*Grenze International Journal of Engineering and Technology, June Issue*

# Early Detection of Parkinson's Disease by Neural Network Models

Mohamed Suhail S
Computer Science and Engineering, Saveetha Engineering College Chennai
Email: mohmaedsuhail1263@gmail.com, sujathae@saveetha.ac.in

***Abstract*— This paper establishes neural network models designed to detect Parkinson's disease (PD) during its initial phases. PD, a prevalent neurodegenerative condition, manifests with gradually reduced movement, tremors, limb stiffness, and alterations in walking patterns, including bent posture, shuffling steps, festination, gait freezing, and falls. Identifying PD early on is crucial for timely implementation of therapeutic measures, reducing morbidity. Nonetheless, accurately recognizing PD, particularly in the early stages, poses a challenge due to the elderly population's increased prevalence of PD and common occurrence of progressive gait slowness in other conditions like joint osteoarthritis or sarcopenia. Hence, creating a dependable and objective method is essential for distinguishing PD gait features from those typical in the elderly. This study aimed to devise neural network models utilizing participants' walking motion data to detect PD. We enrolled 32 drug-naïve PD patients with varying disease severity and 16 age/sex-matched healthy controls, measuring their movements using inertial measurement unit (IMU) sensors. The IMU data facilitated the development of neural network models, achieving an average accuracy of 92.72% in identifying advanced-stage PD during validation processes. Furthermore, the models accurately differentiated early-stage PD patients from normal elderly subjects with a 99.67% accuracy. An independent group of participants, recruited to assess the developed models, validated their success in distinguishing PD-affected individuals from healthy elderly, as well as patients at different severity stages. These findings offer robust evidence supporting early diagnosis and monitoring of disease severity in PD patients.**

***Index Terms*— Parkinson's disease, PD stage, IMU, neural network, gait.**

## I. INTRODUCTION

The aging of contemporary society correlates with a growing populace grappling with neurodegenerative conditions. Parkinson's disease (PD), among these disorders, is anticipated to witness a more than twofold increase, surging from 4 million in 2005 to 9 million by 2030 according to current estimates. Clinical manifestations of PD encompass gradually decelerating movements, limb rigidity, rest tremor, and posture instability. Laura Celentano served as the associate editor overseeing the review and approval for publication of this manuscript. Regrettably, even individuals undergoing dopaminergic treatment or deep brain stimulation witness deterioration with advancing age, with their mortality rate reaching two to three times that of the general population. Thus, the recognition of PD in its initial phase is pivotal to instigate appropriate treatments, reduce morbity, and alleviate the healthcare burden among the elderly.

The clinical severity of PD is categorized into five stages, denoted as the Hoehn-Yahr Stages I–V. In Stage I, patients exhibit unilateral symptoms, such as asymmetrical gait or hand swing; Stage II witnesses bilateral

*Grenze ID: 01.GIJET.10.2.220*

influences and a degradation of the patient's stability; Stage III involves central reflex mechanism impairment, leading to falls due to trunk instability; Stage IV necessitates a wheelchair and additional assistive devices; and in Stage V, patients become wheelchair-bound or even bedridden. PD patients can be classified into early-stage or advanced-stage disease. Nevertheless, early PD detection is intricate due to the normal aging population displaying senile gait, characterized by progressive gait slowness resulting from joint osteoarthritis or sarcopenia. Therefore, the objective of the present study was to formulate a neural network model aiding physicians in recognizing PD gait based on motion characteristics observed during walking. The model would also streamline the monitoring of PD disease severity stages for appropriate medication adjustments and interventions.

Advancements in technology are presently enhancing the prompt, early, and precise diagnosis of Parkinson's disease (PD), particularly through the application of machine- learning techniques. For instance, Saad et al engineered a Bayesian classifier utilizing features derived from video images to identify freezing of gait in PD patients. Similarly, Tripoliti et al employed a Random Forest algorithm on features extracted from multiple inertial measurement units (IMUs), achieving a 96.11% accuracy in detecting freezing of gait. Rocha et al analyzed gait parameters from Kinect- provided skeleton joint data, successfully distinguishing non- PD subjects, PD patients in the STIM ON state, and those in the STIM OFF state.

