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Parkinson's Disease Detection based on Gait Pattern using a Hybrid Feature Selection Approach

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***Abstract*— Parkinson's Disease (PD) is a neuro-degenerative disorder, affecting the mobility of persons. The symptoms of PD include trembling, tight muscles, and unsteady walking motions. PD has been classified in various studies in the past, although in this work an attempt is made to differentiate between patients suffering from PD and the healthy persons by concentrating on the specific aspects of gait rhythms. The experiment is performed on the dataset with 15 PD patients and 16 healthy control individuals. Eight statistical features are extracted from the thirteen time-series gait data. As feature selection plays a crucial role in improving model's performance, an optimal subset of features is obtained by calculating Mutual Information Gain (MIG) and by Recursive Feature Elimination (RFE). The top 10% features are chosen from the extracted statistical features and they are classified separately. In the next step, the features obtained by both the techniques are then concatenated together and further classified using Machine Learning classifiers to enhance the model's performance. In the current work, we have proposed a hybrid MIG-RFE feature selection approach for classification of PD from healthy people using the gait data. When evaluated using 10-fold cross validation technique, the proposed MIG-RFE feature selection approach provided the maximum classification accuracy of 96.82% by Naïve Bayes classifier with only fourteen features. The experimental analysis shows that the obtained results are better than some of the state of art methods.**

***Index Terms*— Parkinson's Disease, Gait, Mutual Information Gain, Recursive Feature Elimination, Machine Learning**

I. INTRODUCTION

In today's world, there are number of persons suffering from various neurodegenerative disorders like Alzheimer, Parkinson's disease (PD), multiple sclerosis etc. These brain disorders are progressive, chronic and persistent that affects the proper functioning of the human brain [1]. After Alzheimer, PD is second most common neurodegenerative movement disorder [2]. There is no recognized etiology for PD, no long-term therapy and has a very few available treatments. PD is caused due to decrease in the synthesis of dopamine chemical which acts as a neurotransmitter that helps to regulate the movement and coordination. The dropping of neurons in the substantia ganglia reduces the dopamine production [3]. PD symptoms can be broadly categorized into two categories: 1) Motor symptoms include tremors, stiffness, sluggishness of movement, unbalanced posture. These symptoms are widely recognized as the cardinal indicators of PD [4]. Tremors are characterized by the presence of involuntary and rhythmic twitching of the limbs. Stiffness refers to the heightened muscular tone that results in rigidity in

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motions. Bradykinesia, which refers to the sluggishness of movement, is a prominent hallmark of PD. Unbalanced posture results in compromised balance and the occurrence of abrupt falls. The other motor symptoms include changes in handwriting, difficulty in speech (dysphonia) [5]. whereas 2) Non motor symptoms results in loss of weight, taste and smell, tiredness and indigestion. As a result of these difficulties in mobility, individuals afflicted with PD exhibit distinct gait features in comparison to individuals without the condition [6]. The authors in [7] analyzed that patient suffering from PD had a significant impact on their gait that results in reduction in their walking speed and stride length. Similarly, the authors in [8] calculated spatio-temporal and kinematic features and observed a vast difference in stride velocity and stride length between the two groups. Hence, based on certain investigations it is seen that when compared to healthy group, PD patients' gait dynamics showed significant variations.

