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Improved Bi-GRU for parkinson's disease severity analysis

Malathi Arunachalam[1], Ramalakshmi Ramar[2], Vaibhav Gandhi[3], Bhuvanesh Ananthan[4]
[1]Department of Computer and Software Engineering, Anand Institute of Higher Technology, Chennai, India
[2]Department of Computer Science and Engineering, Kalasalingam Academy of Research and Education, Krishnankoil, India
[3]Department of Design Engineering and Mathematics, Middlesex University, London, United Kingdom
[4]Department of Electrical and Electronics Engineering, PSN College of Engineering and Technology, Tirunelveli, India

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ABSTRACT

Parkinson's disease (PD) is a common neuro-degenerative issue, evaluated via the continuous deterioration of motor functions over time. This condition leads to a gradual decline in movement capabilities. For diagnosing clinical set of PDs, medical experts utilize medical observations. These observations are highly based on the expert's experience and can vary among clinicians due to its subjective nature, leading to differences in evaluation. The gait patterns of individuals with PD typically exhibit distinctions from those of adults. Evaluating these gait malformations not only aids in diagnosing PD but can also enable the categorization of severity stages with respect to symptoms of motor movement. Therefore, this paper introduces a classification of gait model based on the optimized deep learning (DL) model bidirectional gated recurrent unit-artificial hummingbird optimizer (BI-GRU-AHO). The training and testing involved the sequential segmentation of the right and left instances from the signals of vertical ground reaction force (VGRF) based on the identified gait cycle. The outcomes of the proposed BI-GRU-AHO exhibits reliable and accurate assessment of PD and achieved better accuracy of 98.7 %. The proposed model is trained and tested satisfactorily; hence it can be implemented in a real-time environment by integrating the model into a software application or system capable of receiving real-time data from PD patients.

Corresponding Author:

Malathi Arunachalam
Department of Computer and Software Engineering, Anand Institute of Higher Technology
603103 Chennai, Tamil Nadu, India
Email: malathiarunachalam83@gmail.com

1. INTRODUCTION

Gait analysis plays a major role in diagnosing various neurodegenerative conditions such as parkinson's disease (PD), dementia and alzheimer. Gait analysis offers essential insights into joint movement, spatio-temporal features, and the treatment process [1]. Of recent, the gait patterns have proved to be valuable method in diagnosing PD. There is significant advancement in gait analysis methodologies, driven by the introduction of sophisticated analysis of motion models [2]. Various techniques have been employed for the gait process includingthe use of cameras for capturing motion paths. These innovations collectively contribute to a comprehensive understanding of human gait without duplicating existing content [3].

Currently, medical evaluation approaches for PD patients continue to depend on questionnaires and self-descriptions like freezing of gait questionnaire (FOG) and assessments of daily living (ADL) [4]. Experts frequently assess PD severity in specific criteria based on the patient's performance in questions outlined in questionnaires. However, this process takes more time and provides inaccurate outcomes, limiting its

effectiveness in the treatment and screening of PD. Gait process also poses several challenges, such as high dimensional data, non-linear dependencies and intricate correlations among spatio-temporal features [5].

Addressing the highly non-linear nature of gait patterns requires specialized and efficient approaches for finding the severity stage of PD. In recent developments, the machine learning (ML) and deep learning (DL) models have demonstrated significant possibilities in aiding medical experts [6]. These models diagnose the occurrence of PD through gait flexibility analysis and classify the stages of PD based on the motor symptoms exhibited by individuals. Leveraging DL models in the gait process can markedly reduce the time associated with the processing of data, as these algorithms possess the ability to identify hidden features and manage huge databases [7]. This, in turn, can significantly enhance the treatment quality received by patients and efficiently enhance clinical results. Even though the gait process has been extensively analyzed for PD diagnosis, a more thorough investigation of hidden gait biomarkers is necessary for enhanced identification and quantitative evaluation of symptoms of PD. Moreover, DL models have the potential to surpass ML models when there is a sufficient amount of data, a factor that may vary based on the effectiveness of the adopted indication models. Some of the DL models like recurrent neural network (RNN), convolutional neural network (CNN) and long short term memory (LSTM). This paper presents an optimized DL model to model the gait analysis of PD patients using the wearable sensor data. Subsequently, gait classification is achieved using gated recurrent unit-artificial hummingbird optimizer (BI-GRU-AHO) and VGRF.