Different diagnostic methodologies were explored by researchers like Daliri, Wahid, and Caliskan, employing ground reaction forces, multiple regression normalization strategies, and deep neural networks, respectively, achieving accuracies ranging from 86.10% to 92.6%. Various other models, including those by Kim, Haq, and Baby, utilized convolutional neural networks, wavelet transformations, and support vector machines, achieving accuracies in PD diagnosis ranging from 0.85 to 98%. Moreover, techniques such as ViBe algorithm and Hilbert-Huang transform, as well as vocal features and magnetic resonance imaging data, were utilized by researchers like Aydin, Siva ranjini, and Sahu, achieving PD recognition accuracies up to 98.79%. The application of machine-learning techniques extends beyond gait analysis to include voice features, imaging data, and spectroscopy signals for recognizing mild cognitive impairment (MCI). In these contexts, researchers achieved accuracies ranging from 60% to 97.01% using various methods such as linear discriminant analysis, convolutional neural networks, and statistical approaches.

Guayacán and Martínez introduced a 3D convolutional network to recognize PD from gait videos without extracting special features, achieving an accuracy of 94.89%. In the current study, participants' motion data were directly employed to develop a neural network model capable of accurately distinguishing PD gait from that of healthy elderly individuals, while also effectively differentiating between early and advanced PD stages, serving as a surrogate marker for disease progression monitoring.

This paper is organized as follows: the experimental setup. We enrolled PD patients and healthy participants matched for age and gender for the experiments and assessed their motions using IMUs. the architecture of the neural network models designed for PD detection and its stages. Due to the training progressive nature of PD symptoms, the model comprises two sub-models classifying data into Adv_PD, Early_PD, or Non-PD categories. the procedures for model development, involving the utilization of k-fold cross-validation for model and validation. Subsequently, new participants were enlisted to evaluate the developed models.

## II. Data Collection

In this section, we outline the conducted experiments designed to amass clinical data, engaging both patients diagnosed with Parkinson's disease (PD) and healthy elderly individuals as control subjects. The kinematic data derived from Inertial Measurement Units (IMUs) were harnessed to construct a neural network model, a pivotal tool for PD detection and classification of its stages Maintaining the Integrity of the Specifications A total of 32 patients diagnosed with PD underwent recruitment, and their clinical motion data were meticulously measured. The inclusion criteria comprised a PD diagnosis adhering to the United Kingdom PD Society Brain Bank clinical diagnostic criteria.

Exclusions were made for individuals displaying signs of atypical parkinsonism or other features associated with secondary cause-related parkinsonism. Furthermore, the Hoehn-Yahr Stage, a critical parameter, was determined by an experienced movement disorder specialist (Dr. Lin CH).

Selection criteria also mandated the absence of musculoskeletal disorders that might influence typical PD motions, the capability to walk ten meters indoors without assistance, and a Mini-Mental State Examination score exceeding 24. Simultaneously, 16 healthy subjects, matched for age and sex, were recruited as the control group, and their data are outlined in Table 1, with designations such as PD1–PD16 representing patients with Early_PD, PD17–PD32 indicating patients with Adv_PD, and N1–N16 denoting healthy elderly controls.

TABLE I. BASIC DATA OF THE PARTICIPATED SUBJECTS

| Subjects with PD | | | | | Health Control Group | | |
|---|---|---|---|---|---|---|---|
| No. | Gender | Age | Stage | Side | No. | Gender | Age |
| PD1 | M | 72 | I | R | N1 | F | 67 |
| PD2 | F | 64 | I | L | N2 | F | 62 |
| PD3 | F | 67 | I | L | N3 | F | 69 |
| PD4 | M | 52 | I | R | N4 | M | 56 |
| PD5 | F | 69 | I | R | N5 | M | 77 |
| PD6 | F | 67 | I | L | N6 | F | 58 |
| PD7 | M | 68 | I | R | N7 | M | 76 |
| PD8 | F | 73 | II | L | N8 | M | 61 |
| PD9 | F | 81 | II | L | N9 | F | 57 |
| PD10 | F | 65 | II | L | N10 | M | 76 |
| PD11 | M | 69 | II | L | N11 | F | 78 |
| PD12 | F | 53 | II | R | N12 | F | 64 |
| PD13 | M | 62 | II | L | N13 | F | 60 |
| PD14 | M | 49 | II | L | N14 | F | 66 |
| PD15 | M | 74 | II | L | N15 | M | 85 |
| PD16 | M | 66 | II | L | N16 | F | 63 |
| PD17 | M | 79 | III | R | | | |
| PD18 | F | 56 | III | L | | | |
| PD19 | M | 77 | III | R | | | |
| PD20 | M | 84 | III | R | | | |
| PD21 | F | 74 | III | L | | | |
| PD22 | M | 70 | III | R | | | |
| PD23 | M | 73 | III | R | | | |
| PD24 | F | 61 | III | R | | | |
| PD25 | M | 78 | III | R | | | |
| PD26 | M | 79 | III | L | | | |
| PD27 | F | 72 | III | R | | | |
| PD28 | F | 66 | III | L | | | |
| PD29 | M | 72 | III | R | | | |
| PD30 | F | 70 | IV | L | | | |
| PD31 | M | 75 | IV | L | | | |
| PD32 | F | 80 | IV | L | | | |

