Severity Identification of Parkinson’s Disease

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Disease severity identification using computational intelligence-based approaches is gaining popularity nowadays. Movement disorders caused by PD may not remain the same in different patients. Thus, it is essential to develop an automated tool to evaluate a patient’s gait.

disease severity deep learning machine learning Parkinson's Disease

1. Introduction

Early and accurate diagnosis of diseases is essential for the right treatment. In addition to accurate and rapid diagnosis, the severity identification using computational intelligence-based approaches is becoming popular and challenging nowadays. Traditional computational approaches (i.e., classification) are mainly focused on solving two-class classification problems, i.e., positivity or negativity of disease, or presence or absence of certain values. However, nowadays, with the advancements in deep learning technologies, one can easily diagnose the disease and its severity. Most of the work on severity identification is based on recent deep-learning-based models. The training of these models depends on the labeling of disease severity levels by expert personnel. However, the process of multi-class manual labeling is quite tedious, time-consuming, and non-quantitative [1]. Here the problem of severity identification is addressed with the help of multi-class classification. A comprehensive review of various research articles concentrating on disease severity identification of Parkinson's Disease (PD) using computational intelligence-based approaches is presented.

2. Severity Identification of Parkinson’s Disease

Movement disorders caused by PD may not remain the same in different patients. Thus, it is essential to develop an automated tool to evaluate a patient’s gait. Xia et al. [2] presented a novel gait evaluation approach (known as “dual-modal attention-enhanced deep learning network”), which not only distinguishes between normal gaits and PD gaits but also computes the severity of PD by quantification of gaits. The system is capable of modeling both left and right gaits separately. Multiple 1D vertical ground reaction force (VGRF) signals achieve the segmentation of left and right samples. A CNN-LSTM-based dual-modal attention-enhanced network was utilized to analyze the gait movements on the gait dataset [3] with two severity levels, viz. Hoehn and Yahr (H&Y) and the Unified Parkinson’s Disease Rating Scale (UPDRS). Their architecture utilizes an input with the dimensions B × 150 × 9 × 1, where B indicates the batch size of samples, 150 indicates the period of a sample, and 9 indicates the number of VGRF signals. Their CNN consists of three layers in which every convolution operation is followed by the ReLU activation function for feature extraction. However, pooling is not incorporated due to the limited data samples. After the last convolution, the output of the feature map comprises dimensions of B × 150 × 9 × C3. Using flattening, the feature map 9 × C3 is converted into a tensor, i.e., C4, which was fed to an attention-enhanced LSTM (AE-LSTM). The AE-LSTM concatenates the branches and passes them to the fully connected (FC) layer. Finally, the severity of PD is achieved using probability distribution by mapping the output of FC using a SoftMax classifier. Experimental results claim 99.01% accuracy in classifying PD patients into different severity levels.

Pereira et al. [4] have reviewed several papers to predict PD at the earliest stage. After reviewing the papers, the authors have concluded that there are still many problems that need to be addressed, so they proposed image processing techniques to address these existing problems. For this experiment, handed datasets are utilized, collected from Brazil University. It contains the meander and spiral images gathered through the handwritten exam and 92 handwritten exams conducted on healthy people (control group) and PD patients. Handwritten Trace (HT) and Exam Template (ET) features are extracted through the blurring method. The feature extraction technique is applied to compare and evaluate both the HT and ET features. The Support Vector Machine (SVM) with some modifications, Naïve Bayes (NV) technique, and Optimum path forest (OPF) pattern recognition methods are used for the severity classification. The experimental results show 67% accuracy in identifying the precise class to predict the stage of the severity. As per the amount of information concerned for PD identification, meander images represent more information than spiral images. Although they presented an automated system that diagnosed the PR at an early stage, the performance can be improved by considering large as well as consistent datasets.

