Early Diagnosis of Parkinson's Disease and Severity Assessment based on Gait using 1D-CNN

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***Abstract*—Gait irregularities are among the crucial signs that doctors should take into account when making a diagnosis. However, gait analysis is difficult and can depend on the knowledge of experts and the clinician's subjectivity. To assess gait data, this research suggests a smart cutting-edge system, for diagnosis of Parkinson's disease (PD) based on a deep learning approach. The proposed method analyzes 1-D inputs from sensors (which are connected to foot) that measure the virtual ground reaction force (VGRF). The first section of the network is composed of eighteen parallel 1D-CNNs that correlate to the system's inputs. In the second section, the eighteen number of 1D-CNN outputs are concatenated into one unique deep array. In the third section, various classifiers such as support vector machine, multi-layer perceptron and random forest are used for final classification. The proposed methodology is used to predict between the two classes, i.e., control (CO) and PD subjects, as well as to predict the severity of Parkinson's gait according to the Unified Parkinson's Disease Rating Scale (UPDRS). Our test shows that the suggested method is highly effective in detecting PD from gait data. Experiments were conducted on the Physionet dataset, and the results specify that the suggested model outperforms alternative methods in terms of classification outcomes. This model can assist in the severity diagnosis of PD by using gait data.**

***Index Terms*—1D-CNN, Parkinson's disease (PD), control (CO), gait analysis, virtual ground reaction force (VGRF), Unified Parkinson's Disease Rating Scale (UPDRS), deep learning.**

I. Introduction

PD has been identified in more than 10 million persons worldwide. Following Alzheimer's, it comes in second place and is a common neurological disease [1]. PD is a neurological condition that primarily affects the dopamine producing neurons in a particular region of the brain [1]. Early diagnosis is therefore crucial to enhancing the patient's care. Most medical professionals use the Hoehn and Yahr scale of 0-5 in which 0 is considered as normal and 5 as severe to assess PD severity. Treatment during the early stages (Stages 1 and 2) slows the progression of the disease and improves patients' quality of life. Since gait impairments have been shown to occur in the early stages of PD [2], gait analysis is a crucial stage of the diagnostic procedure. The key features of the Parkinson's gait include a slower gait cycle, a rise in stride variability, a lengthier stance phase, small steps, a shortened swing phase and a flat foot strike rather than a toe-to-heel strike[3]. These characteristics are assessed by doctors throughout the diagnosis procedure to determine if a patient is diagnosed with Parkinson's or not. Although evaluating gait can be difficult because it depends on a number of variables, including age and health, the goal of our research is to create an intelligent technology that can analyze gait data to identify the symptoms of PD and estimate the severity of Parkinson's according to UPDRS. The UPDRS is a rating scale used to assess a patient's progression of Parkinson's disease as well as its severity. To distinguish between normal and Parkinsonian gait, previous studies have used different feature extraction techniques, such as temporal analysis [4] or frequency analysis [5]. Table I includes a literature review of related work on different techniques. In this paper, a unique gait classifier built on deep learning, without manually extracting features, to avoid custom signal processing is proposed. The proposed methodology consists of three sections. In the first section, the VGRF signal from the foot sensor is processed by each of the 18 parallel 1D-CNNs. Deep features are extracted by each 1D-CNN. In the second section, the extracted deep features are concatenated. In the third section, machine learning algorithms are applied for the final classification.

The following is the paper's outline: The second section includes the contribution of the paper. The proposed methodology for the suggested approach is reported in Section III. The setup of the experiment is described in Section IV. In Section V, the results are provided. Section VI serves as our conclusion.

II. CONTRIBUTIONS OF THE PAPER

The contribution of the approached work are given as follows:

- It is possible to avoid manual feature extraction by using a simple 1D-CNN as it extracts important deep features from sensor data for precise gait classification.
- The paper also presents the algorithm to predict UPDRS severity, which can be valuable for clinical decision-making.
- The paper employs several machine learning techniques for effective classification and compares the performance outcomes of all the classifiers.

