Data-driven Gait based Severity Classification for Parkinson's Disease using Duo Spatiotemporal Convoluted Kernel Boosted ResNet model

Original Scientific Paper

Arogia Victor Paul M
Research Scholar, Department of Computer Science and Engineering,
B.S. Abdur Rahman Crescent Institute of Science and Technology,
Chennai, India
victorpaul_cse@crescent.education

Sharmila Sankar
Professor & Dean, Department of Computer Science and Engineering,
B.S. Abdur Rahman Crescent Institute of Science and Technology,
Chennai, India
sharmilasankar@crescent.education

Abstract – *Parkinson's disease (PD) is one of the reformed brain syndromes that results in unintended stiffness and difficulty with balance and dexterity. To detect PD in medical scenery, physicians commonly use experimental indicators like motorized and non-motor symptoms and the severity rating depends on the unified PD Rating Scale (UPDRS). However, these medical assessments highly rely on expertized clinicians and lead to inter-variability discrepancies. Nowadays, gait sensor data assists doctors in diagnosing PD and estimates the severity level of gait abnormalities in patients. However, the gait sensor data increases the dimensionality issues and is subjected to high non-linear complexity. Hence, this study suggests an innovative deep learning (DL) technique for accurate PD analysis using gait patterns. Initially, the gait sensor data is preprocessed by performing data cleaning, and decimal scaling normalization (DS-Norm) to enhance the data quality. The Hoehn and Yahr (H&Y) scale is a commonly used rating scale for measuring the progression of Parkinson's disease symptoms. It's typically used to assess motor symptoms like tremors, rigidity, and bradykinesia. The scale ranges from 0 to 5, with higher numbers indicating more severe symptoms and disability. The preprocessed data are then fed into the proposed Duo spatiotemporal convoluted kernel boosted ResNet (DSCK-RNet) model for classifying the PD severity rating by learning the gait spatiotemporal features. The developed method is processed and scrutinized via the Python platform and a publicly available Physio-Net dataset is utilized for the simulation process. Various assessment measures like accuracy, precision, sensitivity, specificity, PPV, FPR, and MCC are examined and compared with traditional studies. In the experimental section, the developed DSCK-RNet model achieved an accuracy of 100%, 99.6%, 99%, and 99.64% for different classes like healthy, severity-2, severity-2.5, and severity-3 respectively. Compared to the conventional techniques, our suggested approach performs better. The experimental findings demonstrate the clinical significance of the suggested approach for the impartial evaluation of gait motor impairment in PD patients.*

Keywords: *Parkinson's disease classification, severity estimation, Hoehn and Yahr scale, gait patterns, decimal scaling normalization, spatiotemporal features, Duo Spatiotemporal Convoluted Kernel Boosted ResNet model*

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1. INTRODUCTION

PD (Parkinson's disease) is a distressing condition that causes serious illness to both non-motorized and motorized functions of the human body [1]. The insufficient nerve cells in the brain result in the production of a chemical named dopamine, which is the main reason behind PD illness [2]. Dopamine assists in sending messages for controlling coordination and movement. However, the shortage of dopamine leads to slowness in movement, uncontrolled shaking, problems with balance, etc. These kinds of problems are termed motor symptoms that can be easily identified [3]. The PD can also produce some non-motor symptoms that can be determined using gait patterns effectively. The integration of force-sensitive devices and machine learning algorithms for gait analysis holds promise for improving the early diagnosis and management of neurodegenerative diseases [4]. The most common traditional techniques like high-speed cameras are utilized for analyzing the gait patterns that measure the pressure sensors and motion trails to obtain leg movements and muscle activities.

However, neuroimaging techniques are cost-effective in capturing motion illuminations and other force estimations [5]. Hence, the gait analysis via placing sensors on the human foot becomes an integral role in analyzing leg movements which is a highly accurate and affordable technique [6]. Also, the spatiotemporal (ST) features provide the quantitative measure of stroke, pace length, and strike time that can manipulate the motor deficiencies and predict the PD severity level with minimal complexities [7]. Therefore, determining the gait patterns not only identifies PD but also analyses the severity level of PD effectively. Despite this, the gait analysis based on sensor data faces numerous challenges such as increased data dimensionality and non-linear correlations among the spatiotemporal features [8]. To overcome this issue, highly effective data processing methods are required to assist physicians in detecting PD accurately.

Currently, artificial intelligence (AI) established machine learning (ML) and deep learning (DL) techniques have played an important role in the medical field, especially in the disease identification process [4, 7]. Several existing studies pointed out that ML-based techniques like support vector machine (SVM), decision tree (DT), random forest (RF), multilayer perceptron (MLP), artificial neural network (ANN) and naïve Bayes (NB) assist in detecting the abnormal PD level based on the changes in gait patterns from the motor symptoms [9]. The ML techniques can overcome complex nonlinear features by considering the essential gait patterns [10]. However, the ML models have low learning capability while processing the data with a larger population. Moreover, it fails to detect invisible gait features (non-motor symptoms) due to increased processing time and high amenability issues [11]. To overwhelm this issue, an effective and automatic severity rating classification technique is required for investigating invisible gait patterns. Nowadays, DL-based techniques aid doctors in assessing quantitative gait spatiotemporal features using an enhanced feature learning process [12]. Subsequently, it can train larger data for a huge population and can generate quality treatment with proven clinical outcomes. The DL models have various neurological-related applications such as diagnosis, severity assessments, and disease identification [13]. Henceforth, this study presents an innovative DL approach in PD decision making and severity assessment using gait ST analysis.