Prashanth et al. [5] addressed the fact that if PD disease is detected at an early stage, it can be cured by the proper therapies and medicines. In this regard, they utilized Single-Photon Emission Computed Tomography (SPECT) along with 123I-Ioflupane to diagnose the PD disease at an earlier stage on the PPMI database. The dataset contains the Striatum Binding Ratio (SBR) value of 179 normal people and 369 PD patients in the initial stage. The logical regression is applied for the calculation of the significant numerical features. The visualization of each SBR feature is calculated through histograms. The notched plots mark the patients separately in normal, PD, and early-stage categorization. The classifications and prediction have been acquired through the Support Vector Machine (SVM) and Logistic Regression (LR). The SVM uses a linear kernel to classify the decision boundary through by input features. The binomial logistic regression model uses the logit transformation method to develop the prediction model to predict the risk factor in PD patients. The experimental results report that the SVM classification method has achieved 96.14% accuracy and 95.03% specificity for the classification of PD patients. Although this system provided high performance and distinguished early PD patients from normal patients, the system can be enhanced through the Scans Without Evidence of Dopaminergic Deficit (SWEDD) and other validation approaches.

Parkinson’s Disease can be identified on various input signals, as depicted in **Figure 1**. In this regard, Cernak et al. [6] proposed a model to identify voice characteristics to predict the PD patient’s information. They utilized the read Voice Quality (VQ) datasets by Kane (2012) and Laver (1980). They covered the five non-model vocalizations, viz. creaky, breathiness, falsetto, harsh, and tense. To study the vocalization features, the Spanish database contains the speech recording detail of PD patients and a healthy control group. With the help of statistical measures, the authors differentiated the model and non-model vocalization. They computed the probability of the vocalization features through a machine-learning-based approach. The Euclidean distance calculates the similarity of the model in PD, and the alignment of the non-model is calculated through the inverse distance. The vocalization analysis section is computed through the Deep Neural Network (DNN). Further, the binary classification method was utilized to identify the probability of a specific vocalization class. They also applied the acoustic model for the phonic configurations. The experimental results reported the characteristics of PD patients: the composition of a maximum of 30% of breathy voice and a minimum of 12% of harsh voice. The system provided the accuracy of the vocalization speech based on the voice quality, but analysis of the speech was limited due to available datasets.

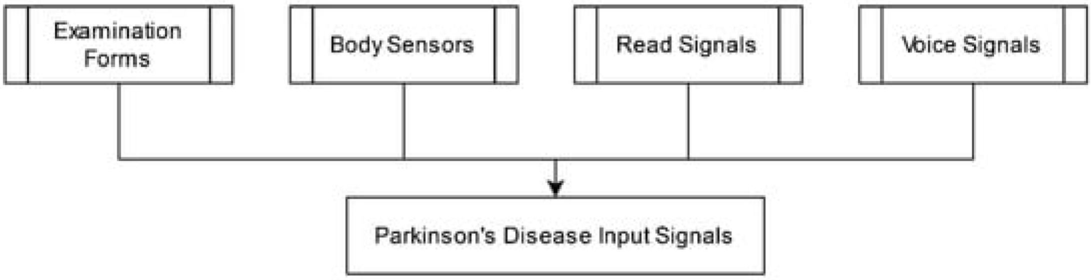

Figure 1. Various inputs to Parkinson’s Disease diagnosis.

Lahmiri et al. [7] also proposed a method to detect PD through voice patterns. They utilized the 195 vowels and voices data set comprising 147 PD-affected and 48 healthy patients. The Wilcoxon and ROC techniques were used to identify eight different patterns. The well-established SVM classification technique was applied to classify the PD patient and the healthy one. The system reported a 92.21% accuracy, 82.79% specificity, and 99.63% sensitivity. Although this automated system provided a good performance through voice patterns only, the researchers may combine some other parameters for the identification of PD patients at an early stage because voice is not the only symptom that characterizes PD.

Ertuğrul et al. [8] presented a machine-learning model to detect PD disease at an earlier stage. Initially, the data are collected from the gaitpdb datasets that contain information about healthy people and PD patients. Eight sensors are placed under the foot for 2 min, and the recorded sensor information is converted into the LBP domain and processed through shifted 1D-LBP. The LBP signal value lies between 0 and 255, matched with a special and distinct pattern formed through the shifted 1D-LBP signal. Then, the histogram technique illustrated the 256 different signal patterns according to their corresponding signal. The statistical features such as correlation, entropy, and skewness are computed through the 1D-LBP histogram sensor. The classification and design features were processed through the machine-learning approach. The experiment evaluation on 10-fold cross-validation reported an accuracy of 88.89% and a sensitivity of 0.89. The authors implemented the proposed system on biomedical information, and in addition to this, some other symptoms such as speech may be considered in the future.