Section 2 presents recent works of literature based on different PD models. Section 3 presents the PD model and section 4 discusses the analysis of results. In section 5 concludes the paper.

2. RELATED WORKS

Sigcha *et al.* [8] developed a model based on the RNN and tri-axial accelerometer for enhancing the detection of FOG. The experimentation was demonstrated by the cross-validation. Camps *et al.* [9] developed automated detection FOG) utilizing DL model CNN and data from wearable sensors. This approach demonstrates superior performance compared to existing methods, achieving an accuracy level of 90%.

Vidya and Sasikumar [10] developed a method for predicting PD through a CNN with LSTM. The signals of VGRF were extracted by the EMD (empirical mode decomposition) to obtain the significant intrinsic features. Accuracy achieved was 98.3% for multi-classification. CNN with locally weighted random forest (LWRF) was introduced by Aşuroğlu and Oğul [11] for the categorization of parkinson's disease. The LWRF was utilized to identify PD and extract local characteristics.

Xia *et al.* [12] presented CNN model to detect FOG in PD patients; here, the discriminative features were analyzed using multi-1D data. Comparative analysis was performed for two feature fused models like patient dependent and independent settings. Ferreira *et al.* [13] presented ML approaches to detect PD with respect to spatio-temporal features. Here, the accuracy and precision values achieved of 84% and 92.3% respectively.

Borzì *et al.* [14] presented real time identification of FOG in PD using sensor and multi head CNN. The performance was carried out by varying threshold values of 0, 0.4 and 0.7 on three databases. Upon evaluating this existing approach using the 6MWT database, a decrease in sensitivity and an enhancement in specificity were noted. Nilashi *et al.* [15] developed early identification PD using DL and fuzzy models. For handling massive datasets expectation maximization and clustering were utilized. Then, for removing the noise, the PCA (principal component analysis) was presented. At last, the K-nearest neighbour (KNN) was presented to identify PD.

An approach to PD detection using speech recognition was suggested by Nissar *et al.* [16]. They evaluated eight different classifiers using feature selection methods including minimum redundancy maximum relevance (mRMR) and recursive feature elimination (RFE). An accuracy of 95.39% was achieved by combining RFE with extreme gradient boosting (Xgboost), which was better than previous methods. Using voice data from UCI, Gunduz [17] presented a CNN-based PD classification method. Their combined use of features and models resulted in an 86.0 percent model-level accuracy. By combining BAT with the PD classification dataset from UCI, Olivares *et al.* [18] created a method for PD diagnosis. They were able to attain a 96.74 percent accuracy with a 3.27% loss by feeding 23 characteristics into the model's input layer.

As a means of pre-diagnosis for PD, Lavalle and Romero [19] suggested using voice data. They used KNN, random forest (RF), support vector machine (SVM), and multilayer perceptron (MLP) classifiers to choose features and classify them. With a precision of 94.7%, the SVM-RBF classifier was a success. To identify PD, Yaman *et al.* [20] relied on vowels. For the purpose of classification, KNN and SVM classifiers were used after ReliefF was used to extract acoustic features from the dataset. A 91.25% success rate was attained with the SVM classifier. An ML-based system for parkinson's disease diagnosis using chosen features, RFE, and feature importance was proven by Senturk [21]. They used RFE and SVM classifiers in conjunction with artificial neural networks (ANNs) and regression trees to get a 93.8% accuracy rate.