PD has been portrayed for the past few centuries as a reformed neurodegenerative illness that causes movement, cognitive abnormalities, and other non-motor symptoms. Even though PD cannot be cured, early detection and treatment with the right drugs and surgery can manage the symptoms. Even sleep issues, depression, tremors, uncontrollably shaking, and cognitive difficulties can be brought on by Parkinson's disease. Nevertheless, some of the concealed symptoms are imperceptible and necessitate precise methods to identify PD. Although there are other methods available, gait-based sensor data is becoming more and more common since it is an inexpensive and effective way to analyze the hidden symptoms of Parkinson's disease. Unfortunately, the gait data lead to low accuracy, complicated interpretation, and high dimensionality, particularly when identifying the severity level of Parkinson's disease. Numerous previous studies have described using gait spatiotemporal characteristics to determine the PD scores through machine learning. Nevertheless, the machine learning model requires more time to train on a larger population. Furthermore, it performed poorly in categorization since it was unable to precisely learn the non-motor symptoms. Therefore, to detect and categorize PD levels with minimal complexity, an efficient and highly accurate technique is needed. This served as inspiration for the created study, which presented a novel DL study that used gait patterns to analyze the PD. Below is a detailed illustration of the developed study's principal contributions:

- To introduce a novel DL model (DSCK-RNet) that uses sensor data based on gait to determine Parkinson's disease.
- To include crucial preprocessing steps to improve the quality of the gait data, such as data cleaning and decimal scaling normalization (DS-Norm).
- To present a novel Duo spatiotemporal convoluted kernel boosted ResNet (DSCK-RNet) model that learns the gait spatiotemporal features in order to classify Parkinson's disease.

The forthcoming sections are: Section 2 interprets the literature studies associated to PD classification using DL techniques. Section 3 describes the developed methodology. Section 4 determines the results and Section 5 represents the Concluded portion of the developed study.

2. RELATED WORKS

The medical industry has seen a significant surge in the use of AI and deep learning for disease diagnosis and prognosis due to their rapid expansion and research. Using a range of datasets, numerous research has been carried out to diagnose Parkinson's disease.

Balaji et al. [14] defined the DL method for perceiving the severity rating of PD accurately. Here, the LSTM model was presented to analyze the severity level of PD using gait data. For solving the overfitting issues, L2 regularization and dropout were utilized. To reduce the cost-utility, SGO and ADAM optimizers were utilized. Finally, the rating of PD was estimated via the H&Y and the unified PD Rating (UPDR) scales. The overall accuracy obtained by this method was about 98.6%. However, this method faces high gradient sufficiency problems and high training time.

Aşuroğlu and Hasan [15] introduced the multiclass PD analysis using the hybridized DL technique. A hybridized CNN with a Locally Weighted Random Forest (LWRF) technique was introduced to classify the PD effectively. Here, essential gait features like frequency and time components were extracted. The overall Correlation Coefficient (CC), MAE, and RMSE obtained values of 0.89, 3.0, and 4.5 respectively. However, this method was a high cost for training with larger data.

Setiawan and Che-Wei [16] established the DL model for analyzing PD severity using time and frequency features. Three major stages were performed namely preprocessing, feature extraction, and classification. Here, the PD rating was analyzed based on VGRF signals. For the preprocessing, the signals were separated into different time-varying windows. Then, the continuous wavelet transform (CWT) was exploited to extract the phase-frequency features. In addition to this, principal component analysis (PCA) was introduced to enhance the extracted features accurately. Finally, 5 types of CNNs were utilized to detect and classify the PD severity levels. The overall accuracy achieved by this study was about 96.5%. However, this method increases the error due to a lack of noise filtering techniques.

Sai et al. [17] introduced the DL technique for predicting PD using gait spatiotemporal features. In this study, CNN-LSTM was introduced to forecast the PD rating on the basis of H&Y scale study. Various spatiotemporal features like swing and stance phases were extracted to identify the PD disease accurately. The overall accuracy, precision, and recall obtained the value of 88%, 86%, 94%, and 90% respectively. However, this method failed to maintain generalizability while appliedto wider datasets.

Vidya and Sasikumar [18] defined the PD severity analysis using a hybridized DL technique based on gait signals. Initially, the useful VGRF signals were obtained by the EMD technique that accurately extracts the fundamental functions. Then, power spectral analysis was utilized to select the essential intrinsic functions of the VGRF signals. Then, the CNN LSTM technique was introduced to analyze the severity of the PD accurately. Then, the overfitting issues were solved using L2 regularization and dropout mechanisms. The overall accuracy achieved by this method was about 98.3%. However, this method was highly time-consuming and subjected to increased error.

A residual network with 50 layers called ResNet50 was suggested by Omar El Ariss et al. [19] as a tool for Parkinson's disease diagnosis. The patient's speech recordings were subjected to spectral analysis techniques, which resulted in the gathering of frequency features that were used as data. Next, a 2-D heat map was created using the frequency features. ResNet50 receives this heat map and uses it to forecast whether or not the patient has Parkinson's disease.

A novel methodology for the precise identification of Parkinson's disease using handwritten records from a standard NewHandPD dataset was proposed by Sura Mahmood Abdullah et al. [20]. To lessen the strain of training time, the suggested framework is built on transfer learning models like ResNet, VGG19, and InceptionV3. To create an optimized feature vector for improved classification outcomes, the combined features from the TL models are fed into the genetic algorithm optimization process.