To record kinematic data, the APDM OPAL system with wearable IMUs was employed due to its portability, cost-effectiveness, and rapid data acquisition capabilities. The developed neural network model was based on the data collected by the OPAL system. Five IMUs were strategically attached to each subject's shanks, lower arms, and waist during experiments, wherein subjects were instructed to walk comfortably forward and back along a straight ten-meter line. A research assistant accompanied each subject, especially those with PD, ensuring safety during the experiments. The recorded data, encompassing 3- axial accelerations and 3-axial angular velocities, exhibited varied responses among PD patients at different stages. For instance, Figure 2 displayed angular velocities of the left shanks for subjects N16, PD7, and PD29, revealing distinctions in gait cycles. The analysis further delved into gait events such as mid-swing (MS), heel-strike (HS), and toe-off (TO), with a complete gait cycle comprising stance and swing phases. These phases demonstrated differences in gait cycles between healthy subjects and those with PD, emphasizing challenges in distinguishing patients from healthy elders due to shared gait characteristics. Moreover, the swing of the arms emerged as a pivotal distinguishing factor, particularly crucial in delineating between the Early_PD and Adv_PD stages. For instance, as depicted in Figure 4, the angular velocities of the lower arms on the sagittal plane were examined for subjects N16, PD7, and PD29. Notably, the asymmetrical arm swing observed in subject PD7, characteristic of unilateral early-stage PD effects, stood out as a significant feature for identifying Early_PD. Overall, these experiments underscored the pivotal role of IMU data and gait characteristics in delineating PD and its various stages. The comprehensive analysis brought to light nuanced features such as gait irregularities and asymmetrical arm swing patterns, emphasizing their potential as valuable indicators for distinguishing between PD patients and healthy individuals, especially in the early phases of the disease. This elucidation highlights the importance of leveraging advanced technologies like IMUs in capturing subtle yet crucial gait dynamics, providing insights into the progression and manifestation of PD symptoms and facilitating early diagnosis and intervention strategies.

## III. NEURAL NETWORK MODELS FOR PD RECOGNITION

This segment employs clinical IMU data to construct a neural network framework for the identification of PD and its various stages. Numerous machine learning techniques are at our disposal, such as KNN, SVM, and Random Forest [41]. Among these, neural networks offer the benefit of scrutinizing extensive input data and automatically choosing operations to extract features that can facilitate nonlinear transformations with precision and resilience [42], [43]. Consequently, we introduced a neural network model designed for the recognition of PD and the categorization of its stages. The model consists of two sub-models: sub-model I and sub-model II. Sub-model I

gauges whether the input IMU data are indicative of Adv_PD, while sub-model II categorizes the input data as either Early_PD or Non-PD if the IMU data do not exhibit Adv_PD characteristics. The model's architecture includes the input layer, three convolutional layers, the flatten layer, three fully connected layers, and the output layer. Synchronized IMU data were integrated as the model input. Initially, we segregated the IMU data based on the MS events of the gait responses, considering the repetitive and periodic nature of gait motions. The IMU data were divided according to the MS events on the left or right sides, depending on the affected side. Subsequently, we standardized the IMU data by partitioning them into one hundred points in each gait cycle to account for variations in walking speeds and data length across different gait cycles.

Using the selected IMU data X, the models underwent application through three convolutional layers with maximum pooling sizes of 2, accompanied by a flatten layer, and concluded with three fully connected layers, resulting in an output layer. Each convolutional layer integrated numerous filters with a window and a max-pooling operation. The model parameters surpass sixty thousand and are too extensive to elaborate on here. The flatten layer was utilized to establish connectivity between the convolutional layers and the fully connected layers. Each fully connected layer comprised 70 neurons, employing ReLU [44] as the activation function for both the convolutional and fully connected layers. Subsequently, the sigmoid function [45] was employed as the activation function for the output layer, generating two neurons. This approach capitalizes on the inherent capabilities of neural networks to process complex data such as IMU readings, leveraging convolutional layers for feature extraction and fully connected layers for classification. The choice of activation functions, namely ReLU and sigmoid, enhances the model's ability to capture non-linear relationships within the data and produce meaningful predictions. Overall, this architecture enables the model to effectively analyze IMU data and discern patterns indicative of Parkinson's disease.