In their 2019 study, Aich *et al.* [22] utilized a dataset from Max Little University, Oxford, to categorize the PD group using principal component analysis (PCA) and online feature selection based on regression (OFS) non-linear features. Their methodology used nonlinear classifiers, bagging classification, regression trees, RF, and RPART, which allowed them to get a 96.83 percent accuracy rate when RF was combined with PCA. When it comes to PD prediction, Rustempasic and Can [23] highlighted biomedical voice analysis. They were able to acquire a sensitivity of 75.34%, a specificity of 45.63%, and an accuracy of 68.04% using pattern recognition and fuzzy c-means (FCM) clustering to forecast PD from patients' speech. Researchers Silveira *et al.* [24] administered the pennsylvania smell identification test (UPSIT)-40 and sniffin's sticks 16-item smell tests to members of the Brazilian population. For every attribute, logistic regression was used. The specificity and sensitivity levels for sniffin sticks were 89.0% and 81.1%, respectively, whereas for UPSIT-40 they were 83.5% and 82.1%. The sleep behavior disorder questionnaire and the olfactory impairment scale (UPSIT) were used by Prashanth *et al.* [25]. A sensitivity level of 90.5% and an accuracy of 85.4% were the outcomes of training using support vector machines and classification trees.

From the detailed literature review, the following research gaps are identified.

Data scarcity and quality

- Data imbalance: existing datasets may be imbalanced, with more data for certain severity levels, leading to biased model performance. Developing techniques to handle imbalanced data in the Bi-GRU model is a gap worth exploring.

Feature engineering

- Advanced feature extraction: there might be a lack of advanced feature engineering tailored specifically for PD, such as extracting non-linear patterns from time-series data. Research could focus on identifying or creating novel features that enhance the Bi-GRU's ability to detect subtle changes in disease severity.

3. PROPOSED METHOD

Figure 1 shows the block diagram of the proposed gait pattern analysis in PD. This approach leverages optimized DL model and incorporates the capability of physionet dataset [8]. The optimized DL model BI-GRU-AHO is presented and the dataset is collected using VGRF.

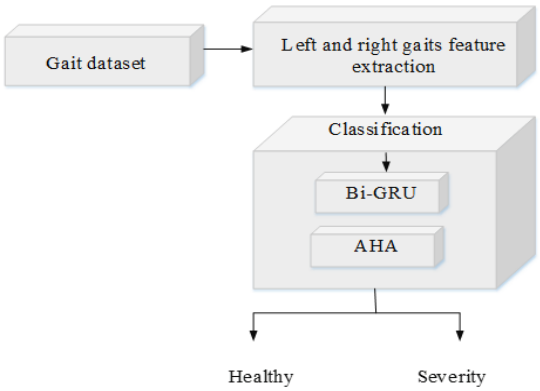

Figure 1. Framework of the proposed gait pattern analysis in PD

3.1. Database

The database considered is physionet [7] and includes gait measurements from 73 normal people (average age is 66.3 years) and 93 people (average age is 66.3 years) with idiopathic PD. The database has VGRF instances of individuals walking on level terrain for about two minutes at their typical, self-determined pace. Eight sensors in the right and left foot track force overtime and it is computed by Newton's. The sampling frequency is 100 Hz and the outcome from the sixteen sensors is digitalized and stored. Two signals that represent the total of the outcomes from every eight sensors for every foot are also included in the instances. The database has severity ratings of healthy, severity 2, 2.5, and 3.

3.2. Preparing data samples

The gait observed on regular walking for the lower leg on the left or right exhibits a quasi-periodic model. Therefore, for effective modelling and understanding of the inherent behaviour of gait, it is advisable

to segment gait data based on walk cycles. To achieve this, the work employed the overall force for identifying the walk cycles for the respective lower leg. The cycle for gait in the single lower leg is delineated as the duration from the initial instance when the respective foot makes a set with the floor to the concluding motion if the foot lifts off the floor. Employing a threshold process enables the detection of the zero-crossed point, facilitating the segmentation of the gait cycle. Utilizing the identified gait cycle, the multiple ranges of VGRF data are split to different samples of data to train and train the classifier. The zero-padding approach is utilized for making every identified gait cycle with an equal length of 140.