PD generally affects the people with above 60 years of age. PD cannot be prevented, so diagnosing it early is one of the reliable methods to enhance the PD health. Levodopa is most common medication used to treat PD. The movement disorder organization suggests two clinical rating scales for assessing the severity of Parkinson's disease: the UPDRS and the H&Y scale. Nowadays; Computer aided diagnosis (CAD) systems are gaining more popularity in the healthcare industry as a result of technological improvement. They are highly accurate and may be accessed remotely. Therefore, these CAD systems can now be used by medical experts to diagnose PD [8]. On the basis of these motor symptoms of the PD patients, the researchers have suggested different ways to diagnose PD by using modalities like handwritten images [6], speech [9], Electroencephalography (EEG) signals [10], with Magnetic Resonance Imaging (MRI) images [11], and SPECT images. Despite these different detection mechanisms, the most cardinal indicator of the PD diagnosis still remains the gait. Numerous research works have been conducted for automatic detection of PD. Different Machine Learning (ML) and Deep Learning (DL) algorithms are used for CAD system development to help neurologists in accurate detection. The CAD systems can discriminate between PD patients and healthy ones with the usage of powerful features extracted from gait data. PD diagnostic systems employ a variety of signal processing methods to extract clinically relevant features of the signals extracted from gait sensors. These are fed as an input to ML models, which produce accurate judgements. The performance of such models is closely connected to the utilization of relevant features in ML model training. High relevance features are acquired by either feature selection or by dimensionality reduction approaches. These obtained robust features tends to increase the classification performance of the ML models. In this paper, the time series gait data is used for distinguishing between patients suffering from PD to healthy individuals. The authors have developed a hybrid feature selection framework named MIG-RFE on the basis of Mutual Information Gain (MIG) and Recursive Feature Elimination (RFE) to improve the quality of life of PD patients via early diagnosis.

The remaining paper has been arranged as follows: Section II gives a brief overview of the past work in the corresponding domain. Section III provides dataset description with proposed methodology. The results are analyzed and are discussed in the Section IV. Conclusion of the paper along with the direction in future scope is provided in Section V.

II. LITERATURE REVIEW

Gait signal processing is carried out utilizing several gait sensors that detects Ground Reaction Force (GRF) value. When walking, a person exerts a GRF. This force can vary in value depending on the type of walking activity, making it a common instrument for personal gait analysis study [12]. There are numerous research works who have used gait patterns to study PD and they mostly concentrate on the diagnostic findings about the existence of the illness. The authors in the paper [13] have detected PD using gait data. The dataset was gathered from Physionet consisting of 29 PD patients and 18 healthy individuals. Time domain and frequency domain features were calculated from the GRF signals and prominent features were extracted using a dimensionality reduction technique Principal Component Analysis (PCA) and with filter-based feature selection technique i.e., minimum redundancy maximum relevance (mRMR) algorithm. The maximum classification accuracy of 93.6% was attained by them using ML classifiers. The authors in the paper [14] detected PD by extracting features through Wavelet Transform (WT) from the significant gait patterns. They deployed a fuzzy neural network for PD classification reporting the highest accuracy of 77.33%. In paper [15], the authors have used 1-dimensional Local Binary Pattern (LBP) for feature extraction and classified PD patients from gait data using Multi-Layer Perceptron (MLP). Similarly, the authors in [16] developed an automatic PD diagnosis system utilizing gait data. After the preprocessing of GRF signals, spatio-temporal features were extracted from them. Random Forest (RF), a wrapper-based approach was used for selecting the most prominent features. An accuracy of 92.86% was achieved using k-Nearest Neighbour

(KNN) by them. The researchers on paper [17] retrieved a variety of statistical features from 93 PD patients and 73 healthy people and passed them into a neural network architecture. Further, the authors have contrasted the effectiveness of several cross-validation techniques and published their outcomes on PD stage classification. The final accuracy obtained by them was 87.1%. Along with ML models, various DL architectures were used by the researchers for PD identification via gait signals. As DL models require a large amount of data the authors in the paper [18] have trained and tested their model on three publicly available databases. The main aim of their paper was to find the severity of the disease. Gait signals were passed through two channel model consisting of Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM). The results obtained were compared with pre-existing ML models and their approach outperformed past works. In paper [19], the authors have used a deep learning model for PD diagnosis. They merged CNN and Bidirectional LSTM (Bi-LSTM) architectures to retrieve features from each gait cycle. Their proposed algorithm achieved an accuracy of 99.2% surpassing the other ML models. The authors in [20] used accelerometers to measure the freezing and non-freezing of gait signals and the features are extracted by combining Discrete Wavelet Transform (DWT) and Fast Fourier Transform (FFT). Firstly, they classified using Support Vector Machine (SVM) and ANN and later by LSTM achieving an average accuracy of 83%.

