategiesfor converting raw data as an appropriate form for effectualParkinson Diseasedetection.

PREPROCESSING TECHNIQUES

The input signal is noisy and non-stationary, as a result, it ishard to differentiate. Preprocessing technique is usedto take away the unnecessary and noise information, also derive the effectual information. Several techniques have been established to remove noise from EEG signal. Some of them are discussed below,

3.1 Discrete wavelet transforms (DWT)

In, [7] have presented Parkinson's disease classification using gait characteristics and discretewavelettransformsbased preprocessing. DWT is a form of time-frequency representation for continual time signals. The DWT complements the faultof Fourier Transform from the frequency properties analysis, which offers the frequency properties. In discrete wavelet transform, the signal passed via high-pass (HP) and low-pass (LP) filters to derive the split frequency information. As per Nyquist sampling theorem, the frequency information is represented as detail coefficientfrom the HP filter. It reserves the higher frequency bandwidth of the original signal. Likewise, the frequency information is represented as approximation coefficientfrom the low pass filter. It reserves the lower frequency bandwidth of the original signal. The discrete wavelet analysis is expressed in equation (1),

$$DWT(m,n)=\frac{1}{\sqrt{|2^m|}}\int_{-\infty}^{\infty}x(s)\Psi\left(\frac{s-2^m k}{2^m}\right)ds \tag{1}$$

Where, $\Psi\left(\frac{s-2^m k}{2^m}\right)$ represents the analyzing wavelet function, $2^m k$ denotes the shifting or time localization parameters and 2^m represents scaling or reciprocal of frequency parameters. The irregularities produced by noise, such as random fluctuation or stochastic processes are not managed by a discretewavelet transform.

3.2 Altered Phase Preserving Dynamic Range Compression (APPDRC)

In [8],analteredphase preserving dynamic range compression modeis presented for preprocessing. In the preprocessing stage, the data is filtered using APPDRC method. This method automatically detects the neurologicaldiseases at an early stage. The data are reconstructed with the help of 2D equivalent function of Hilbert transform and resized filter with the frequency domain is f_1, f_2 and it is expressed in equation (2) as follows,

$$S_1 = w\frac{f_1}{\sqrt{f_1^2+f_2^2}} \tag{2}$$

Where the spatial representations of the vector are expressed as $S=(S_1,S_2)$ this is known as convolutional kernel resize transform, w represents the amplitude of the signal.The alteredphase preserving dynamic range compression method doesn't eliminate high frequency noise and the power frequency interference may occur.

3.3 Hilbert transform

In [9], suggested electrocardiogram signal preprocessing based on Hilbert transform.The Hilbert transform is a widely used transform in signal processing. The Hilbert transform is a generally used tool in interpreting Electroencephalogram (EEG). With the Hilbert transform it is possible to expand a real valued signal into an analytic signal. A Hilbert transform yields the analytic signal is represented in equation (3),

$$x^{(j)}(t)+i\tilde{x}^{(j)}(t)=A^{(j)}(t)\exp(i\varphi^{(j)}(t)) \tag{3}$$

From equation (3), i denotes the imaginary unit, $A^{(j)}(t)$ represents the instantaneous amplitudes and $\varphi^{(j)}(t)$ denotes theinstantaneous phases. By using Hilbert transform, the signal is not preprocessed efficiently and it provideslower standard deviation. Finally, Hilbert transform technique is demonstrated to be ineffective in removing the general EEG noise.

3.4 Hidden Markov Model (HMM)

In [10], presented hidden Markov model based preprocessing technique. A hidden Markov model has 2 layers: (i) state, (ii) observation, wherein a Marcovian process regulates the selection of state at each time [12]. At standard hidden Markov models, all the information needed before this time known by the use of distinct hidden state at this time, so attention depend upon its current hidden state only. The hidden Markov model is located in one state at each time, and transition among these states isdepending onrelated probability. Each state is linked with output observation together with its related probability. A continuous data preprocessing is indicated by 3 matrix, which is expressed in equation (4) as follows,

$$\lambda = (\pi, a, b) \tag{4}$$

Where, π represents vector of initial probabilities, a denotes matrix of transition probabilities, b denotes vector of probabilistic output process. A vector of initial probabilities is calculated using equation (5),

$$\pi_i = \Pr\left(s_i \quad at \quad t = 0\right) \tag{5}$$

Where, s_i denotes the state of HMM model and t represents the time. A matrix of transition probabilities is calculated using equation (6) as follows,

$$a_{ij} = \Pr\left(s_i \quad at \quad t+1 \middle| s_i \quad at \quad t\right) \tag{6}$$