TABLE I
LITERATURE SURVEY

Approaches	Authors	Work Done
Sensor-based (SB)	Ertugrul *et al. [4]*	They used shifted 1D-LBP (local binary patterns) to build 1D-LBP histograms, from which they extract statistical properties including energy, correlation and entropy for each signal from the foot sensors. They classified the feature vectors using a number of supervised classifiers after combining the features from each of the 18 histograms.
	Zhao *et al. [5]*	A deep learning method was created to identify Parkinson's illness. A 2D-Convnet was used in the first network to study how the forces were distributed spatially. Recurrent neural networks were used by the second network to examine the temporal variations. The average of the two channels was used to determine the final classification.
	Johri *et al. [9]*	Two neural network-based models, the VGFR Spectrogram Detector and Voice Impairment Classifier, have been presented in this research with the goal of assisting medical professionals and the general public in early disease diagnosis.
Vision-based (VB)	Cho*et al. [10]*	In this investigation, we initially recorded a number of recordings of both healthy volunteers and parkinson patients. Then, in order to describe the subjects, we analysed the video images. To enable us to apply LDA and PCA for feature extraction, all subjects were vectorized. The classifier employed next was Minimum Distance Classifier (MDC).
	Aich *et al. [11]*	A unique approach is suggested for quantifying the gait parameters using 3D motion recordings. The most useful characteristics are then selected using a variety of feature selection algorithms, including Principal Component Analysis (PCA), Fisher's score (FS), and minimum redundancy maximum relevance (MRMR). Finally, two groups composed of control subjects and Parkinson patients were automatically classified using machine learning-based approaches like SVM, RF, and NB.

III. PROPOSED METHODOLOGY

Our suggested approach is based on deep learning. Some fundamental ideas are briefly explained in this section as they are self-explanatory. Deep learning relies on intermediate layers, also known as hidden layers, for learning complex representations of the input data. Stochastic optimizers are used to minimize the loss function at each iteration during the training process, increasing the accuracy of deep learning. Each layer is made up of several neurons, and each neuron has a non-linear activation function. The network's initial weights are chosen at random, but as it is iteratively trained, the weights are optimized to ensure accurate predictions. Overfitting is avoided by using regularization strategies like dropout, which deactivates specific neurons at each iteration of the training process. Our model employs convolution, max-pooling and fully-connected layers.

Our algorithm's goal is to classify person's gait into either the PD or control (CO) category. A total of 18 VGRF 1D signals from foot sensors were recorded. These signals are recorded as a function of time in Newton. For the examination and characterization of gait, the VGRF signals contain significant information. These VGRF signals can be used to extract clinical spatiotemporal gait parameters such as the stride time, stance phase, swing phase, etc. By providing raw VGRF sensor data to our deep learning model, it will be able to surpass the hand-crafted features by automatically extracting key gait characteristics.

The deep neural network is made up of three sections (Fig. 1). There are 18 parallel 1D-CNN in the first section. The second section creates a single deep vector by concatenating all of the outputs of 1D-CNN. The third section is used for classification using different machine learning algorithms.

A. 1D-CNN

The network's first segment comprises of eighteen parallel 1D-CNN network. Each network takes a VGRF signal as input, processing it through four convolutional layers. The proposed architecture consists of 12 layers, including 4 convolutional layers and 2 max-pooling layers. Batch normalization and ReLU layers were also used to speed up network training and convergence.

The best features are automatically extracted by CNNs feature extraction method from the gait sensor data. Each signal can be treated independently thanks to 1D-CNN parallel processing. With the network's learning rate set to 0.0001 and the batch size set to 32, the algorithm was trained using the Adam optimizer. The early stopping method was used to avoid overfitting. When the network's accuracy and loss on the validation set do not improve for N consecutive times, the early stopping strategy can be employed to stop the network training. Table II displays the final hyper-parameters of the 1D-CNN.

B. Concatenation

Concatenation is the combination of extracted features from different layers or branches of 1D-CNN as shown in Fig. 2. In the second segment, the output of all the 18 parallel 1D-CNN are concatenated into a single deep vector. Equation 1 describes the basis of concatenation process where S_{conc} is the concatenated feature set given by,