This is essential to note that significant outcomes on diagnosing PD utilizing ML techniques have been reported in the literature. The main drawback of applying ML algorithms is that the classifier uses manually extracted features. Consequently, a lot of attention is being devoted towards DL techniques to eliminate such laborious feature extraction. One of the limitations of using DL is requirement for huge amount of dataset. The number of instances in the medical research is often limited. The datasets have a small number of occurrences and have a huge number of features, due to which the feature selection is an important procedure for removing the negative impacts of high dimensional feature space. Reduction of features also ignores the noisy aspects in the data while emphasizing on those with high importance. The success of the model is entirely interconnected to the quality of the features used. The literature survey shows that only few works are reported on feature selection for PD identification using gait data. In this paper, we have shown the potential of feature selection by combining the features obtained from filter and wrapper-based feature selection approach and classifying using machine learning.

III. Materials And Methods

This section describes about the dataset used, data preprocessing technique, feature extraction and feature selection strategies with the type of classifier utilized for PD classification. The block diagram of our suggested approach is portrayed by Figure.1.

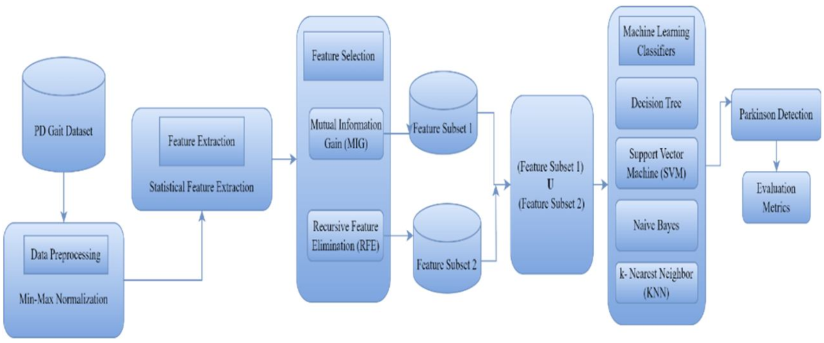

Figure.1. Block diagram of the proposed framework.

A. *Dataset*

A gait signal is defined as the series of actions between two successive contacts of same limbs. The gait dataset utilized in this work was obtained from 'The National Institutes of Health- sponsored Research Resource complex for physiological signals contributed by the scientist Hausdorff et al. [21][22]. The dataset includes 64 gait signal recordings from four separate groups: 16 healthy control participants, 20 HD patients, 13 ALS patients, and 15 PD patients. In the current study, the focus is on classifying only between PD and healthy control people, therefore a total of 31 recordings were utilized in this work. During the time of data collection, the participants were instructed to walk normally for 300 s along a straight, 77 m long corridor as per the experimental protocol. An ultrathin force-sensitive switches were installed within each subject in order to measure the gait signals. With a 300-Hz sampling rate and 12-bit resolution per sample the gait signals were recorded by an analog-to-digital (ADC) converter. This dataset includes following 13 attributes which are connected to the human gait cycle: Left and Right Stride Interval; Left and Right Swing Interval (sec); Left and Right Swing Interval (%); Left and Right Stance Interval (sec); Left and Right Stance Interval (%); Double support interval (sec); Double support interval (%); Elapsed time (sec). The stride times for the PD patient and a healthy person are shown in Figure.2 and Figure.3 respectively. The stride times linked to neuro-degenerative illnesses are clearly more unpredictable and variable.

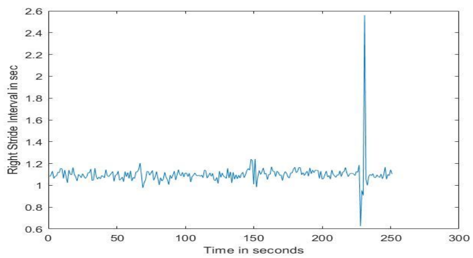

Figure.2. Right Stride Interval of PD affected patient.