A vector of probabilistic output functions is calculated using equation (7) as follows,

$$b_i(x) = \Pr\left(O_t = x \middle| s_i \quad at \quad t\right) \tag{7}$$

From equation (7), x represents the observed signal value, s_i denotes state ofhidden Markov model. Hidden Markov Model doesn't removeelectromyogram (EMG) noise from the input signal.

3.5 Gabor Transform (GT)

In [11],aGabor transformis presented for preprocessing EEG signals. Itis utilized tocreate the spectrogram that plotted frequency not in favor of time. Gaussian distribution function (GDF) scales the multiplication of Fourier transform and Gaussian function on its window, in this manner, presenting information on time resultingoccurs various frequencies. Gabor transform is the consolidation of Fourier transform and GDF, this is represented in equations (8),(9), its consolidation leads to Gabor transform which is expressed below,

$$\hat{f}(w) = \int_{-\infty}^{\infty} f(x) e^{-iwx}\, dx \tag{8}$$

$$G_a(t) = e^{-(t-\tau)^2 / a^2} \tag{9}$$

$$g(f)(t, w) = \int_{-\infty}^{\infty} f(\tau) e^{-iwt} G_a(\tau - T)\, d\tau \tag{10}$$

Where, (t, w) represents the time and frequency domain respectively, τ denotes the center of the window in gaussian function, likewise a denotes the spread of the window. By using Gabor transform, the preprocessed signals have higherEEG noise.

CLASSIFICATIONS

In Parkinson Disease recognition, the classification isclassifies different classes (normal/ abnormal) depending on its gait features. Nowadays, Parkinson Disease recognitionis performed by different deep learning strategies. CLASSIFICATION TECHNIQUE IS USED classifies the PD diseases as normal and abnormal region. Several deep learning techniques have been established to classify the PD diseases from EEG signal. Some of them are discussed below,

4.1 Radial basis function neural networks (RBFNN)

Here, the PD disease classification is implemented by utilizing radial basis

eISSN1303-5150

function (RBF) neural networksclassifier [7] This RBF classifier is utilized for classifyingGait Disorders in PD utilizing EEG Signal. The gait dynamics depending on gait patterns of healthy controls, whereas Parkinson Disease patients are estimated by RBFNN. The estimated gait dynamics is saved in stableRBFNN. A training set is represented by the gait patterns of healthy controls and PD patients. The Parkinson Diseasepatients classification and healthy control subjectshave been considered dynamical gait patternsas ψ_{ξ}^{k},Parkinson Disease patients $k=1,...M$ with k^{th} gait training pattern is ψ_{ξ}^{k} utilizing equation (11)

$$\bar{a}=E^{k}(a:q^{k})+u^{k}(a:q^{k}),\quad a(t_0)=a_{\xi 0} \tag{11}$$

Where $E^{k}(a:q^{k})$ represents the gait system dynamic $u^{k}(a:q^{k})$ represents the modeling uncertainty, q^{k} is the parameter vector of the system. The gait system dynamics $\psi^{k}(a:q^{k})=E^{k}(a:q^{k})+u^{k}(a:q^{k})$ is identified accurately, and then saved in steady RBF networks $\overline{W}^{k^T}R(a)$. In classification, by comparing a test gait pattern created through the human gait system with the set of estimators in M is described in equation (12)

$$\bar{a}_i^k=-y_i\hat{a}_i^k+\overline{W}^{k^T}R_i(a)-\psi_i(a:q),\quad k=1,...M \tag{12}$$

Where $\bar{a}_i^k=\hat{a}_i^k-a_i$ denotes the state estimation error. The Parkinson disease patients classification and health control subjects is a test gait pattern that is created via certain PD patients parallel to trained gait patterns $r(r\in\{1,...,k\})$. Then the stable RBFNN $\overline{W}^{k^T}R_i(a)$ is embedded the matched estimator r providing the accurate estimation of gait dynamics.If finite time $t^{r},r\in\{1,...k\}$ and $i\in\{1,...n\}$ such as $\|\hat{a}_i^{s}(t)\|_1<\|\hat{a}_i^{k}(t)\|_1$ for all $t>t^{s}$, then the appearing Parkinson disease patient iscategorized.Whencompared to the set of estimators, the Parkinson Disease patient test gait pattern is not properlyclassified resulting occurs a set of classification errors.