3.3. Gait classification

For modelling the left and right gaits, the DL model BI-GRU-AHO is presented. The effectiveness of RNN has been demonstrated in processes like signal and language recognition. However, the conventional RNN encounter challenges such as gradient vanishing, especially with increasing input data. Addressing these challenges, an LSTM is developed and because of its gating model, LSTM can effectively utilize for storing and accessing useful features. In the advanced model of LSTM, previous works indicate that GRU outperforms LSTM in various domains. In this work, O-GRU has the gates like update gate u_t and reset gate r_t as shown in Figure 2.

$$r_t = \sigma(W_r y_t + U_r \mathrm{h}_{t-1} + b_r) \quad (1)$$

$$z_t = \sigma(W_z y_t + U_z \mathrm{h}_{t-1} + b_z) \quad (2)$$

$$c_t = tan\mathrm{h}(W_c y_t + U_c \mathrm{h}_{t-1} + b_c) \quad (3)$$

$$\mathrm{h}_t = (1 - r_t)\mathrm{h}_{t-1} + r_t c_t \quad (4)$$

Where, σ,y_t,h_t and c_t are the sigmoid, input vector, hidden phase and storage medium. W_r, W_z, W_c, and U_r, U_z, U_c are the weighting matrices and b_r, b_z, b_c are the bias values.

But, the GRU network considers the input series in only one direction, limiting its ability to learn the representation of the feature. Consequently, the Bi-GRU model has been devised to address this limitation by generating a series of inputs from both forward and backward directions. The formulation of the Bi-GRU model in both directions is presented below:

$$\vec{\mathrm{h}}_t = \vec{GRU}(y_t, \mathrm{h}_{t-1}) \quad (5)$$

$$\overleftarrow{\mathrm{h}}_t = \overleftarrow{GRU}(y_t, \mathrm{h}_{t-1}) \quad (6)$$

At last, the last outcomes of the Bi-GRU model are given as (7).

$$Y_t = \left[\vec{\mathrm{h}}_t, \overleftarrow{\mathrm{h}}_t\right] \quad (7)$$

Then, for optimizing the parameters of Bi-GRU model, the optimizer AHA is presented. HB (hummingbirds) assess the characteristics of food sources, including the context and quality of honey specific flowers, the rate of honey production, and the time elapsed since their final visit to a flower. The foraging behaviour encompasses three strategies guided, relocation, and territorial foraging. These three foraging behaviours are presented below.

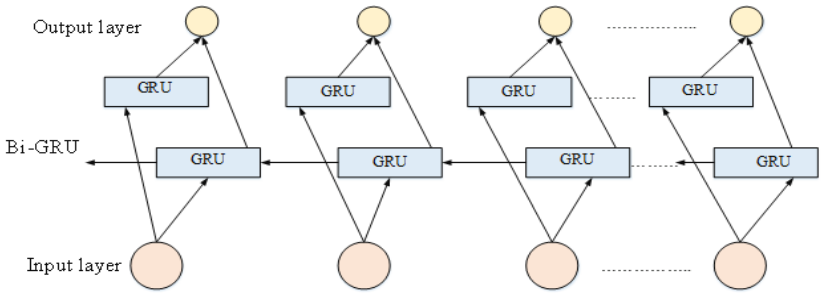

Figure 2. Bi-GRU model

Initialization: the population of HB is kept in a randomized manner on the source of food and it is given as (8).

$$y_j = LB + rand \times (UB - LB) \tag{8}$$

Where, UB, LB is the upper, and lower bounds and $rand$ is the random number.