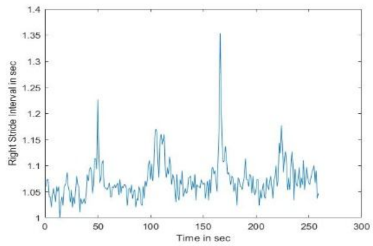

Figure.3. Right Stride Interval of Healthy Person

B. Data Preprocessing

In order to remove biasness from the raw gait time series data, min-max score normalization is applied in our work for scaling the values in the common range between 0 to 1 using (1):

$$x_{normalized} = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (1)$$

C. Feature Extraction

Features are essential for defining the kind of neurological disorder and determining classification performance. The following features are extracted for all preprocessed gait time series data to describe the key statistical traits like: (a) MEAN (M) (b) Median (Med) (c) Standard Deviation (Std) (d) Variance (Var) (e) Minimum (Min) (f) Maximum (Max) (g) Skewness (Skew) and (h) Kurtosis (Kurt). Table I provides a list of the formulae for calculating these statistical parameters.

TABLE I CALCULATION OF STATISTICAL FEATURES

Statistical Parameter	**Formula**
Mean (M)	$M = \frac{1}{n}\sum_{i=1}^{n} x_i$
Median (Med)	When n = odd then $Med = (\frac{n+1}{2})^{th}\ term$ When n = even, $Med = \frac{(\frac{n}{2})^{th}\ term + (\frac{n}{2}+1)^{th}\ term}{2}$
Standard Deviation (Std)	$Std = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - Mean)^2}$
Variance (Var)	$Var = Std^2$
Minimum (Min)	$\min(x_i)$
Maximum (Max)	$\max(x_i)$
Skewness (Skew)	$Skew = \frac{1}{n}\frac{\sum_{i=1}^{n}(x_i - Mean)^3}{(Std)^3}$
Kurtosis (Kurt)	$Kurt = \frac{1}{n}\frac{\sum_{i=1}^{n}(x_i - Mean)^4}{(Std)^4}$

D. Feature Selection

Due to the small sample size, the extracted features are often redundant and certain irrelevant features may also overfit the diagnostic model. Therefore, procedures for selecting features have been created to either choose discriminative characteristics or eliminate redundant ones [2]. Typically, the feature selection methods are divided into filter- based techniques and wrapper method. Here in this work, the authors have designed a hybrid (filter and wrapper combined) feature selection approach for accurately classifying PD. The two feature selection methods used in our work are explained in detail below:

1) Mutual Information Gain (MIG): This is a filter-type based feature selection (FS) technique that allows for the selection of the most discriminative features, performing magnificently during classification. The MIG is calculated for each feature, ranging from 0 to 1. The feature subset with the maximum MIG value is chosen [23]. The MIG is expressed on the basis of entropy and is calculated by (2):

$$MIG(X,Y) = S(X) - S\left(\frac{X}{Y}\right) \qquad (2)$$

Where MI is calculated with the two random variables X and Y. S(X) represents the uncertainty present in the Variable X and S(X/Y) shows the conditional entropy obtained when observing the random variable Y as shown in (3) and (4) respectively. By using MIG the top 10% features (top 10) are selected according to their score obtained.

$$S(X) = -\sum_{X} P(X)\log\big(P(X)\big) \qquad (3)$$

$$S\left(\frac{X}{Y}\right) = \sum_{Y}\sum_{X} P(y,x)\log\left(P\left(\frac{x}{y}\right)\right) \qquad (4)$$

2) Recursive Feature Elimination (RFE): This is a wrapper-based feature selection approach that builds a model with the use of classifier [24]. The significance score of all the features is determined and one-by-one feature with the minimum score is eliminated from the subset. The entire procedure is repeated continuously, until the required number of features are remaining. In our case the top 10% (also top 10) features are selected via RFE. The mathematical formula for the calculation is shown by (5):

$$s(i) = \sum_{m=i}^{n}(r_{min} - r_{im}) \qquad (5)$$

Where $s(i)$ denotes the feature's score, n is the total no. of features, r_{min} depicts the value of minimum rank and r_{im} gives the score obtained by the I in the feature set of m. The algorithm discards the attribute with the smallest score at each stage. One feature is eliminated in a single phase, and the process is then repeated with the left-over features. The procedure for adjusting the model is continued, unless the desired quantity of features is acquired. The features required are provided as an input to this algorithm. In our experiment, a sum of top 10 features (top 10%) is chosen by using RFE algorithm after applying statistical feature extraction from gait data.