3. PROBLEM STATEMENT

From the deep scrutiny of the existing approaches, many issues have been reported such as increased dimensionality issues, high training time and error, etc. Several existing studies pointed out electroencephalogram (EEG) signals and vocal and handwritten features for detecting PD accurately. However, these features failed to analyze the severity level of PD due to low capability in processing with complex nonlinear features. Moreover, the gait signals are also utilized in various recent studies to analyze the PD conditions effectively. However, the gait signals are highly complex and increase the diagnosing time, and are highly cost-effective. To overcome this issue, gait sensor data is utilized in present studies in which the sensors are placed on the foot of a human leg to obtain useful spatiotemporal features. Various scaling methods like VGRF and H&Y scale are employed to analyze the rating of PD. However, the accuracy of using sensor data is not very effective due to high nonlinear correlation, poor data quality, complex interpretation, etc. Hence, this study presents a novel DL technique to learn the gait spatiotemporal features and to achieve better performance in classifying the PD levels accurately. To our knowledge, the proposed study overcomes all the issues faced in the existing studies and provides outstanding performance with minimal complexity.

4. PROPOSED METHODOLOGY

PD is one of the progressive brain disorders that results in inadvertent stiffness and difficulty with balance and agility. To detect PD in medical scenery, physicians commonly use irrefutable indicators like motorized and non-motorized symptoms and the rating based on the UPDRS. However, these medical assessments highly rely on expertized clinicians and lead to intervariability discrepancies. Fig. 1 illustrates the workflow of the developed model.

Nowadays, gait sensor data assists doctors in diagnosing PD and estimates the severity level of gait abnormalities in patients. However, the gait sensor data increases the dimensionality issues and is subjected to high nonlinear complexity. Hence, this study suggests an innovative model for accurate PD analysis using gait patterns. Initially, the gait sensor data is preprocessed by performing data cleaning, and decimal scaling normalization (DS-Norm) to enhance the data quality. The preprocessed data are then fed into the proposed Duo spatiotemporal convoluted kernel boosted ResNet (DSCK-RNet) model for classifying the PD severity rating by learning the gait spatiotemporal features. Finally, different classes like healthy, severity-2, severity-2.5, and severity-3 are classified by the developed model accurately.

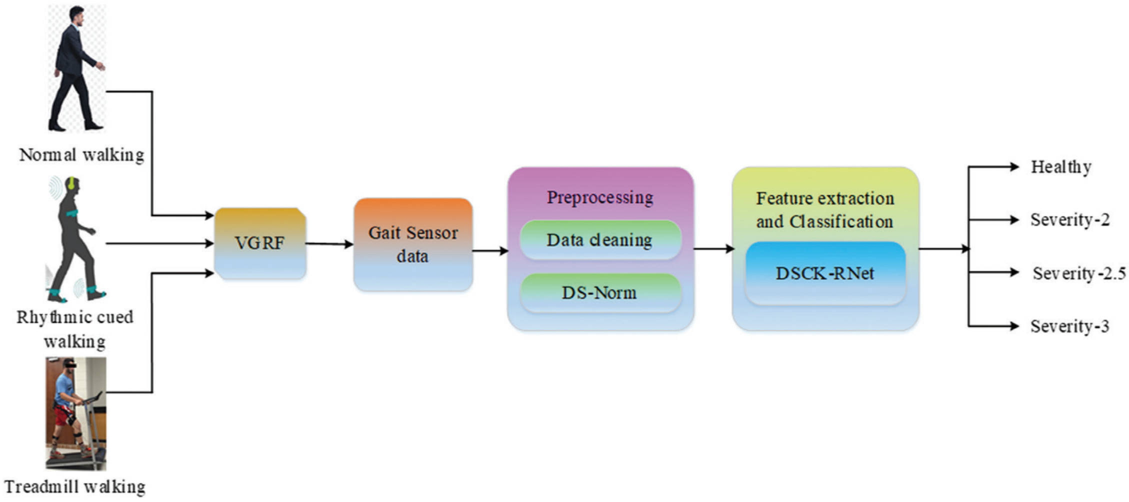

Fig. 1. Workflow of the developed model

4.1. PREPROCESSING

The raw sensor data collected from the human foot contains high noises, missing values, and data redundancy problems. To overcome this issue, data cleaning, and decimal scaling normalization (DS-Norm) processes are introduced in the initial stage to enhance the data quality. Initially, the data cleaning process is done in which the corrupted or missing values are identified and removed from the database. This process improves the accuracy performance and prevents data redundancy problems. Moreover, the overfitting issues and unwanted training complexities are eliminated using a data cleansing process.

After cleaning the data, a decimal scaling normalization technique is used that can minimize the non-linear complexities and speed up the training process. In the DS-Norm technique, the decimal points of the gait parameters are moved to obtain a normalized value. Here, the decimal points are altered using the extreme absolute value of the gait patterns. It can be mathematically formulated as,

$$\widetilde{D}_x = \frac{D_x}{10^n} \tag{1}$$

Here, $\tilde{D}_x$ indicates the normalized data, D_x represents the actual gait sensor data, and nrepresents the smallest integer in which $Max([d])<1$.

4.2. FEATURE EXTRACTION AND PD CLASSIFICATION USING THE DSCK-RNET MODEL

The preprocessed data are then fed into the proposed Duo spatiotemporal convoluted kernel-boosted ResNet (DSCK-RNet) model to classify the presence of PD by learning the gait spatiotemporal features.