Guiding foraging: HB individually navigates towards the nectar source containing the highest nectar content. These birds utilize three distinct flight modes: axial, diagonal, and omnidirectional. The axial flight is given as (9).

$$D^{(j)} = \begin{cases} 1 & when\ j = rand \\ 0 & elsewhere \end{cases} \tag{9}$$

The diagonal flight is given as (10).

$$D^{(j)} = \begin{cases} 1 & when\ j = P(k) \\ 0 & elsewhere \end{cases} \tag{10}$$

Where, $P = randp(k)$, $randp$is the random permutation.

The omnidirectional flight is given as (11).

$$D^{(j)} = 1 \tag{11}$$

The foraging characteristic is mathematically expressed as (12).

$$v_j(t+1) = y_{j,tar}(t) + g \times D \times \left(y_j(t) - y_{j,tar}(t)\right) \tag{12}$$

Where $y_{j,tar}(t)$ is the j^{th}HB position of food source and $g$is the guiding term.

The j^{th} HB position of food source is given as:

$$y_j(t+1) = \begin{cases} y_j(t) & f((y_j(t)) \le v_j(t+1)) \\ v_j(t+1) & f((y_j(t)) > v_j(t+1)) \end{cases} \tag{13}$$

When the food source of candidate's honey fill ration is larger than the present source of food, the HB avoids the present source of food. Figure 3 shows the flowchart of the AHA.

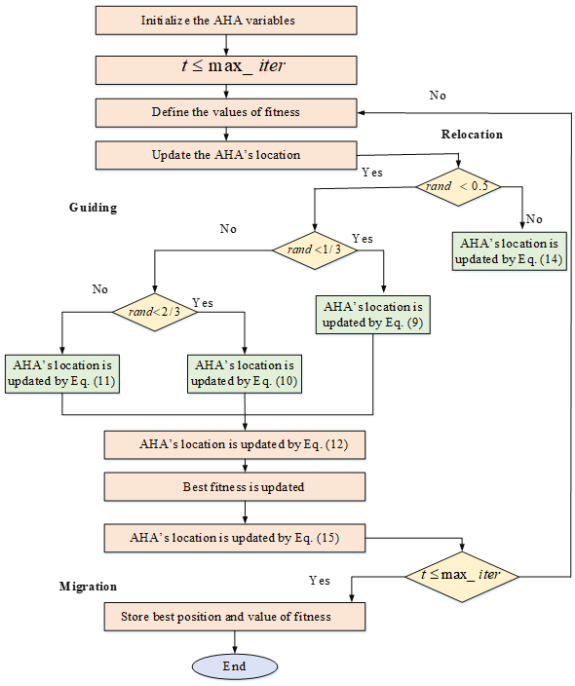

Figure 3. Flow-chart of the AHA

Territorial foraging: the mathematical equation below outlines the local forage process employed by HB and defines a proper source of food within their territorial foraging model.

$$v_j(t+1) = y_j(t) + l \times D \times y_j(t) \quad (14)$$

Where l is the territorial term.

Relocation foraging: the relocation of a HB, transitioning from the honey source with the less refill ratio to a randomly generated new source, can be elucidated as (15).

$$y_{low}(t+1) = LB + rand \times (UB - LB) \quad (15)$$

Where y_{low} is the source of food having less refill ratio.

4. RESULTS ANALYSIS

To assess all classification models, a stratified 10-fold cross-validation approach is employed. Initially, the original database is split into 10 separate fold values. Nine out of the ten folds are integrated and utilized as a train model, while the rest folds served as a test model. Each train model underwent resampling and resizing using the SMOTE algorithm to ensure a more balanced distribution of instances across all classes. Table 1 defines the performance metrics considered in this work. These metrics are evaluated using four criteria like Y_{po}, Y_{ne}, Z_{po}, and Z_{ne} as true positive, false negative, false positive and false negative respectively.