Marek et al. [9] stated that PD detection at the earliest age is crucial because there is no accurate method to detect PD. Either motor symptoms or non-motor symptoms can be detected through PD diseases. They proposed an automated multi-modal feature and machine-learning techniques based on non-motor symptoms for detecting PD.

Based on biomarkers, the feature description is processed through the REM sleep Behavior Disorder Screening Questionnaire (RBDSQ) and CerebroSpinal Fluid (CSF). The Wilcoxon sum test is applied for the feature analysis. The PD classification is achieved through SVM, random forest, and logistic regression. The experimental result reported a 96.0% accuracy for the tested dataset.

Acharya et al. [10] differentiated PD patients from normal persons by drawing movements. They investigated handwriting markers for muscular movements and interpretation of other activities of the patients. To experiment with this model, the dataset was categorized into two parts, i.e., 20 healthy and 57 PD patients. The data pre-processing was achieved through five different score vectors. The Normalized Velocity Variability (NVV) is applied to identify the speed of the pen of the subject. They applied the NVVALL score to focus on healthy and PD patients. The receiver operating characteristic (ROC) was observed to be 0.9354. The UPDRS score represented the writing behavior of PD patients on the Hoehn (H) and Yahr (Y) scale. Naïve Bayes, Adaboost, and logistic regression methods were applied for the PD classification. The experimental results reported the highest accuracy of 90.90% through Naïve bays and the lowest accuracy of 86.36% through the SVM classifier.

Nilashi et al. [11] presented a new automated method to predict and monitor PD disease patients with characteristic motor and total UPDRS. Clustering was applied to form a cluster with similar characteristics and merge similar features into one cluster. Thus, in the output, different clusters were created of different sizes. A self-organizing map (SOM)-based cluster approach effectively handled the large datasets and provided similar clusters. The R^2 method was utilized to evaluate the value of the SOM. In addition, the PCA method was applied for the feature analysis of the cluster approach. Further, the deep belief network was also applied to identify PD patients better. The RMSE method was applied to find the exact and accurate information about PD patients. They also included the SVR [12] and ANFIS [13] learning techniques and presented an accuracy of 89.4%.

Sztaho et al. [14] proposed a method to detect the severity level of Parkinson’s disease through speech signals. To implement this method, the authors used the Hungarian speech database that consists of the speech signals of 51 patients. The severity of patients was classified according to the Hoehn (H) and Yahr (Y) scales. The sound card was utilized to record the speech of patients. The feature extraction technique was utilized to categorize speech, such as pause ratio and speech speed. The authors implemented this method using two types of detection methods, viz. binary classification and regression. The classification method was processed by the K-Nearest Neighbor (K-NN) method and SVM. They utilized two types of regression methods, viz. linear regression and support vector regression. The Root Mean Square Error (RMSE) was used to evaluate the performance of the regression method. The binary classification method reported an overall accuracy of 83.56% for the read text, 85.11% for the speech signal, and 84.62% for both.

Xia et al. [2] proposed a dual model based on the deep-learning method to detect the characteristics of Parkinson’s disease from the gait signals. The left and right gaits were recorded by the VGRF tool. The severity level is identified with the help of the Hoehn (H) and Yahr (Y) scales. They applied an N-size vector for feature extraction and selection through this vector gait cycle detection, which is processed by fixing the N = 150. The dual-mode consists of two-channel levels for processing separate signals. The VGF gait signals are first passed through the two-layer CNN model to understand the features of gait signals, followed by LSTM for temporal features. Further, they utilized the attention method, which provided meaningful information on the subject that can be accessed with the help of a score. A Fully Connected layer (FC) was incorporated to combine both left and right gait signals, followed by final classification through the SoftMax layer. The efficacy of the model was measured using a five-fold cross-validation approach. The model experimentally reported an accuracy of 99.31% and a sensitivity of 99.23%.