The developed network model consists of a spatiotemporal network for extracting the gait spatiotemporal patterns and it is finally fed into a convoluted kernel-boosted ResNet model to select the appropriate features and to classify the PD severity levels accurately. The developed model decreases the processing time and prevents dimensionality issues with the aid of an effective kernel mechanism.

Initially, the preprocessed data are given into two different streams for extracting the gait spatiotemporal features. The initial stream considered the temporal features based on convoluted residual blocks and temporal attention (AT) blocks. Here, the narrow multi-layer feature extractor, max-pooling (MP) layer, AT blocks, and multi-scale residual blocks (RBs) are deployed. At first, the narrow gait features are extracted through multi-scale convolution blocks (CBs). Then, the AT blocks are emphasized to evaluate the inter-channel relationship between the gait parameters. Then, the MP layer is implemented to overcome the dimensionality issues during the training process. The multi-scale RBs help the model to understand the extracted features for enhancing the accuracy performance. In the same way, the spatial attention (SA) block and MP layer were determined effectively. At the final stage, the extracted features are then fed into the multi-scale RBs and SA blocks to generate high-level gait features. The second stream evaluates the extracted gait patterns and concentrates mostly on spatial features while processing with SA blocks. Similar to The A block, the SA contains single multi-scale CB and triple multi-scale RBs. After connecting the CBs, the TA blocks and MP layers are determined. Fig. 2 illustrates the architecture of the DSCK-RNet model.

After extracting the features, the convoluted kernel boosted the ResNet (CK-RNet) model to choose the best features thereby minimizing the time complication and data idleness problems. In the RBs, convoluted kernel widths are utilized to select the most relevant gait parameters from the entire feature. The resultant Y_a of the a^{th} kernel is determined using a convolutional process and it is depicted below:

$$Y_a(i) = f(\sum \beta_a(i) * p + Bias_a(i)) \quad (2)$$

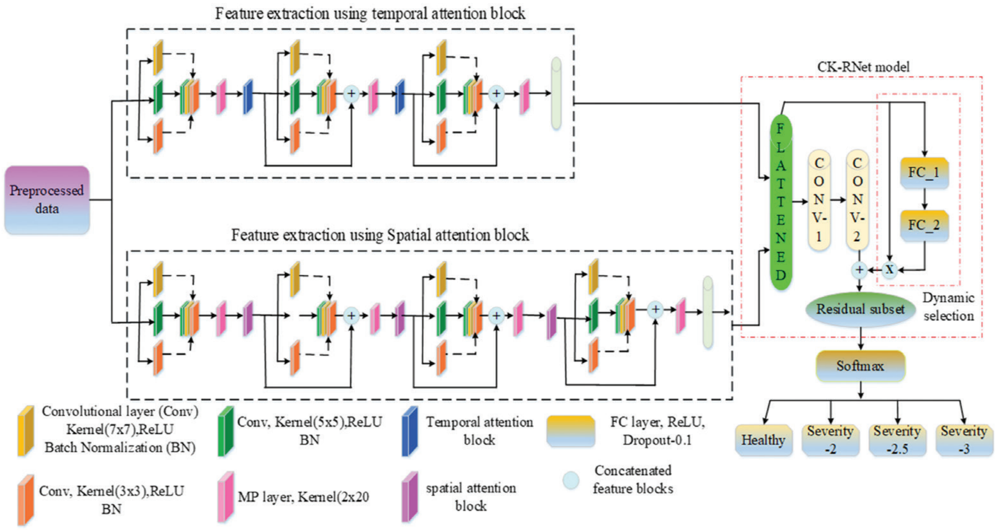

Fig. 2. Architecture of DSCK-RNet model

Here, findicates the activation function (AF), βrepresents the convoluted kernel, *represents the convolutional operation, and iindicates the number of channels. To highlight the useful features and to prevent irrelevant ones, an active selection of gait feature subsets is introduced behind the MP layers of each stream. The active selection comprises global average pooling, (GAP), and dual fully connected (FC) layers in which the GAP indicates the squeeze operation, and the FC layer indicates the excitation operation. For generating the relevant gait patterns, the obtained weights and channel-wise multiplication between incoming feature maps are trained carefully. The mathematical operations for selecting the appropriate features are depicted as follows:

$$x_c = G_{sq}(y_c) = \frac{1}{N}\sum_{n=1}^{N} y_c(n) \quad (3)$$

$$u = G_{ex}(x,U) = \sigma\big(\sigma(x,U)\big) = \sigma\big(U_2\sigma(x,U_1)\big) \quad (4)$$

$$\hat{y}_c = u_c \times y_c \quad (5)$$

Here, $U_1 \in R^{c/d}$and $U_1 \in R^{c/d}$ indicates the weights of dual FC layers, drepresents the reduction ratio and its value is 2, σ indicates the rectified linear unit (ReLU), u_c represents the scalar, and y_c indicates the actual extracted features.The feature subsets obtained by varying kernel widths are then combined using channel-wise concatenation operation and it is mathematically formulated as,

$$\tilde{Y} = con(Y_a), a = 1,2,.....M \quad (6)$$

Here, M indicates the total number of convoluted kernels. Finally, the outcome from the CK-RNet model can be mathematically defined as,

$$z = F(p,[U]) + u \bullet p \quad (7)$$

Here, p indicates the input of RB, $F(p,[U])$indicates the residual subsets, and Uindicates the weights of active feature selection. The outcome of a convoluted kernel block contains the features obtained under varying kernels. The outcome of MP in the a^{th} channel can be mathematically expressed as,

$$MP_a(m) = max[z_a(mU,(m+1)U], 0 \le m \le \frac{n}{r} \quad (8)$$

Here, z represents the input, U indicates the width of the pooling window, r indicates the stride windows, and n indicates the feature-length. After the MP layers, the learned features are given into the dual FC layers to reduce the feature dimensions and severity classification. A total 9 different features like phase time, pace time, strike time, posture time (s), rhythm (phase/sec), phase length (cm), pace length (cm), and speed (m/s) are considered for learning the severity levels of PD. The consequence of a a^{th} neuron can be mathematically formulated as,

$$F_a = f\big(u_a^{fc} MP_a + Bias_a\big) \quad (9)$$

Here, findicates the AF (ReLU) and the softmax are utilized to predict the outcome under each class. Also, u_a^{fc} indicates the weights of FC layers in a^{th} neurons.