4.2 Two dimensional convolutional neural networks (2D-CNN)

Two dimensional convolutional neural networks (2D-CNN) [8] isconsidered for PD disease classification with EEG signal. The deep two-dimensional convolutional neural networks are to realize the Electroencephalogram features of healthy controls. The convolutional neural network models are considered for its image-recognition capability. In general, convolutional neural network model consists of 3 layers: convolutional, pooling, fully connected layers. In which, convolutional combine the input imageries with multi kernels to create various kinds of feature maps. Pooling emulates the convolutional to lessen the complexity of feature maps, it protect the convolutional neural network from over fitting. In this model, zero padding is deemed to protect the loss of information at the edges of the imagery. The feature map dimension is similarto the input image. The operation of convolutional and pooling layer (g_{xy}^{l}) is described in equation (13)

$$(R*W)(i,j)=\sum_{m}\sum_{n}R(m,n)W(i-m,j-n) \tag{13}$$

$$g_{xy}^{l}=\max_{i=0,....,R,j=0,....,R}g_{(x+i)(y+j)}^{l-1} \tag{14}$$

Where R represents the input image along (i,j) dimension under distinct convolution operations $(*)$ with (W), the convolutional kernel update the weight with each kernel slides across the input image. The feature maps are flat as single-list vectors in pooling layer which are given in fully connected layers. This layer outputconsists of nodes that are trained to categorize the gait in PD diseases. The 2D-CNN provides an overlapping problem distribution measurement to enable maximum features.

4.3 Gated recurrent neural network (GRNN)

Prediction/prognostic modeling for PD risk estimation is carried out by using Gated recurrent neural network (GRNN)[9]. In GRNN, the input data is in the form of time series. The count of input data points is varied by combined group, then the input data time series is set at 50 frames. By this, x_t represents input from the time series t, x_t is given tothe input layer, x_t acts through rectified linear unit function (ReLU) that is described in equation (15),

$$x_t = \mathrm{Re}\,LU(W_{ax}a_t + y_x) \tag{15}$$

Where W_{ax} and y_x represents the weight and bias of activation function x_t. The GRNNcontains reset and update gate on every unit. The reset gate r_t, update gate Z_t depends on activation input x_t, pervious hidden state g_{t-1} are described in equation (16),

$$r_t = \sigma(W_{xr}x_t + W_{hr}h_{t-1} + y_r) \tag{16}$$

$$Z_t = \sigma(W_{xZ}x_t + W_{hZ}h_{t-1} + y_Z) \tag{17}$$

Consider W and y signifiesweights and biases of each gate. The GRNNutilizes the consolidationof these 2 gates for updating the current hidden state g_t,

$$g_t = (1 - Z_t) * g_{t-1} + Z_t * \tan g(W_{xg}x_t + s_t * W_{gg}g_{t-1} + y_g) \tag{18}$$

Let the operator * implies Hadamard product. The hidden states have been updated to differentiates well as realize required memory for classification with the help of reset including update gate. The last hidden state is determined in the final frame, this is given to fully connected layer for classifying the data utilizing GRNN classifier. The final output $\hat{b}$ represents predicted result (1×6) vector that isexpressed in equation (19),

$$\hat{b} = soft\max(W_{gb}g_t + y_b) \tag{19}$$

Depending on PD disease, a softmax classifier determines the pathological gait, then the matrix multiplication output at the probabilitymode . But, the disadvantage is maximal error rate.