Park et al. [15] compared the performance of the PD diagnosis system through SVM with the two methods, viz. Multiple Layer Perceptron (MLP) and Radial Basis Function Network (RBN). Seventy-four-year-old data are utilized to implement this method, and the signal Electromyograph (EMG) is recorded through the AgCI conductor. In the pre-processing stage, signals are firstly filtered into 3 to 10 Hz by a type-2 filter followed by Fast Fourier Transformation (FFT) to identify the same frequency band of the tremor. After these steps, EMG signals are classified into two stages, viz. experienced and visual signal to detect the exact tremor status. The MLP network consists of the input layer, hidden layer, and output layer, and it is used to reduce the overfitting issue in the datasets. The status of tremors is detected through −1 and 1. On the other hand, the radial basis function utilized the fuzzy c-mean clustering method to identify the initial stages of the cluster. Overall, 81.14% accuracy was reported using the SVM classification of tremor status.

Hariharan et al. [16] presented an intelligent system based on a hybrid model. They initially incorporated the Gaussian mixture method as a pre-processing step to remove the unwanted noise present in the dataset. They also utilized two types of feature reduction methods, viz. PCA (Principal Component Analysis) to identify the hidden features presented in the datasets and LDA for mapping 22 features into a one-dimensional space. General Regression Neural Network (GRNN), Probabilistic Neural Network (PNN), and SVM were utilized for the severity classification of PD. The promising classification was reported based on the cross-validation method.

On the other hand, Balaji E. et al. [17] proposed a machine-learning model that can assist clinicians in detecting the stages of PD through gait information. Gait information provides all mobility information about healthy people and PD-affected people. This model is trained and tested with the public datasets based on the gait pattern provided by Physionet. VGRF is placed under the foot to provide gait information through different sensors. The feature extraction process is achieved using statistical and kinematic feature extraction approaches. The statistical feature extraction process is used to identify the four levels of PD through H and Y scales. It created a 16 × 166 matrix based on the sensor and subject-level PD severity. In contrast, the kinematic features were used to identify PD patients' steps, swing time, and speed. A 10-fold cross-validation is adopted in which 90% of data are used for training purposes and the remaining for testing purposes. Decision Tree (DT), SVM, Bayes, and Ensemble classifier were utilized for the classification. Experimental evaluation reported that the Decision Tree (DT) classifier has the highest accuracy of 99.04%, the sensitivity of 99.06%, and the specificity of 99.08%.

Kim et al. [18] presented a novel approach based on CNN to detect the severity rate of Parkinson's disease by performing tremor quantification from raw datasets. For experimental evaluation, 92 PD patients' tremor sensor datasets were collected using a wrist sensor device as wearable equipment. A neurologist was provided with the information on PD on four-level severity, i.e., normal to severe, based on the unified Parkinson's disease rating scale (UPDRS). In addition, they designed a neural network to assess the severity in PD patients. In this network, 2D images are used as input for the convolution layer, and a 3 × 50 convolution filter combines both local and sensor information. They processed the input signals computed by the wrist sensor in the form of gyroscope signals and accelerometer signals. Experimental evaluation depicted a classification accuracy of 85%.

Oung et al. [19] addressed that the existing system does not differentiate between people infected with Parkinson's Disease (PD) and healthy people. Therefore, to handle this issue, they proposed a multi-class classification system to classify PD severity levels (low, mid, high) and a healthy control group. For experimental evaluation, datasets of 65 persons of different ages were collected from the Neurology hospitals and the severity level in Hoehn (H) and Yahr (Y) was rated through the UPDRS measure. The dataset signal is assorted through two stages, i.e., motion and speech-based signals. The speech signals were recorded through the Motion Node Bus (MNB) from the IMU wearable device, and the speech signals were recorded through the audio sensor, i.e., a headset placed at 5 cm away from the mouth. The authors acquired the Empirical Wavelet Transform (EWT) to decompose the motion signals to find the approximate information from the detailed information, and the Empirical Wavelet Packet Transform (EWPT) was developed to decompose the speech signals. The EWPT method uses Fast Fourier transform (FFT) to obtain the exact frequency, i.e., lies between 0 and π. Feature extraction was processed through the Hilbert transform based on amplitude and frequency. Extracted features are categorized into three groups: speech signals, motion signals, and a mix of motion and speech. They employed Probabilistic Neural Network (PNN), Extreme Learning Machine (ELM), and K-Nearest Neighbor (kNN) for the classification. Experimental evaluation reported an accuracy of 90% on classification using an Extreme Learning Machine (ELM) for both motion and audio signals.