The output of sub-model I, denoted as Y1 =[1 0] or Y1 =[0 1], signifies whether the input IMU data indicate Adv_PD or not Adv_PD, respectively. If the input data is categorized as not Adv_PD, sub-model II is engaged to determine whether the input belongs to Early_PD or Non- PD, represented as Y2 =[1 0] or Y2 =[0 1], respectively. It is noteworthy that sub-model I and sub-model II . same architecture but possess distinct model parameters due to individual training. Throughout the training process, a batch size of 300 and 40 epochs were set, Adam was chosen as the optimizer, and Dropout with a 10% dropout rate was applied to each hidden layer

## IV. Results And Discussion

This segment outlines the procedures for developing the model, encompassing model training, validation, and testing. We amassed 6540 instances of gait cycles from 48 participants and implemented the k-fold cross-validation technique with k = 5 (i.e., partitioning the normalized dataset into five folds for model training and validation). On each iteration, four portions were employed for training the model, while the remaining part served for model validation. Ultimately, we established five distinct models (A, B, C, D, and E), each comprising two sub-models: sub-model I and sub-model II. Subsequently, we enlisted new PD patients and healthy elderly subjects to assess the performance of the five models. The evaluation of a neural network model's performance is typically depicted through a confusion matrix [46],

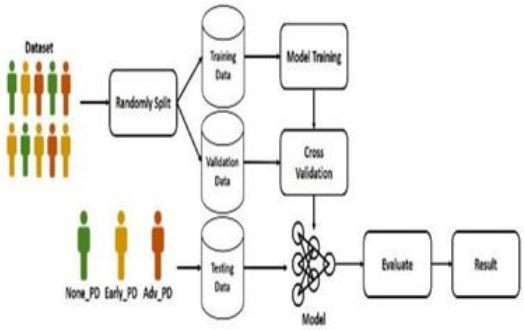


TABLE II. THE CONFUSION MATRIX.

| | | Ground truth | |
|---|---|---|---|
| | | Positive | Negative |
| **Model Prediction** | Positive | TP | FP |
| | Negative | FN | TN |

$$\text{Accuracy} = TP+TN / TP+FP+FN+TN \quad (1)$$

$$\text{Precision} = TP / TP+FP \quad (2)$$

$$\text{Sensitivity} = TP / TP+FN \quad (3)$$

$$\text{Specificity} = TN / TN+FP \quad (4)$$

$$F1 - \text{score} = 2\ TP / 2\ TP+FP+FN \quad (5)$$

We combined the two sub-models to classify the input data as Adv_PD, Early_PD, or Non-PD. The confusion matrix can be represented as Table III. The performance of sub- model I in identifying Adv_PD is defined as follows:

$$\text{Accuracy1} = \frac{M11+M22+M23+M32+M33}{M11+M12+M13+M21+M22+M23+M31+M32+M33} \quad (6)$$

$$\text{Precision1} = \frac{M11}{M11 + M12 + M13} \quad (7)$$

$$\text{Sensitivity1} = \frac{M11}{M11 + M21 + M31} \quad (8)$$

$$\text{Specificity1} = \frac{M22 + M23 + M32 + M33}{M12 + M13 + M22 + M23 + M32 + M33} \quad (9)$$

$$F1 - \text{score1} = \frac{2 \cdot M11}{2 \cdot M11 + M12 + M13 + M21 + M31} \quad (10)$$

Similarly, the performance of sub-model II in recognizing Early_PD is quantified as follows:

| | Ground Truth | | |
|---|---|---|---|
| Prediction | Adv_PD | Early_PD | Non-PD |
| Adv_PD | 18 | 0 | 1 |
| Early_PD | 0 | 15 | 0 |
| Non-PD | 0 | 3 | 17 |

$$\text{Accuracy2} = \frac{M22 + M33}{M22 + M23 + M32 + M3} \quad (11)$$

$$\text{Precision2} = \frac{M22}{M22 + M23} \quad (12)$$

$$\text{Sensitivity2} = \frac{M22}{M22 + M32} \quad (13)$$

$$\text{Specificity2} = \frac{M33}{M23 + M33} \quad (14)$$

$$F1 - \text{score2} = \frac{2 \cdot M22}{2 \cdot M22 + M23 + M32} \quad (15)$$

TABLE III. CONFUSION MATRIX FOR THE THREE-CLASS CLASSIFICATION MODELS

| | | Ground Truth | | |
|---|---|---|---|---|
| | | Adv_PD | Early_PD | Non-PD |
| **Model Prediction** | Adv_PD | $M_{11}$ | $M_{12}$ | $M_{13}$ |
| | Early_PD | $M_{21}$ | $M_{22}$ | $M_{23}$ |
| | Non-PD | $M_{31}$ | $M_{32}$ | $M_{33}$ |