Table 1. Performance metrics

Metrics	Expressions
Accuracy	$\frac{Y_{po} + Y_{ne}}{Y_{po} + Y_{ne} + Z_{po} + Z_{ne}}$
Precision	$\frac{Y_{po}}{Y_{po} + Z_{po}}$
Sensitivity	$\frac{Y_{po}}{Y_{po} + Z_{ne}}$
Specificity	$\frac{Y_{ne}}{Y_{ne} + Z_{po}}$

4.1. Comparative analysis

Following section defines comparison of accuracy by varying different iterations, confusion matrix, region of characteristics (RoC) and comparative analysis are given. Figure 4 states the accuracy by varying different iterations from 1 to 14,000. Accuracy performance is carried out by varying loss values from $\lambda_1 = 10^{-5}$, $\lambda_1 = 10^{-4}$, $\lambda_1 = 10^{-3}$, and $\lambda_1 = 10^{-2}$. It is observed that when the iteration is increased, the accuracy value is also increased. Moreover, the value of accuracy is high at $\lambda_1 = 10^{-5}$ and value of accuracy is low at $\lambda_1 = 10^{-2}$.

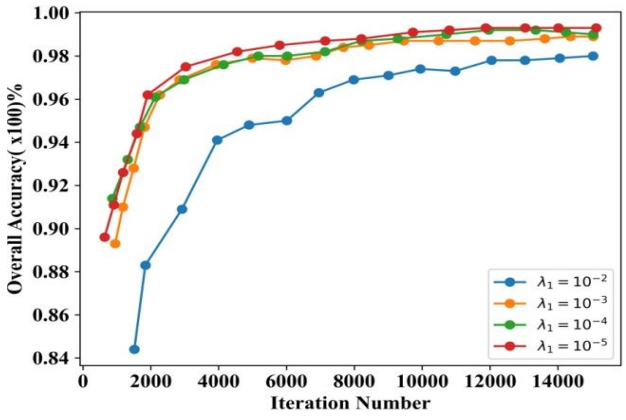

Figure 4. Accuracy at different iterations

Figure 5 presents the confusion matrix of the proposed DL model BI-GRU-AHO with respect to four classes as healthy, severity 2, 2.5, and 3. It is noted that the proposed BI-GRU-AHO classified 99.96% samples as healthy, 97.02% samples as severity 2, 96.59% samples as severity 2.5 and 99.74% samples as severity 3. Figure 6 presents the receiver operating characteristic (ROC) of the proposed DL model BI-GRU-AHO with respect to four classes like healthy, severity 2, 2.5, and 3. The area under the curve (AUC) value achieved by the healthy, severity 2, 2.5, and 3 are 0.977, 0.961, 0.963, and 0.97.