5. RESULTS AND DISCUSSION

The developed study is processed and investigated via the Python platform and a publicly available Physio-Net dataset [21] is utilized in this study. This dataset consists of both the H&Y scale and UPDRS score in which three walking styles were collected from the movement disorder unit of the Tel-Aviv Sourasaky Medical Centre, Israel, and Laboratory for Gait & Neuro-dynamics. Totally 8 resistive force sensors are placed at the insole of individual foot and asked to walk at a regular interval of 2 minutes. Finally, 16 VGRF signals are sampled to 100Hz. The utilized gait dataset was contributed by three researchers from [22]. For investigating the cause of outer cueing especially in pace length, and gait speed, [22] is utilized that consists of 29 PD patients with the severity-2.5 on the H&Y measure. In addition to this, 18 healthy samples for three mobile scenarios such as rambling on the ground without assistance, rambling on the ground with a rambler, and rambling on the drudgery.

In, gait patterns from 29 PD samples and 26 normal samples are considered for analyzing the pulsating acoustic stimulus (PAS) on pace-to-pace changeability. The cognitive and gait functions can be analyzed via which consist of 29 healthy samples and 35 PD patients with an average age of 71. It is noted that the pressure level of foot sensors in PD patients is half while compared with the healthy samples. In this dataset, a total of 18K samples are recorded for 2 minutes under rhythmic auditory stimulation (RAS). Totally 173 VGRF sensor data are available with a total number of gait samples represented in18×13K×173.

5.1. ASSESSMENT METRICS

In this section, the several metrics like accuracy (Acc), sensitivity (Sen), specificity (Spe), PPV (positive predictive value (PPV), FPR (false positive rate), MCC (Mathew's correlation coefficient (MCC) and precision (Pre) are analyzed and its mathematical formula is provided below:

$$Acc(\%) = \frac{w+x}{w+x+y+z} \times 100\% \tag{10}$$

$$Sen(\%) = \frac{x}{x+y} \times 100\% \tag{11}$$

$$Spe(\%) = \frac{w}{w+z} \times 100\% \tag{12}$$

$$PPV(\%) = \frac{x}{x+z} \times 100\% \tag{13}$$

$$F-score(\%) = 2 \times \frac{Pr\,e \times Sen}{Pr\,e+Sen} \times 100\% \tag{14}$$

$$MCC = \frac{x \times w - z \times y}{\sqrt{(x+z)(x+y)(w+z)(w+y)}} \tag{15}$$

$$FPR(\%) = \frac{z}{w+z} \times 100\% \tag{16}$$

Here, w, x, y, zindicates the true negative (TN), true positive (TP), false negative (FN), and false positive (FP) respectively.

5.2. PERFORMANCE STUDY OF DEVELOPED METHOD OVER CONVENTIONAL METHODS

In Fig. 3, 0 represents healthy, 1 represents severity-2, 2 represents severity-2.5, and 3 represents severity-3. For class 0 (healthy), a total of 3704 trials are deliberated and in these 3445 trials are correctly classified as healthy. The remaining 259 trials are wrongly classified as class 1 (84 trials), class 2 (158 trials), and class 3 (17 trials) respectively. For class 1 (severity-2), a total of 2090 trials are considered and in this 1886 trials are correctly classified as class 1. The residual 204 trials are misclassified as class 0 (121 trials), class 2 (64 trials) respectively, and class 3 (19 trials). For class 2 (severity-2.5), a total of 2843 trials are deliberated and in this 2245 trials are correctly classified as class 2. The remaining 598 trials are misclassified as class 0 (487 trials), class 1 (101), and class 3 (10 trials) respectively. For class 3 (severity-3), a total of 323 trials are considered and in these 307 trials are correctly classified as class 3. The residual 16 samples are wrongly classified as class 0 (15 trials) and class 1 (1 trial) respectively. The performance obtained by the developed method over the existing methods is analyzed via graphical illustration.