The results of the model validation procedures are presented in Table IV, showcasing the confusion matrices. Across the five models, an average Accuracy1 of 92.72%, an average Precision1 of 79.86%, an average Sensitivity1 of 99.51%, an average Specificity1 of 90.02%, and an average F1−score1 of 88.60% were attained for the identification of Adv_PD. In the context of distinguishing between Early_PD and Non- PD, the five models demonstrated an average Accuracy2 of 99.67%, an average Precision2 of 99.71%, an average Sensitivity2 of 99.24%, an average Specificity2 of 99.86%, and an average F1−score2 of 99.48% during the validation processes.

TABLE IV. CONFUSION MATRIX FOR MODEL VALIDATION

| | | Ground Truth | | |
|---|---|---|---|---|
| Model | Prediction | Adv_PD | Early_PD | Non-PD |
| A | Adv_PD | 365 | 71 | 60 |
| | Early_PD | 0 | 247 | 4 |
| | Non-PD | 0 | 2 | 559 |
| B | Adv_PD | 363 | 28 | 49 |
| | Early_PD | 2 | 289 | 3 |
| | Non-PD | 1 | 2 | 571 |
| C | Adv_PD | 389 | 46 | 63 |
| | Early_PD | 0 | 245 | 1 |
| | Non-PD | 1 | 4 | 559 |
| D | Adv_PD | 358 | 55 | 36 |
| | Early_PD | 1 | 269 | 0 |
| | Non-PD | 0 | 2 | 587 |
| E | Adv_PD | 368 | 47 | 48 |
| | Early_PD | 0 | 267 | 0 |
| | Non-PD | 2 | 1 | 575 |

TABLE V. MODEL PREDICTIONS FOR THE TESTING SUBJECTS.

| | Ground Truth | | |
|---|---|---|---|
| Prediction | Adv_PD | Early_PD | Non-PD |
| Adv_PD | 18 | 0 | 1 |
| Early_PD | 0 | 15 | 0 |
| Non-PD | 0 | 3 | 17 |

## V. CONCLUSION

This study focused on identifying individuals with Parkinson's disease (PD) through the development of neural network models. Our primary goal was to distinguish PD patients from the normal elderly population using these models. Additionally, we sought to differentiate individuals with early-stage PD from those in advanced stages. The importance of early PD detection lies in facilitating timely therapeutic interventions to mitigate disease progression and decrease patient morbidity. However, differentiating a PD gait from a senile gait, which is often

common in the normal elderly population, can present challenges. To address this, we utilized clinical data to construct neural network models capable of effectively detecting and classifying PD based on motion data obtained from Inertial Measurement Units (IMUs). By incorporating features specific to PD gait patterns, we aimed to enhance the accuracy and reliability of PD diagnosis, particularly in the early stages of the disease. This approach holds promise for improving patient outcomes by enabling early intervention and personalized treatment strategies tailored to individual disease severity.

Hence, it is crucial to establish an objective model for categorizing gait characteristics to proficiently address the needs of Parkinson's disease (PD) patients across different disease stages. In this investigation, we employed clinical data measurements to devise neural network models capable of detecting and classifying PD using motion data acquired from Inertial Measurement Units (IMUs). Acknowledging the evolving nature of PD symptoms as the disease advances, our proposed models comprised two sub-models. These sub-models were specifically crafted to accommodate the variability in PD symptoms, thereby offering a more comprehensive approach to PD detection and classification. By incorporating features tailored to the distinct manifestations of PD at different stages, our models aimed to enhance the accuracy and reliability of PD diagnosis. This approach holds promise for facilitating early intervention and personalized treatment strategies, ultimately improving patient outcomes. Future research endeavors may focus on refining and validating these models on larger and more diverse patient populations to further enhance their effectiveness and clinical utility in managing PD.