4.4 Long Short Term Memory (LSTM)

Early predictions as well as early diagnosis of the Parkinson's disease for many developed methods are introduced. By this,Deep learning architecture based long short term memory [10] network for severity rating of PD utilizing gait pattern. LSTM has ability to learn the long-term dependencies amid the sequential datasets. Unlike RNN, long short term memory contains memory cells at every traditional node location on hidden layer to improve the learning process and alleviate the vanishing gradient problem, so that the information is stored for a longer time period. The long short term memory contains memory cells and memory blocks in hidden layer. The memory block has 3 gate units. Owing todissimilar inputs, the multiplicative gate units have beenemployed to avert negative effects are determined in equation (20)

$$e_t = \sigma(W_{ge}g_{t-1} + W_{ae}A_t + y_e) \tag{20}$$

Where y represents the bias vector, g_{t-1} denotes the pervious block output, A_t represents input sequence, W_{ge} and W_{ae} denotes the output vector weight matrices

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*e*ISSN1303-5150

for precedent cell and current cell'sinput vector, at last σ represents sigmoid function. The activation function ReLU substantially upgrade thelong short term memoryperformancefor attainingrapid convergence withgreater accuracy likened with its saturated counterpart activation processes, viz sigmoid, tanh. ReLU provides efficient gradient distribution during the training process, prune the negative input to zero and apply identity mapping on positive side. The disadvantage of LSTM network is introducedhigh vanishing gradient faultin memory blocks,by this the prediction accuracy is low.

Table 1: Comparison table of existing methods

Title	Preprocessing	Classification	Research Gap Identification
Discrete wavelet transform based data representation in deep neural network for gait abnormality detection	Discrete wavelet transforms (DWT)	Radial basis function neural networks (RBFNN)	The Parkinson Disease patient test gait pattern is not properly classified resulting occurs a set of classification errors.
Gait anomaly detection of subjects with Parkinson's disease using a deep time series-based approach	Altered Phase Preserving Dynamic Range Compression (APPDRC)	Two dimensional convolutional neural networks (2D-CNN)	The 2D-CNN provides an overlapping problem distribution measurement to enable maximum features.
Parkinson's Disease Rating Scale Using Synchronization Analysis of Gait Dynamics	Hilbert transform	Gated recurrent neural network (GRNN)	Depending on PD disease, a SoftMax classifier determines the pathological gait, then the matrix multiplication output at the probability mode. But, the disadvantage is maximal error rate.
Segmentation of gait sequences in sensor-based movement analysis	Hidden Markov Model (HMM)	Long Short Term Memory (LSTM)	The disadvantage of LSTM network is introduced high vanishing gradient fault in memory blocks; by this the prediction accuracy is low.
Prediction of freezing of gait in patients with Parkinson's disease using EEG signals	Directed Transfer Function (DTF)	Back Propagation Neural Network	Disadvantages caused by artificial selection of disease spot features, make plant disease feature extraction more objective, and research efficiency and technology transformation speed is less.
Deep 1D-Convnet for accurate Parkinson disease detection and severity prediction from gait	vertical ground reaction force (VGRF)	Deep neural network (DNN)	Parkinson's disease identification with lower accuracy

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Prediction of Parkinson's disease severity based on Gait signals using a neural network and the Fast Fourier Transform	Fast Fourier Transform	Artificial Neural Network	Disadvantages caused by Parkinson's disease with higher running time
Deep Learning Approaches for Detecting Freezing of Gait in Parkinson's Disease Patients through On-Body Acceleration Sensors	Mel Frequency Cepstral Coefficients (MFCCs)	recurrent neural network (RNN)	This approach to improve accuracy and reduce computation overhead
Detection of parkinson's disease from gait using neighborhood representation local binary patterns	Neighborhood Representation Local Binary Pattern	Artificial Neural Network (ANN)	Disadvantage of Parkinson's disease identification with low specificity.
Classification of gait patterns between patients with Parkinson's disease and healthy controls using	Empirical mode decomposition (EMD)	radial basis function (RBF) neural network	Disadvantages of using ECG of signals and thus provide less evidence for an accurate diagnosis of Parkinson's disease detection.

CONCLUSION

Recently, the count of PD affected people has risen significantly and recorded as a most dangerous health problems globally. With some effort, this article presents a complete overview of existing studies related to vision-based PD detection by 2018 from 2021. This article accurately explores the pre-processing and classification mannersemployed to produce Parkinson Disease gait data and explores various types of gait features that are useful for Parkinson Disease gait evaluation. Here, numerous PD gait preprocessing with classification approaches are deemed. Furthermore, this article surveys deep learning strategies, which classifies PD and normal subjects. Finally, this article proficiently deals with the identified gaps.

REFERENCES

[1] Stuart, S., Wagner, J., Makeig, S. and Mancini, M., 2021. Brain activity response to visual cues for gait impairment in Parkinson's disease: an EEG study. Neurorehabilitation and neural repair, 35(11), pp.996-1009.