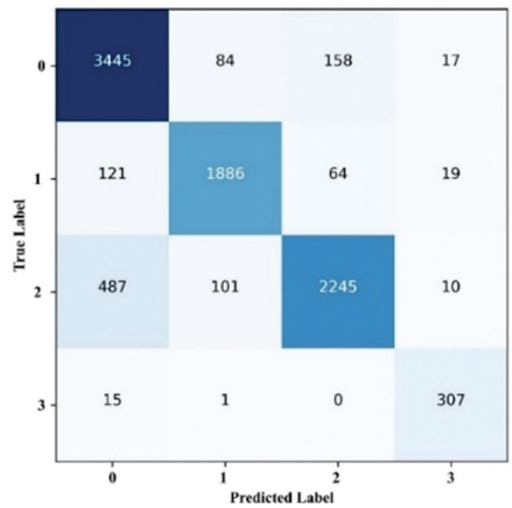

Fig. 3. Confusion matrix to describe the performance of the classification model

Numerous performance measures like accuracy, F-measure, sensitivity, specificity, PPV, FPR, and MCC are analyzed and compared with other conventional techniques like SVM, NB, KNN, and EC. A detailed analysis of the graphical illustrations depicted below: Fig. 4 indicates the accuracy analysis for different techniques under varying classes. In the graphical elucidation, it is clear that the suggested DSCK-RNet technique shows better outcomes compared to existing studies. Further, the proposed and existing techniques show better performance for identifying healthy samples by learning the gait patterns. However, the existing studies reduce its performance while analyzing the gait patterns for PD severity levels. This is due to that the existing techniques are trained with complex data and failed to consider non-motor symptoms effectively. The developed method considers the most relevant spatiotemporal patterns and can determine the invisible symptoms with minimal complexity.

Fig. 5 indicates the sensitivity analysis for different techniques under varying classes. In the graphical interpretation, it is clear that the suggested DSCK-RNet technique shows better outcomes compared to current studies. It is also illustrious that the proposed and existing techniques show better sensitivity performance for identifying healthy samples by learning the gait patterns. However, the existing studies reduce its performance while analyzing the gait patterns for PD severity ratings. The existing techniques increase the overfitting issues due to high data redundancy problems. The developed method considers the most relevant spatiotemporal patterns and can determine the hidden symptoms without the aid of experienced clinicians.

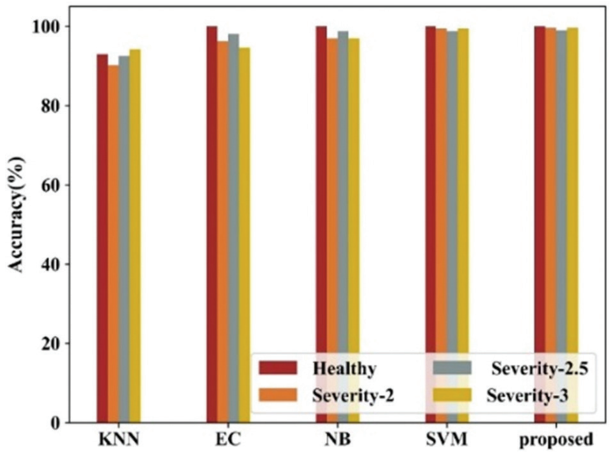

Fig. 4. Accuracy analysis for different techniques under varying classes

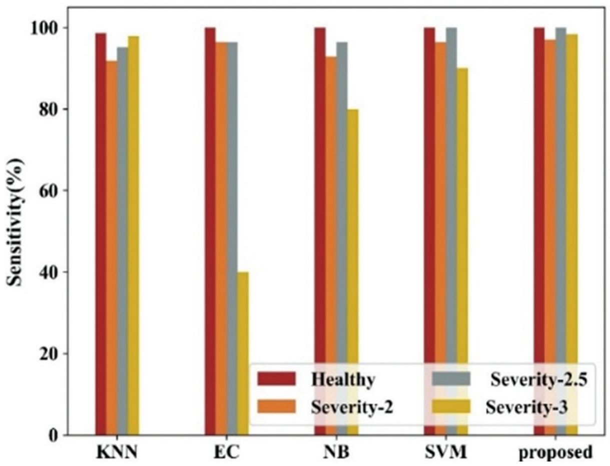

Fig. 5. Sensitivity analysis for different techniques under varying classes

Fig. 6 indicates the specificity analysis for different techniques under varying classes. In the graphical interpretation, it is clear that the developed DSCK-RNet technique demonstrates better outcomes compared to existing studies. It is also illustrating that the proposed and existing techniques show better specificity for identifying healthy samples by learning the gait patterns. However, the existing studies reduce its performance in learning the gait patterns, especially for PD severity levels. This is due to that the existing techniques lack effective preliminary stages to overcome the non-linear problems and also fail to consider non-motor symptoms effectively. The developed method considers the most relevant spatiotemporal gait patterns and can determine the motor and non-motor symptoms with minimal complexity.

Fig. 7 indicates the PPV analysis for different techniques under varying classes. In the graphical interpretation, it is clear that the developed DSCK-RNet technique demonstrates better outcomes compared to existing studies. It is also illustrating that the proposed and existing techniques show better performance for identifying healthy samples by learning the gait patterns. However, the existing studies reduce its performance while analyzing the gait patterns for PD severity levels. Moreover, the existing studies have very low performance while the complex data are under advanced PD levels. The proposed model tackles the discrepancies by considering the larger gait patterns into small ranges to minimize the network complexity.