The initial sub-model was designed to evaluate whether the data corresponded to Adv_PD, whereas the second sub-model aimed to differentiate Early_PD from the healthy control cohort. Utilizing the k-fold validation approach for model training and validation, our model demonstrated an accuracy of 92.72% in identifying Adv_PD and 99.67% in distinguishing Early_PD during the validation phase. Subsequently, new participants were enlisted to evaluate the performance of the developed models. Recognizing that trained models may generate independent judgments and potentially conflicting outcomes, we introduced a voting mechanism that rendered final decisions based on the majority of model estimations. The results validated the effectiveness of both the neural network models and the voting mechanism in successfully discerning Adv_PD, Early_PD, and the control groups. These results imply that the devised neural network models hold promise in aiding physicians with early-stage PD diagnosis, facilitating timely intervention within the crucial time frame from a senile gait to a diseased gait pattern. This underscores the importance of leveraging advanced technologies like neural networks in capturing subtle gait dynamics and providing insights into disease progression for improved patient care..

Moreover, the utilization of the models and the voting mechanism could potentially act as a surrogate marker for tracking disease progression in Parkinson's disease (PD), effectively distinguishing between Early_PD and Adv_PD stages. A comprehensive future study involving a larger cohort of PD patients is imperative to validate the effectiveness of our established framework. Additionally, we aim to harness IMU data from test subjects to develop novel neural network models, thereby augmenting the accuracy of PD prognostication. Our forthcoming efforts also entail expanding these PD gait models to differentiate PD patients from individuals with atypical parkinsonism, who initially manifest PD-like symptoms but exhibit a more unfavorable prognosis. The architectural frameworks established in this study may also hold promise for classifying other medical conditions, such as discerning benign tremors from early PD, contingent upon the availability of adequate sample sizes.

## REFERENCES


[1] F. B. Horak, D. Dimitrova, and J. G. Nutt, ‘‘Direction- specific pos tural instability in subjects with Parkinson’s disease,’’ Exp. Neurol., vol. 193, no. 2, pp. 504–521, Jun. 2005, doi: 10.1016/j.expneurol.2004. 12.008.

[2] A. Ul Haq, J. Li, M. H. Memon, J. Khan, S. U. Din, I. Ahad, R. Sun, and Z. Lai, ‘‘Comparative analysis of the classification performance of machine learning classifiers and deep neural network classifier for predic tion of Parkinson disease,’’ in Proc. 15th Int. Comput. Conf. Wavelet Act. Media Technol. Inf. Process. (ICCWAMTIP), Dec. 2018, pp. 101–106, doi: 10.1109/ICCWAMTIP.2018.8632613

[3] S. Sivaranjini and C. M. Sujatha, ‘‘Deep learning based diagnosis of Parkinson’s disease using convolutional neural network,’’ Multimedia Tools Appl., vol. 79, nos. 21–22, pp. 15467–15479, Jun. 2020, doi: 10.1007/s11042-019-7469-8.

[4] B. Karan and S. Sekhar Sahu, ‘‘An improved framework for Parkinson’s disease prediction using variational mode decomposition-Hilbert spectrum of speech signal,’’ Biocybern. Biomed. Eng., vol. 41, no. 2, pp. 717–732, Apr. 2021, doi: 10.1016/j.bbe.2021.04.014.

[5] M. Pistacchi, M. Gioulis, F. Sanson, E. D. Giovannini, G. Filippi, F. Rossetto, and S. Z. Marsala, ‘‘Gait analysis and clinical correlations in early Parkinson’s disease,’’ Funct. Neurol., vol. 32, no. 1, p. 28, Jan. 2017, doi: 10.11138/FNeur/2017.32.1.028.

[6] Y.-R. Yang, Y.-Y. Lee, S.-J. Cheng, P.-Y. Lin, and R.-Y. Wang, ‘‘Rela□tionships between gait and dynamic balance in early Parkinson’s dis□ease,’’ Gait Posture, vol. 27, no. 4, pp. 611–615, May 2008, doi: 10.1016/j.gaitpost.2007.08.003