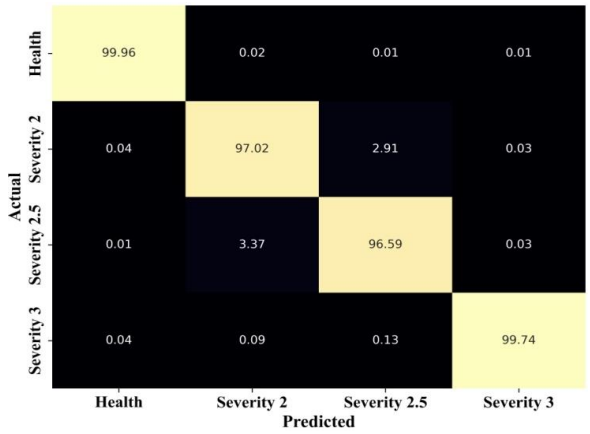

Figure 5. Confusion matrix

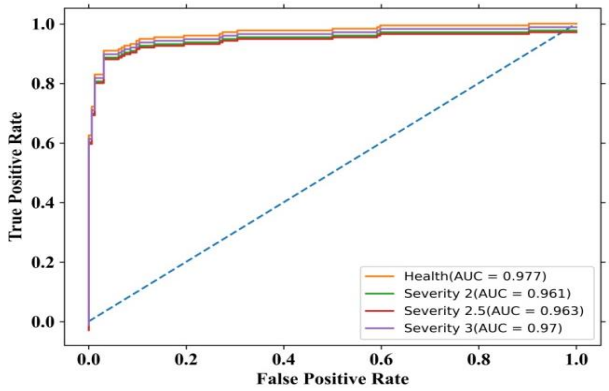

Figure 6. ROC curve of the severity stages

Table 2 depicts the comparative analysis of different approaches like RNN, LSTM, Bi-LSTM, GRU, Bi-GRU, and the proposed BI-GRU-AHO. The performance is carried out by varying the healthy and severity values. In all comparative performance the proposed BI-GRU-AHO outperformed the conventional DL model and suitable for gait analysis.

The practical impacts of using improved Bi-GRU for PD severity analysis can be substantial across various domains, particularly in healthcare, patient care, and research. Here are some of the key impacts:

Enhanced diagnostic accuracy

- Improved early detection: the Bi-GRU model, with its ability to capture complex temporal dependencies in sequential data, can significantly enhance the accuracy of early detection of PD. This leads to timely interventions, potentially slowing disease progression.
- Precision in severity classification: by accurately classifying the severity of PD symptoms, the model enables more tailored treatment plans. This precision is critical in managing the disease effectively and adjusting therapies as needed.

Clinical decision support

- Supporting clinicians: the model can serve as a decision support tool for clinicians, providing data-driven insights into the severity of a patient's condition. This can assist in making informed decisions regarding treatment options and interventions.

– Reducing diagnostic variability: by providing consistent and objective severity assessments, the improved Bi-GRU reduces the variability in diagnoses that can occur due to subjective judgment, leading to more standardized care.

These practical impacts highlight the potential of the improved Bi-GRU model to revolutionize the management and understanding of PD, leading to better patient outcomes and more efficient healthcare systems.

Table 2. Comparative analysis

Class	Method	Accuracy	Sensitivity	Specificity	Precision
Healthy	RNN	90.2	91.2	91.7	89.3
	LSTM	91.3	92.4	93.9	90.4
	Bi-LSTM	94.3	94.9	94.5	93.2
	GRU	94.7	95.1	95.6	94.8
	Bi-GRU	95.6	95.9	96.9	95.3
	Proposed	98.7	97.7	97.2	96.9
2	RNN	94.2	91.9	91.4	90.3
	LSTM	94.3	92.3	95.9	90.5
	Bi-LSTM	95.3	94.1	94.9	93.4
	GRU	95.7	95.5	96.7	94.1
	Bi-GRU	95.9	94.9	97.8	95.9
	Proposed	96.7	97.3	97.8	99.9
2.5	RNN	90.4	91.2	90.1	89.6
	LSTM	91.3	92.4	92.2	90.7
	Bi-LSTM	94.3	94.9	94.7	93.4
	GRU	94.7	95.1	95.8	94.9
	Bi-GRU	95.6	95.9	96.2	96.2
	Proposed	98.5	96.7	97.9	98.9
3	RNN	90.6	91.6	91.9	90.3
	LSTM	91.5	91.4	94.9	91.4
	Bi-LSTM	93.1	95.8	95.5	93.5
	GRU	94.4	95.4	95.2	94.6
	Bi-GRU	95.2	95.8	96.1	95.2
	Proposed	98.1	97.6	97.4	97.1