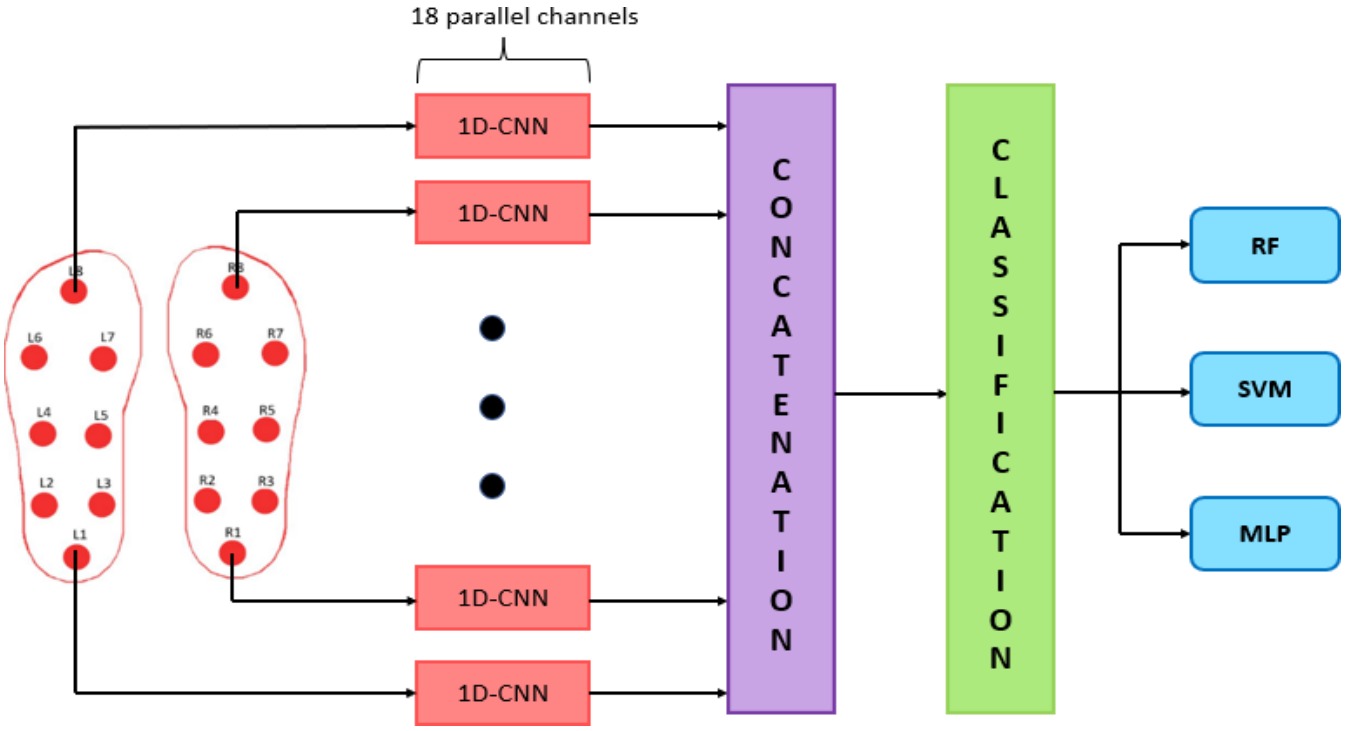
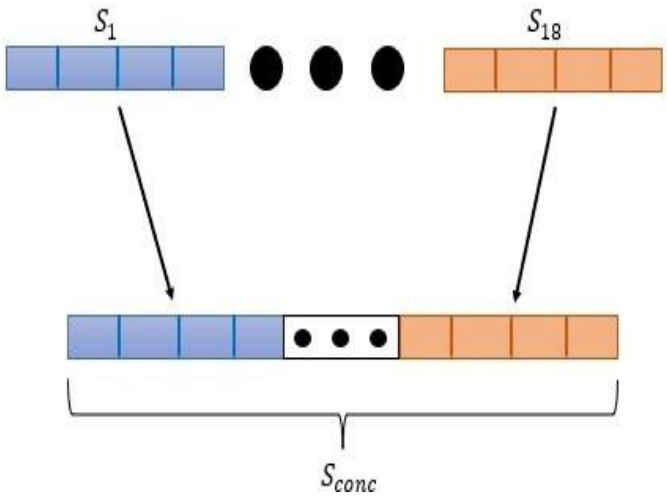


Fig. 1. Framework of proposed system

TABLE II
PARAMETER CONFIGURATION FOR CNN LAYERS

Layer Name	Filters	Kernel Size	Feature Map
Input	-	-	100×1
Conv 1	32	9×1	8 @ 92×1
Max-Pool 1	-	2×1	8 @ 46×1
Batch Normalization	-	-	8 @ 46×1
ReLU	-	-	8 @ 46×1
Conv 2	64	3×1	64 @ 44×1
Conv 3	128	3×1	128 @ 42×1
Max-Pool 2	-	2×1	128 @ 21×1
Batch Normalization	-	-	128 @ 21×1
ReLU	-	-	128 @ 21×1
Conv 4	128	6×1	128 @ 16×1
Batch normalization	-	-	128 @ 16×1
ReLU	-	-	128 @ 16×1



$$S_{conc} = S_1 U S_2 U \ldots U S_{18} \quad (1)$$

Fig. 2. Concatenation of feature sets

C. Classification

In the third section of the process, the concatenated vector is fed to the classification block, and various machine learning algorithms are used to classify PD and control subjects.