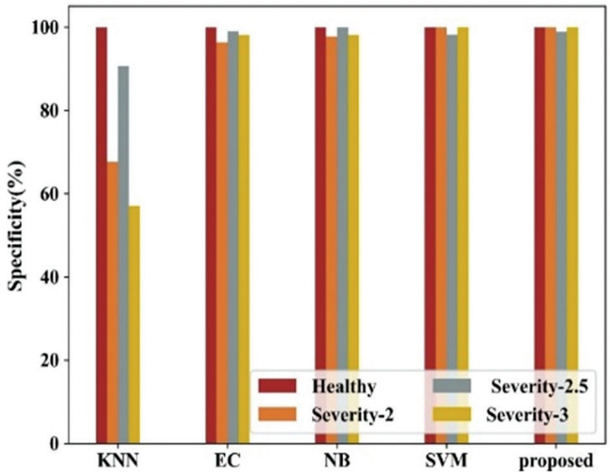

Fig. 6. Specificity analysis for different techniques under varying classes

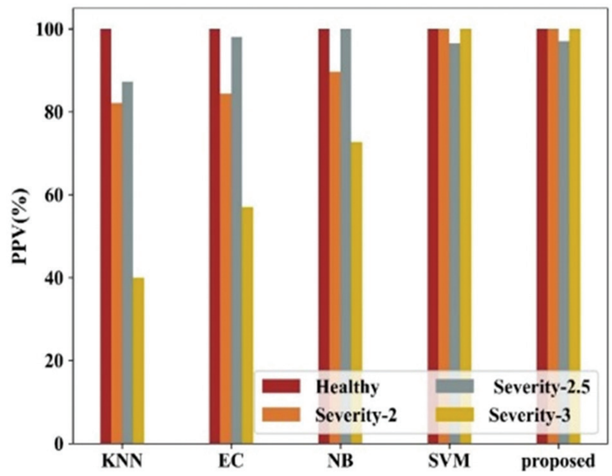

Fig. 7. PPV analysis for different techniques under varying classes

Fig. 8 indicates the FPR analysis for different techniques under varying classes. In the graphical elucidation, it is clear that the developed DSCK-RNet technique illustrates less performance compared to existing studies. It is also noted that the proposed and existing techniques show better performance for identifying healthy samples by learning the gait patterns. However, the present techniques reduce its performance while analyzing the gait patterns for PD severity levels. This is due to that the existing techniques are trained with complex data and failed to consider non-motor symptoms for the training process. The developed method considers the most relevant spatiotemporal patterns and minimizes the training error. Fig. 9 indicates the precision analysis for different techniques under varying classes. In the graphical explication, it is clear that the developed DSCK-RNet technique contemplates better outcomes compared to traditional studies. It is also emaciating that the proposed and existing techniques show better precision for determining healthy samples by learning the gait patterns. However, the existing studies reduce its performance while analyzing the gait patterns for PD severity levels. This is due to that the existing techniques failed to consider the hidden gait patterns and trained with unwanted or corrupted samples. The developed method considers the most relevant spatiotemporal patterns and can determine the invisible symptoms with minimal complexity.

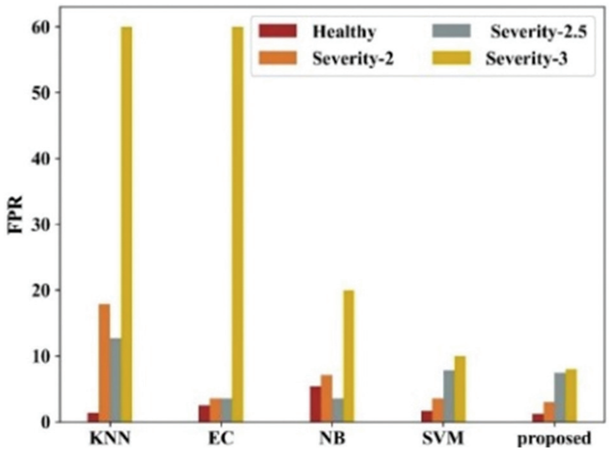

Fig. 8. FPR analysis for different techniques under varying classes

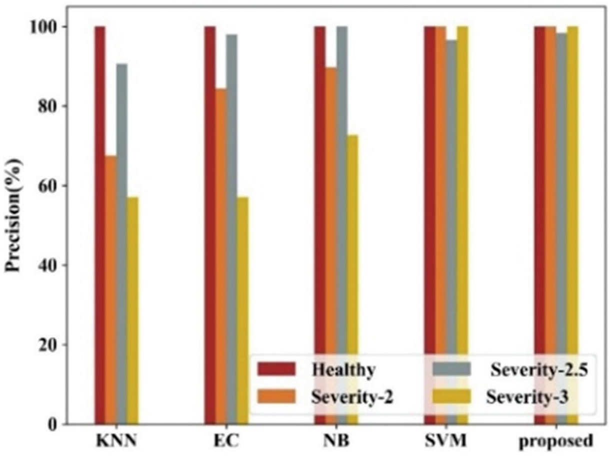

Fig. 9. Precision analysis for different techniques under varying classes

Fig. 10 indicates the F-measure analysis for different techniques under varying classes. In the graphical illustration, it is clear that the developed DSCK-RNet technique provides better outcomes compared to traditional approaches. It is also defined that the proposed and existing techniques show better performance for identifying healthy samples by learning the gait patterns. However, the existing techniques showed less score while it is trained with complex data and failed to consider non-motor symptoms effectively. The developed method considers the most relevant spatiotemporal patterns and can determine the invisible symptoms with minimal complexity.

Fig. 11 indicates the MCC analysis for different techniques under varying classes. In the graphical elucidation, it is clear that the developed DSCK-RNet technique shows better outcomes compared to traditional techniques. It is also illustrating that the proposed and existing techniques show better performance for identifying healthy samples by learning the gait patterns.