[7] N. Giladi, M. P. McDermott, S. Fahn, S. Przedborski, J. Jankovic, M. Stern, and C. Tanner, ‘‘Freezing of gait in PD: Prospective assessment in the DATATOP cohort,’’ Neurology, vol. 56, no. 12, pp. 1712–1721, Jun. 2001, doi: 10.1212/WNL.56.12.1712.
[8] K. Jahn, A. Zwergal, and R. Schniepp, ‘‘Gait disturbances in old age: Classification, diagnosis, and treatment from a neurological perspec□tive,’’ Deutsches Ärzteblatt Int., vol. 107, no. 17, p. 306, Apr. 2010, doi: 10.3238/arztebl.2010.0306.
[9] A. Saad, I. Zaarour, A. Zeinedine, M. Ayache, P. Bejjani, F. Guerin, D. Lefebvre, and L. Havre-France, ‘‘A preliminary study of the causality of freezing of gait for Parkinson’s disease patients: Bayesian belief net□work
[10] E. E. Tripoliti, A. T. Tzallas, M. G. Tsipouras, G. Rigas, P. Bougia, M. Leontiou, S. Konitsiotis, M. Chondrogiorgi, S. Tsouli, and D. I. Fotiadis, ‘‘Automatic detection of freezing of gait events in patients with Parkinson’s disease,’’ Comput. Methods Programs Biomed., vol. 110, no. 1, pp. 12–26, Apr. 2013, doi: 10.1016/j.cmpb.2012.10.016.
[11] A. P. Rocha, H. Choupina, J. M. Fernandes, M. J. Rosas, R. Vaz, and J. P. S. Cunha, ‘‘Parkinson’s disease assessment based on gait analysis using an innovative RGB-D camera system,’’ in Proc. 36th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc., Aug. 2014, pp. 3126–3129, doi: 10.1109/EMBC.2014.6944285.
[12] M. R. Daliri, ‘‘Chi-square distance kernel of the gaits for the diagnosis of Parkinson’s disease,’’ Biomed. Signal Process. Control, vol. 8, no. 1, pp. 66–70, Jan. 2013, doi: 10.1016/j.bspc.2012.04.007.
[13] F. Wahid, R. K. Begg, C. J. Hass, S. Halgamuge, and D. C. Ackland, ‘‘Classification of Parkinson’s disease gait using spatial-temporal gait features,’’ IEEE J. Biomed. Health Inform., vol. 19, no. 6, pp. 1794–1802, Nov. 2015, doi: 10.1109/JBHI.2015.2450232.
[14] A. Caliskan, H. Badem, A. Basturk, and M. E. Yuksel, ‘‘Diagnosis of the Parkinson disease by using deep neural network classifier,’’ Istanbul Univ., J. Elect. Electron. Eng., vol. 17, no. 2, pp. 3311–3318, 2017. [Online]. Available: https://electricajournal.org/Content/files/sayilar/58/3311-3318. pdf
[15] M. S. Baby, A. J. Saji, and C. S. Kumar, ‘‘Parkinsons disease classification using wavelet transform based feature extraction of gait data,’’ in Proc. Int. Conf. Circuit, Power Comput. Technol. (ICCPCT), Apr. 2017, pp. 1–6, doi: 10.1109/ICCPCT.2017.8074230.
[16] A. Samà, C. Pérez-López, D. Rodríguez-Martín, A. Català, J. M. Moreno-Aróstegui, J. Cabestany, E. de Mingo, and A. Rodríguez-Molinero, ‘‘Estimating bradykinesia severity in Parkinson’s disease by analysing gait through a waist-worn sensor,’’ Comput. Biol. Med., vol. 84, pp. 114–123, May 2017, doi: 10.1016/j. compbiomed.2017.03.020
[17] H. B. Kim, W. W. Lee, A. Kim, H. J. Lee, H. Y. Park, H. S. Jeon, S. K. Kim, B. Jeon, and K. S. Park, ‘‘Wrist sensor-based tremor severity quantification in Parkinson’s disease using convolutional neural network,’’ Comput. Biol. Med., vol. 95, pp. 140–146, Apr. 2018, doi: 10.1016/j.compbiomed.2018.02.007.
[18] S. Bilgin and Z. E. Akin, ‘‘Gait pattern discrimination of ALS patients using classification methods,’’ Turkish J. Electr. Eng. Comput. Sci., vol. 26, no. 3, pp. 1367–1377, 2018, doi: 10.3906/elk-1708-221.
[19] E. Abdulhay, N. Arunkumar, K. Narasimhan, E. Vellaiappan, and V. Venkatraman, ‘‘Gait and tremor investigation using machine learning techniques for the diagnosis of Parkinson disease,’’ Future Gener. Comput. Syst., vol. 83, pp. 366–373, Jun. 2018, doi: 10.1016/j.future. 2018.02.009.
[20] E. Rastegari, S. Azizian, and H. Ali, ‘‘Machine learning and similarity network approaches to support automatic classification of Parkinson’s diseases using accelerometer-based gait analysis,’’ in Proc. 52nd Hawaii Int. Conf. Syst. Sci. (HICSS), Jan. 2019, pp. 4231–4242, doi: 10.24251/HICSS.2019.511.
[21] S. Sivaranjini and C. M. Sujatha, ‘‘Deep learning based diagnosis of Parkinson’s disease using convolutional neural network,’’ Multimedia Tools Appl., vol. 79, nos. 21–22, pp. 15467–15479, Jun. 2020, doi: 10.1007/s11042-019-7469-8.
[22] F. Aydın and Z. Aslan, ‘‘Recognizing Parkinson’s disease gait patterns by vibes algorithm and Hilbert–Huang transform,’’ Eng. Sci. Technol., Int. J., vol. 24, no. 1, pp. 112–125, Feb. 2021, doi: 10.1016/j.jestch. 2020.12.005.
[23] H. Gunduz, ‘‘An efficient dimensionality reduction method using filterbased feature selection and variational autoencoders on Parkinson’s disease classification,’’ Biomed. Signal Process. Control, vol. 66, Apr. 2021, Art. no. 102452, doi: 10.1016/j.bspc.2021.102452.
[24] S.-H. Yoo, S.-W. Woo, M.-J. Shin, J. A. Yoon, Y.-I. Shin, and K.-S. Hong, ‘‘Diagnosis of mild cognitive impairment using cognitive tasks: A functional near-infrared spectroscopy study,’’ Current Alzheimer Res., vol. 17, no. 13, pp. 1145–1160, Mar. 2021, doi: 10.2174/ 1567205018666210212154941.
[25] D. Yang and K.-S. Hong, ‘‘Quantitative assessment of resting-state for mild cognitive impairment detection: A functional near-infrared spectroscopy and deep learning approach,’’ J. Alzheimer’s Disease, vol. 80, no. 2, pp. 647–663, Mar. 2021, doi: 10.3233/jad-201163
[26] L. C. Guayacán and F. Martínez, ‘‘Visualising and quantifying relevant parkinsonian gait patterns using 3D convolutional network,’’ J. Biomed. Informat., vol. 123, Nov. 2021, Art. no. 103935, doi: 10.1016/j.jbi.2021.103935.
[27] A. J. Hughes, S. E. Daniel, L. Kilford, and A. J. Lees, ‘‘Accuracy of clinical diagnosis of idiopathic Parkinson’s disease: A clinico-pathological study of 100 cases,’’ J. Neurol., Neurosurg., Psychiatry, vol. 55, pp. 181–184, Mar. 1992, doi: 10.1136/jnnp.55.3.181.
[28] D. Mungas, ‘‘In-office mental status testing: A practical guide,’’ Geriatrics, vol. 46, no. 7, pp. 54–67, Jul. 1991
[29] F.-C. Wang, Y.-C. Li, K.-L. Wu, P.-Y. Chen, and L.-C. Fu, ‘‘Online gait detection with an automatic mobile trainer inspired by neurodevelopmental treatment,’’ Sensors, vol. 20, no. 12, p. 3389, Jun. 2020, doi: 10.3390/s20123389.
[30] S. Bind, A. K. Tiwari, A. K. Sahani, P. Koulibaly, F. Nobili, M. Pagani, O. Sabri, T. V. Borght, K. V. Laere, and K. Tatsch, ‘‘A survey of machine learning based approaches for Parkinson disease prediction,’’ Int. J. Comput. Sci. Inf. Technol., vol. 6, no. 2, pp. 1648–1655, 2015. [Online]. Available: https://citeseerx.ist.