Recent studies analyzed that it is hard to diagnose PD at an earlier stage. Many remote detecting tests were utilized to detect the PD severity and realized that variables in gait signals could easily distinguish PD patients from healthy ones. In this regard, Cantürk et al. [20] proposed a system to detect PD patients' severity using gait signals. Their system was trained and tested with 306 publicly available signals with 93 PD patients and 73 healthy subjects based on different categories. The gait system was measured through Ultraflex Computer Dyno Graphy (UCDG) with eight sensors placed under the foot. The Fuzzy Recurrence Plots (FRP) convert the signals into texture representations for both PD and healthy patients. Further, AlexNet was applied to extract the deep features, followed by implementing SVM and k-Nearest Neighbor (kNN) for binary and multi-class classification. The experimental result of the kNN method reported an accuracy of 99%, whereas the SVM reported 98%.

Zhao et al. [21] presented a machine-learning method to detect the severity level of PD from the gait data. This is the hybrid technique consisting of both Long Short-Term Memory (LSTM) and a Convolutional Neural Network (CNN) to recognize the spatial time-based pattern through the gait data. The hybrid model has five convolution layers and two layers of LSTM to detect the severity rate in PD patients. The authors acquired two convolution layers of 5 × 5, in which the first layer is mapped with 32 features and the second one is mapped with 64 features. LSTM and CNN are trained and tested on the PhysioNet [22] dataset. The pre-processing and L2 normalization were applied to reshape the datasets into 100 × 19 × N (N ="Ga:13592, Si:7744, Ju:11734"). Further core parameters of LSTM were transformed to achieve better classification results into four levels, viz. normal (severity

0), severity 2, severity 2.5, and severity 3. Final classification was achieved using the SoftMax layer. The model reported 98.70% accuracy for the first dataset, 98.41% for the second dataset, and 98.88% for the third dataset. However, this method provided better accuracies in PD detection, and this model is the baseline for detecting the PR disease.

An automated machine-learning-based method is proposed to detect and identify the level of severity of Parkinson’s disease from the gait data by Maachi et al. [23]. They employed a Deep Neural Network with the help of a 1D convolution Neural Network. This algorithm has divided the information into two parts, viz. Parkinson’s and a control group. For the experiment, publicly available datasets are used and cited from the PhysioNet. The datasets contain 93 patients with Parkinson’s disease and 73 patients in the control groups. The Vertical Ground Reaction Force (VGRF) based on 18-1D signals provides the information of a recorded walk with the foot sensors positioned below the foot. The VGRF signal is divided into datasets into m-parts that are based on subject categorization. Further, these parts are the input of the proposed method of DNN. The DNN method is processed with two parts, viz. 18 parallel 1D and a fully connected network. The feature extraction is processed through the 18 1D-CNN. The Parallel 1D network has taken input from the VGRF signal and processed it through the four convolution layers, which are fully connected. Further, this layer has extracted the features used to help categorize the PD and control groups. The output layer generates one neuron to detect the disease and five neurons to classify the level of severity that were categorized into five classes based on some criteria. This method reports an accuracy of 98.7% in detecting the severity and 85.8% accuracy in the classification of the severity level.

Prashanth et al. [24] addressed different stages of PD as a very important factor in a medical decision. The subject’s disordering features were measured by UPDRS, but it does not give information about the PD stage. In this paper, they proposed a new model based on machine-learning to detect the PD and different stages of PD (early, normal, and moderate). This hybrid model supports SVM, AdaBoost, and RUSBoost-based and ordinal logistic regression (OLR) classifiers. It utilized the Parkinson’s Progression Markers Initiative (PPMI) datasets with 197 healthy and 434 PD subjects. The statistical analyzer is used to classify the features into three categories based on a filter. They used classification algorithms such as random forests, SVM, and logistic regression to classify the PD stages. The validation of the performance was measured by the 10-fold cross method. The experimental results indicated that AdaBoost reports the highest detection accuracy of 97.46% for the normal PD subject, and SVM reports 98.04% for the early stage of PD detection. Although automated detection improves the stage of PD, there is a need to address more stages for PD patients.