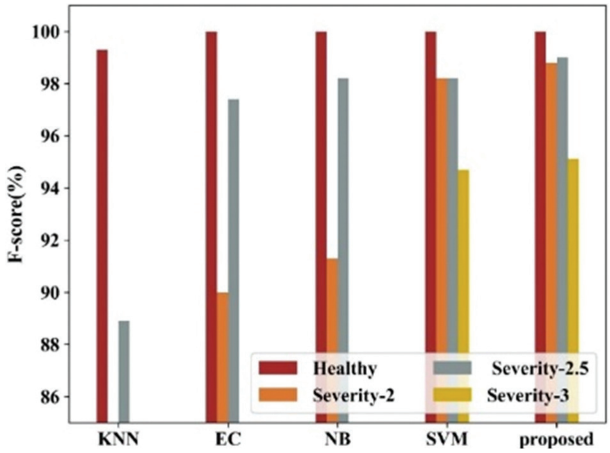

Fig. 10. F-measure analysis for different techniques under varying classes

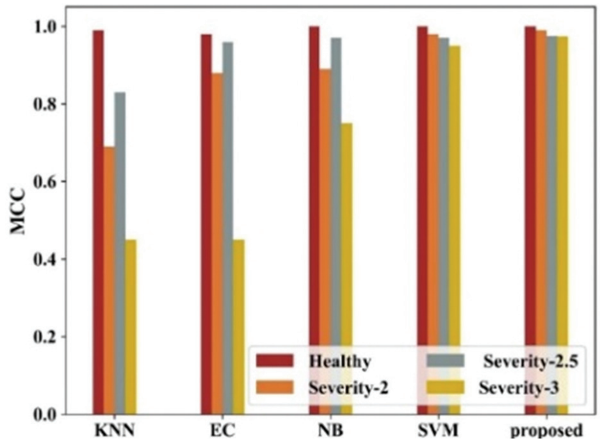

Fig. 11. MCC analysis for different techniques under varying classes

Table 1 shows the comparative analysis of different techniques for PD severity levels. From the table, it is elucidating that the developed approach achieved better outcomes compared to conventional studies. Some mL models like NB, SVM, EC, and KNN are compared with the developed DL model.

Table 1. Comparative analysis of different techniques for PD severity levels

Methods	Severity levels	Acc	Spe	FPR	Sen	F-score	PPV	Pre	MCC
Proposed (DSCK-RNet)	**0**	**100**	**100**	**1.2**	**100**	**100**	**100**	**100**	**1**
	1	**99.6**	**100**	**3**	**97**	**98.8**	**100**	**100**	**0.99**
	2	**99**	**98.9**	**7.45**	**100**	**99**	**97**	**98.4**	**0.975**
	3	**99.64**	**100**	**8**	**98.3**	**95.12**	**100**	**100**	**0.974**
EC [9]	0	100	100	-	100	100	100	100	-
	1	96.3	96.3	3.64	96.4	90	84.4	84.4	0.88
	2	98.1	99	3.62	96.4	97.4	98.1	98.1	0.96
	3	94.6	98.1	60	40	47	57.1	57.1	0.45
NB [9]	0	100	100	-	100	100	100	100	1.0
	1	97	97.8	7.13	92.9	91.3	89.7	89.7	0.89
	2	98.8	100	3.62	96.4	98.2	100	100	0.97
	3	97	98.1	20	80	76.2	72.7	72.7	0.75
SVM [9]	0	100	100	-	100	100	100	100	1.0
	1	99.4	100	3.62	96.4	98.2	100	100	0.98
	2	98.79	98.19	-	100	98.19	96.49	96.49	0.97
	3	99.39	100	10	90	94.69	100	100	0.95
KNN [9]	0	93	100	1.41	98.6	99.3	100	100	0.99
	1	90.2	67.6	17.94	91.9	74.1	82.1	67.6	0.69
	2	92.5	90.6	12.72	95.2	88.9	87.3	90.6	0.83
	3	94.2	57.1	60	97.9	47	40	57.1	0.45

6. CONCLUSION

The developed approach presented and investigated an innovative DL technique for classifying the PD severity level using gait spatiotemporal data. For learning the complex spatiotemporal features accurately, the developed study conquered an effective DSCK-RNet model that proved an outstanding performance in determining PD levels. Moreover, the developed DSCK-RNet technique deliberates the most appropriate features and minimizes the training complexity efficiently. In addition to this, some preliminary stages like data cleaning, missing value imputation, and DS-norm mechanisms helped to achieve better data quality and minimize the nonlinear correlations among the gait patterns. The developed study is processed and analyzed via the Python simulation and a publicly available Physio-Net dataset is utilized for the simulation process. Various assessment measures like accuracy, precision, sensitivity, specificity, PPV, FPR, and MCC are examined and compared with traditional studies like NB, SVM, EC, and KNN. In the experimental section, the developed DSCK-RNet model achieved an accuracy of 100%, 99.6%, 99%, and 99.64% for different classes like healthy, severity-2, severity-2.5, and severity-3 respectively. Even though the developed study achieved a better accuracy, there are some limitations and further extension of the effective PD analysis is required. The gait patterns considered in the present study consist of only healthy and moderate PD levels and failed to consider advanced PD levels due to a lack of data availability. Moreover, several unidentified motor symptoms, especially tremor signals will be integrated with the novel DL frameworks to improve the medical assessments and PD prognosis. Finally, the developed study failed to determine the time and frequency features that can be assessed. While data-driven gait-based severity classification using advanced machine learning models offers significant potential benefits for Parkinson's disease management, addressing the associated challenges is crucial for maximizing the model's clinical utility and ethical appropriateness. Collaboration between clinicians, researchers, and technology experts is essential to overcome these challenges and harness the full potential of this approach in improving patient care. A data-driven strategy utilizing machine learning approaches may, with additional validation, offer a more effective diagnostic and prognostic tool that can support doctors in their decision-making.

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