[31] S. B. Kotsiantis, I. Zaharakis, and P. Pintelas, ‘‘Supervised machine learning: A review of classification techniques,’’ Emerg. Artif. Intell. Appl. Comput. Eng., vol. 160, pp. 3–24, Oct. 2007. [Online]. Available: https://datajobs.com/data-science-repo/Supervised-Learning-[SBKotsiantis].pdf
[32] Y. LeCun, Y. Bengio, and G. Hinton, ‘‘Deep learning,’’ Nature, vol. 521, no. 7553, pp. 436–444, May 2015, doi: 10.1038/nature14539.
[33] S. Sharma, S. Sharma, and A. Athaiya, ‘‘Activation functions in neural networks,’’ Towards Data Sci., vol. 6, no. 12, pp. 310–316, 2017. [Online]. Available: https://www.ijeast.com/papers/310-316,Tesma412, IJEAST.pdf
[34] B. Karlik and A. Vehbi, ‘‘Performance analysis of various activation functions in generalized MLP architectures of neural networks,’’ Int. J. Artif. Intell. Expert Syst., vol. 1, no. 4, pp. 111–122, 2011. [Online]. Available: https://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.740.9413 &rep=rep1&type=pdf
[35] D. M. W. Powers, ‘‘Evaluation: From precision, recall and F-measure to ROC, informedness, markedness and correlation,’’ Oct. 2020, arXiv:2010.16061.