Prashanth et al. [25] also presented a prediction model based on machine-learning to distinguish healthy and early PD patients. The dataset utilized for the experiment is from the Parkinson’s Progression Markers Initiative (PPMI). They further applied the Patient Questionnaire (PQ) to analyze the dataset. In PPMI, data are arranged in the longitudinal format, so they performed the record and subject-wise cross-validations. The dataset is divided into 90% training sets, and the remaining are test sets. To remove the redundancy and select the appropriate features, they have used three different selection methods, viz. Wilcoxon rank, Least Absolute Shrinkage and Selection Operator (LASSO), and Principal Component Analysis (PCA). The Wilcoxon rank method is acquired for the significant features through the sum test. The LASSO method is also applied to shrink the datasets, and the PCA method is the reduction approach used for decomposing the multivariate datasets into one manner format. The authors have processed the logistic regression, SVM, random forests, and boosted trees for the classifications. The experimental results indicated 96.50% accuracy using SVM through the subject-wise validation.

Aydın et al. [26] presented the Hilbert–Huang Transform (HHT) method to detect the severity of Parkinson's Disease (PD) from the gait pattern. The datasets are utilized from the PhysioNET [22], and the signals, such as step swing time, are measured through the VGRF sensor. The authors applied three types of feature selection techniques, i.e., the filter approach, the wrapper approach, and the embedded approach. The filter approach is used to identify the common characteristic of the training datasets. The wrapper feature selection approach is applied for mapping with relevance and extracting the optimal features, and the last approach is applied to check the performance of the features. They also applied the feature creation method, and a 10-fold cross-validation approach checks the performance of this method. The regression tree classification approach is processed to distinguish PD patients from healthy ones. The experimental results showed that the accuracy of the proposed system is 98.79%, sensitivity is 98.92%, and specificity is 98.61%. The performance analysis of some PD identification approaches is depicted in **Table 1**. On the other hand, a systematic review of AI-based approaches for the diagnosis of PD is presented by Saravanan et al. [27].

Table 1. Performance analysis of various Parkinson's Disease (PD) identification approaches.

References	Input	Features Extraction Approach	Classifier	Performance Accuracy (%)
Pereira et al. (2016) [4]	Spiral, Meander images	Zhang–Suen-based thinning algorithm	NB, OPF, SVM	67.00
Cantürk (2021) [20]	Gait Signals	Alexnet	SVM, kNN	99.00
Xia et al. (2019) [2]	Gait information	CNN 2D	CNN & LSTM	99.31
Zhao et al. (2018) [21]	Gait information	CNN model	CNN & LSTM	97.86
Hariharan et al. (2014) [16]	Speech samples	PCA, LDA, SFS	LS-SVM, PNN, and GRNN	100.00
Prashanth et al. (2014) [5]	SPECT images	LR	SVM, LR	96.14
Sztaho et al. (2017) [14]	Speech Rhythm	Feature Vector	SVM, Deep learning	94.87
Maachi et al. (2020) [23]	Gait signals	Manual method	Deep 1D-convent	98.70

References	Input	Features Extraction Approach	Classifier	Performance Accuracy (%)
Lahmiri and Shmuel (2019) [7]	Voice pattern	Wilcoxon-based	SVM	92.21
Ertuğrul et al. (2016) [8]	Gait signals	1D-LBP	LR, MLP, NB, BAyesNT	88.90
Yurdakul et al. (2020) [28]	Gait Signals	Local Binary Patterns	Generalized Linear Regression Analysis (GLRA) and SVM	98.30
Oung et al. (2018) [19]	Speech and Motion signal	Wavelet Energy and Entropy	kNN, PNN, ELM	95.93
Prashanth and Roy (2018) [24]	Motor signals	Wilcoxon rank-sum test	SVM, Random Forest, probabilistic ADAboost-based ensemble	97.46
Aydın and Aslan (2021) [26]	Gait Pattern	One R Attribute Evaluation and vibes algorithm	Hilbert-Huang transform	98.79
Kim et al. (2018) [18]	Wrist sensor pattern	Convolutional filters of CNN	CNN	85.00
Balaji E. et al. (2020) [17]	Gait signals	Statistical analysis	DT, BC, EC and SVM	99.50

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