5. CONCLUSION

Signals in gait typically exhibit periodic and repetitive patterns. Therefore, the evaluation of gait abnormalities proves effective in distinguishing between normal and PD individuals. Medical experts traditionally rely on multiple physical, neurological and physiological analyses for an accurate PD diagnosis. However, this approach heavily relies on the expertise and leads to inaccuracies. The work presented in this paper (DL model BI-GRU-AHO) was subsequently utilized to analyze the gait patterns on the VGRF pattern. The proposed BI-GRU-AHO was trained using a 10-fold cross-validation and achieved better accuracies of 98.7% (healthy), 96.7% (severity 2), 98.5% ((severity 2.5), and 98.1% (severity 3) respectively. The findings suggest that the proposed BI-GRU-AHO, when trained with a larger database of gait data, has the potential to offer improved assessments of patients with PD. This capability can be particularly valuable for clinicians in formulating more effective rehabilitation programs. Future research could focus on validating the improved Bi-GRU model across multiple and diverse datasets. This would ensure the model's robustness and generalizability, making it applicable to different populations and environments. Investigating methods to adapt the Bi-GRU model to new datasets with minimal retraining could enhance its usability in different clinical settings, reducing the need for extensive data collection and model retraining.

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BIOGRAPHIES OF AUTHORS

Malathi Arunachalam is an assistant professor in the Department of Computer Science and Engineering, under Anand Institute of Higher Technology, Kazhipattur, Chennai-603103. She has received her B. Tech. degree in Information technology from SRM Easwari Engineering College in 2004. M. Tech. in Computer Science and Engineering from SRM University in 2013. Her area of interest are artificial intelligence, machine learning, and deep learning. She can be contacted at email: malathiarunachalam83@gmail.com.

Ramalakshmi Ramar received her Doctoral degree and Master of Engineering degree in Computer Science and Engineering. She has been working in the Department of Computer Science and Engineering at Kalasalingam Academy of Research and Education (Previously known as Arulmigu Kalasalingam College of Engineering) since 2001. She has more than 24 years of teaching experience. She is a member of CSI, ISTE, and Network Technology group of TIFAC- CORE in Network Engineering. She has published more than 60 research articles in reputed journals and international conferences. She has received a Young Scientist Fellowship from the Tamilnadu State Council for Science and Technology and an Award of Excellence from SAP India Pvt. Limited. Her areas of research include software defined networking, machine learning, the internet of things, and data analytics. She can be contacted at email: rama@klu.ac.in.

Vaibhav Gandhi is a dedicated educator and researcher at Middlesex University, specializing in Brain-Computer Interface and assistive robotics. With a passion for empowering students, he cultivates a dynamic learning environment that encourages critical thinking and practical application of knowledge. Vaibhav's expertise extends to the exploration of technology's impact on society, particularly in areas such as biomedical signal processing, computational neuroscience, and user-centric graphical user interfaces. He is committed to advancing academic excellence through innovative teaching methods and collaborative research initiatives. As a respected member of the university community, Vaibhav actively contributes to interdisciplinary projects and fosters partnerships that drive positive change. His holistic approach to education and research reflects a deep commitment to preparing students for success in an increasingly digital world. Through his work, Vaibhav inspires both students and colleagues to push the boundaries of knowledge and make meaningful contributions to their fields. He can be contacted at email: V.Gandhi@mdx.ac.uk.

Bhuvanesh Ananthan received the B.E. degree in Electrical and Electronics Engineering from Anna University in 2012, M. Tech. in Power System Engineering from Kalasalingam University in 2014 and Ph.D. degree from Faculty of Electrical Engineering of Anna University in 2019. He has ten years of teaching and research experiences. His research interests are in power systems, electric vehicles, renewable energy sources, optimization techniques and artificial intelligence. He is now an associate professor in Department of Electrical and Electronics Engineering, PSN College of Engineering and Technology, Tirunelveli, Tamil Nadu, India. He has published more than 100 papers in reputed international journals, 65 papers in international conferences and 20 books. He is a life time member of International Society for Research and Development, International Association of Engineers. He can be contacted at email: bhuvanesh.ananthan@gmail.com.