[2] Gérard, M., Bayot, M., Derambure, P., Dujardin, K., Defebvre, L., Betrouni, N. and Delval, A., 2022. EEG-based functional connectivity and executive control in patients with Parkinson's disease and freezing of gait. Clinical Neurophysiology, 137, pp.207-215.

[3] Bohnen, N.I., Costa, R.M., Dauer, W.T., Factor, S.A., Giladi, N., Hallett, M., Lewis, S.J., Nieuwboer, A., Nutt, J.G., Takakusaki, K. and Kang, U.J., 2022. Discussion of research priorities for gait disorders in Parkinson's

disease. Movement disorders, 37(2), pp.253-263.

[4] Pramanik, M., Pradhan, R. and Nandy, P., 2021. Biomarkers for Detection of Parkinson's Disease Using Machine Learning—A Short Review. Soft Computing Techniques and Applications, pp.461-475.

[5] Cuomo, G., Maglianella, V., GhanbariGhooshchy, S., Zoccolotti, P., Martelli, M., Paolucci, S., Morone, G. and Iosa, M., 2022. Motor imagery and gait control in Parkinson's disease: techniques and new perspectives in neurorehabilitation. Expert review of neurotherapeutics, (just-accepted).

[6] Bosch, T.J., Barsainya, R., Ridder, A., Santosh, K.C. and Singh, A., 2021. Interval timing and midfrontal delta oscillations are impaired in Parkinson's disease patients with freezing of gait. Journal of neurology, pp.1-11.

[7] Chakraborty, J. and Nandy, A., 2020. Discrete wavelet transform based data representation in deep neural network for gait abnormality detection. Biomedical Signal Processing and Control, 62, p.102076. [8]Paragliola, G. and Coronato, A., 2018. Gait anomaly detection of subjects with Parkinson's disease using a deep time series-based approach. IEEE Access, 6, pp.73280-73292.

[9] Asmarian, N., Ruzitalab, A., Erjaee, G., Farahi, M.H. and Asmarian, S.M., 2021. Parkinson's Disease Rating Scale Using Synchronization Analysis of Gait Dynamics. BioMed Research International, 2021.

[10] Haji Ghassemi, N., Hannink, J., Martindale, C.F., Gaßner, H., Müller, M., Klucken, J. and Eskofier, B.M., 2018. Segmentation of gait sequences in sensor-based movement analysis: a comparison of methods in Parkinson's disease. Sensors, 18(1), p.145.

[11] van den Berg, M.E.L. and Maeder, A.J., 2018. Prediction of freezing of gait in patients with Parkinson's disease using EEG signals. Telehealth for Our Ageing Society: Selected Papers from Global Telehealth 2017, 246, p.124.

[12] Sigcha, L., Costa, N., Pavón, I., Costa, S., Arezes, P., López, J.M. and De Arcas, G., 2020. Deep learning approaches for detecting freezing of gait in Parkinson's disease patients through on-body acceleration sensors. Sensors, 20(7), p.1895.

[13] Yurdakul, O.C., Subathra, M.S.P. and George, S.T., 2020. detection of parkinson's disease from gait using neighborhood representation local binary patterns. Biomedical Signal Processing and Control, 62, p.102070.

[14] Zeng, W., Yuan, C., Wang, Q., Liu, F. and Wang, Y., 2019. Classification of gait patterns between patients with Parkinson's disease and healthy controls using phase space reconstruction (PSR), empirical mode decomposition (EMD) and neural networks. Neural Networks, 111, pp.64-76.

[15] El Maachi, I., Bilodeau, G.A. and Bouachir, W., 2020.Deep 1D-Convnet for accurate Parkinson disease detection and severity prediction from gait. Expert Systems with Applications, 143, p.113075.

[16] Suquilanda-Pesántez, J.D., Zambonino-Soria, M.C., López-Ramos, D.E., Pineda-Molina, M.G., Milán, N.S., Muñoz, M.C., Villalba-Meneses, G.F. and Almeida-Galárraga, D., 2020, October. Prediction of Parkinson's disease severity based on Gait signals using a neural network and the Fast Fourier Transform.In XV Multidisciplinary International Congress on Science and Technology (pp. 3-18).Springer, Cham.