1) Random Forest (RF): RF is a supervised machine learning technique that classifies data based on the majority votes from N uncorrelated decision trees that together form a larger random forest. It can handle vast amounts of data and does not require data normalization. Since it averages predictions, it can still perform well even when some data is missing. Additionally, it does not suffer from overfitting problems.

2) Multi-Layer Perceptron (MLP): A MLP is made up of several layers, and each layer is completely interconnected. Except for the nodes in the input layer, the neurons in the other layers have nonlinear activation functions. The output layer for Parkinson's detection consists of just one neuron, and

Sigmoid is used as the activation function. The output layer for severity prediction consists of 5 neurons for 5 classes, and Softmax is used as the activation function.

3) Support Vector Machine (SVM): SVM perform complex mathematical transformations on data depending on the chosen kernel function. These transformations aim to maximize the separation between data points according to the provided labels or classes. SVM supports binary classification, which separates data points into two classes. For multi-class classification, the problem is broken into numerous binary classification problems using techniques such as the One-vs-One strategy.

IV. EXPERIMENTS

A. Dataset

This dataset was downloaded from Physionet and consists of 73 healthy subjects and 93 Parkinson's patients. The dataset records the virtual ground reaction force (VGRF) of a person walking for approximately 120 seconds on flat ground at their normal pace. A total number of 8 sensors were placed on each foot, and the output of each of these 16 sensors, as well as the output of two total VGRF signals under each foot, have been digitally recorded and sampled at a rate of 100 Hz. For each subject, the UPDRS score is reported. This dataset is a combination of data from three different experiments: 'Si'[6], 'Ju'[7], and 'Ga'[8].

B. Validation

To test our method, we performed 10-fold cross-validation with a value of K equal to 10. At the subject level, we separated both the control group and the Parkinson's patients into ten folds, ensuring the same balance of data in each fold. To obtain the most accurate results, several values of K were tested.

C. Performance Evaluation

The proposed model is designed to diagnose and classify between control subjects and Parkinson's patients. To evaluate its performance, we calculated the specificity (Sp), sensitivity (Se), and accuracy (Acc) of the model. These metrics were computed by comparing the predicted labels of the model with the true labels of the dataset. Specifically, specificity measures the amount of true negatives amidst all negative cases, sensitivity measures the amount of true positives amidst all positive cases, and accuracy measures the quantity of correct predictions amidst all cases. The following notations were used:

- TP represents that PD patient is correctly classified
- TN represents that CO subject is correctly classified
- FP represents that CO subject is wrongly classified
- FN represents that PD patient is wrongly classified

The specificity (Sp), sensitivity (Se), and accuracy (Acc) are calculated as:

$$Sp = \frac{TN}{TN + FP} \tag{2}$$

$$Se = \frac{TP}{TP + FN} \tag{3}$$

$$Acc = \frac{TP + TN}{TP + TN + FP + FN} \tag{4}$$

The same proposed model is also used to detect Parkinson's severity based on UPDRS scale. UPDRS values range from 0 to 70. These values were divided into 5 classes. In a multi-class experiment, the calculation of precision, recall, and F1-score for each class is shown below:

$$Precision = \frac{TP}{TP + FP} \tag{5}$$

$$Recall = \frac{TP}{TP + FN} \tag{6}$$

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{7}$$

V. RESULTS

SVM works well with 95.2% accuracy in our investigation, where we implemented various classification algorithms are implemented for Parkinson identification. For training, 75% of the data is used as training set, while 25% were used as the test set. Fig. 3 displays a comparison of specificity, sensitivity, and accuracy using several classifiers.

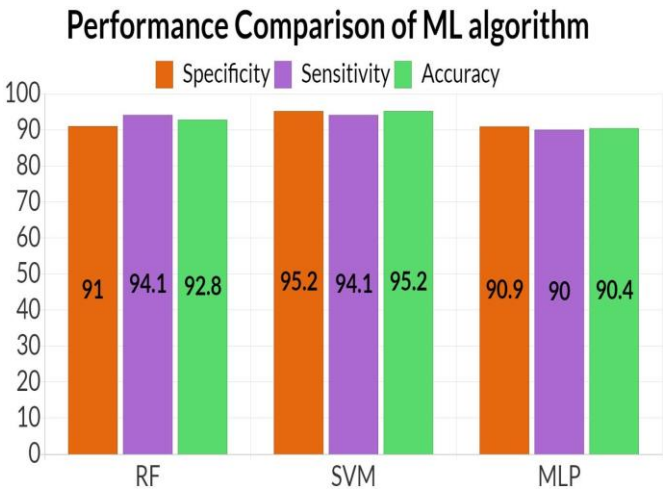


Fig. 3. Comparison of Specificity (Sp), Sensitivity (Se) and Accuracy (Acc) with different classifiers.

Table III, IV and V represents the performance metrics of severity prediction with different classifiers. By comparing all the classifiers, it is seen that MLP classifier gives the best F1-score of 82%.

In Table VI, our methodology is compared with various alternative approaches. The benefit of our approach is that it can process different signals from the input in a different way as compared to other approaches. It can take the most significant and precise features from each signal. Our technique is better suited to the gait classification problem than traditional machine learning techniques. Our algorithm differs from Zhao et al. [5] as in our algorithm, the input signals are independent of one another. Because of that, the method can be applied to different experimental conditions. Firstly, time series in gait are primarily noisy, nonlinear data as a result, our approach employs deep learning, making it suitable for this kind of data. Second, when it comes to obtaining discriminative gait features for a particular recognition challenge, hand-crafted approaches are typically ineffective. Recently, Balaji et al. [14] proposed a LSTM network to rate the severity of PD based on sensor dataset. LSTM networks are known to be computationally intensive, and this can be a limiting factor when dealing with large datasets or real-time applications. Therefore, compared to our work, although Balaji et al.'s [14] approach is effective in rating the severity of PD, it may not be practical in all scenarios. To increase the speed and accuracy of the recognition of human gait actions, an active deep learning model was developed [15,16]. The main limitations of these papers have been high cost sensor installation and gait analysis computing resources.

TABLE III
PERFORMANCE OF RF CLASSIFIER FOR SEVERITY CLASSIFICATION

Class	Precision	Recall	F1 Score
1	1	1	1
2	1	0.83	0.90
3	0.6	1	0.75
4	0.66	0.8	0.72
5	1	0.25	0.4
Mean	**0.85**	**0.77**	**0.75**

TABLE IV
PERFORMANCE OF MLP CLASSIFIER FOR SEVERITY CLASSIFICATION

Class	Precision	Recall	F1 Score
1	1	1	1
2	1	0.91	0.95
3	0.8	0.66	0.72
4	0.8	0.8	0.8
5	0.6	0.75	0.66
Mean	**0.84**	**0.82**	**0.82**

VI. CONCLUSION

Parkinson diagnosis is still a very difficult medical issue. It is technically difficult to diagnose a PD patient by examining its symptoms. Therefore a method is devised to identify between the PD and CO subject and also to classify Parkinson's severity according to gait because gait disruption is one of the key motor symptoms. By utilising deep learning methods, our approach gets around the limitations of manually created feature extraction methods. Parkinson's gait identification accuracy for the suggested approach was 95.2% for SVM, 92.8% for RF and 90.4% for MLP. With a mean F1 score of 82.6% for MLP, 75% for RF and 73% for SVM the suggested method also predict the severity of a subject's UPDRS.

TABLE V
PERFORMANCE OF SVM CLASSIFIER FOR SEVERITY CLASSIFICATION

Class	Precision	Recall	F1 Score
1	1	0.86	0.92
2	1	0.75	0.85
3	0.6	1	0.75
4	0.6	0.6	0.6
5	0.66	0.5	0.56
Mean	**0.77**	**0.74**	**0.73**

This technique can be used as an effective screening tool to identify prospective Parkinson's patients in a clinical setting. The suggested algorithm will eventually be helpful for the elderly by tracking and examining gait features while they go about their daily lives. Such AI techniques might enable the early diagnosis of Parkinson's disease gait anomalies when combined with increasingly potent biometric sensors.

Yet, there is a deficiency in the deployment of the ideal number of sensors across the foot to evaluate the motor symptoms of Parkinson's disease. So, in an effort to significantly enhance the efficacy of the suggested strategy, it is essential to identify the various combinations of sensor placements throughout the trial.

TABLE VI
COMPARISON FOR PARKINSON'S DETECTION OBTAINED IN THIS PROPOSED METHOD WITH OTHER EXISTING METHODS.

Author	Sp(%)	Se(%)	Acc(%)
Zhao et al.,[5] (2018)	76.7	96.2	90.3
Ertugrul et al.,[4] (2016)	82.2	88.9	88.9
Johri et al.,[9] (2019)	NA	NA	88.17
Shyam et al.,[12] (2016)	NA	NA	91.66
Wu et al.,[13] (2017)	NA	NA	84.48
Balaji et al.,[14] (2021)	99.10	98.23	98.60
Bama et al.,[15] (2023)	NA	NA	92.51
Proposed Work(RF)	**91**	**94.1**	**92.85**
Proposed Work(SVM)	**95.2**	**94.1**	**95.2**
Proposed Work(MLP)	**90.9**	**90**	**90.47**

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