3) Proposed MIG-RFE Technique: This hybrid filter and wrapper-based feature selection approach combines the feature set obtained individually from MIG and RFE. An optimal subset of 14 features (by union of features from MIG and RFE features) is formed and this feature set is given as an input to the ML classifiers.

E. Classification

The optimum feature subset that are generated after the feature selection process are then fed to several classifiers to differentiate between healthy people and PD patients. The purpose is to assess how well feature selection technique performs in PD diagnosis, based on gait signals. This section provides explanation of the classifiers used in this work.

1) Decision Tree (DT): This supervised machine learning technique having a tree like structure is used to classify new samples [25]. The algorithms used to generate decision trees are ID3, C4.5, and CART. A tree classifier is a recursive split of the dataset. The root node, internal nodes and leaf nodes are the three main types of nodes in this classifier. The best feature is considered as the root node and the dataset is partitioned into a homogenous way. Important facts can be extracted using this algorithm by IF-THEN rules.

2) Support vector Machine (SVM): It is an effective supervised approach used for data classification and for regression. This solves binary classification problem by creating a hyperplane for the separation of data points into class labels [26]. SVM distinguishes these N features by mapping them into multidimensional space. In the current work, class1 is labelled as PD patient in the dataset and class 0 represents healthy people. Linear kernel is used for the classification in this work. Let $x = (x_1,\ x_2, x_3 \ldots \ldots x_n)$ represents a training dataset belonging to class y € {+1, -1}. The separating hyperplane is given by (6):

$$H = w^T x + b = 0 \qquad (6)$$

The hyperplane separates the two classes by a maximum margin of $2/\|w\|$ and are represented by (7) and (8).

$$w^T x_i + b > 0 \ if \ y_i = +1 \qquad (7)$$

$$w^T x_i + b < 0 \ if \ y_i = -1 \qquad (8)$$

3) Naïve Bayes (NB): It is a parametric ML approach working on the basis of the bayes theorem [27]. This classifier is called naive because it assumes that class conditions are independent as the result of a given class's attribute value is not affected by the values of the other attributes. This claims to save computational cost and reduces burden on models.

$$P(C/X) = \frac{P(X/C) * P(C)}{P(X)} \qquad (9)$$

Where $P(C/X)$ is posterior probability with the probability of instance belonging to class C and features $X = (x_1, x_2, x_3 \ldots \ldots . x_n)$. $P(X/C)$ is named as likelihood where X is the evidence and C represents a hypothesis.

4) k-Nearest Neighbor (KNN): It is a supervised learning algorithm used for classification with a known target variable [28]. The data is initially 'trained' with regard to its respective data points. In order to determine the class of an unknown data point, 'K' nearest points is evaluated. Firstly, initialize number of K neighbors, thereby calculating the Euclidean distance between them. Then among these nearest k neighbors, we count the quantity of the data points in each of the category. The last step is to allocate the new data point into that category for which the number of the neighbour is largest. The 'K' nearby points are taken into consideration as the scale for classification in order to establish the class of an unknown data point. Results shown in our experiment is with the value of k=5.

IV. Results And Discussion

The gait database used in this work consists of total 31 subjects. A total of eight statistical features are extracted from 13 time series gait signal resulting in 104 features from each subject. The top 10% features (top 10 features) are extracted by filter-based MIG feature selection approach depending upon the score obtained by them. Similarly, a subset of another top 10% feature vector is obtained using wrapper- based RFE technique. A total of 20 features are obtained using both the techniques. The feature subsets obtained by these approaches are concatenated by taking union of the received feature vector hence giving a total of 14 features. Hence, the dimension of our dataset becomes 31 x 14. Experiments are performed using MATLAB 2021a with the intel i7 processor, 16 GB RAM, 512 GB SSD having 4 GB Nvidia graphics card. Table II and Table III shows the classification accuracy of MIG and RFE feature selection methods separately. Then to further increase the performance of the ML model concatenation of features is obtained by proposed hybrid MIG-RFE method and is evaluated which is shown in Table IV. Accuracy, precision, recall and F1-score are computed for ML models which are represented by (10), (11), (12) and (13) respectively. For a binary two- class classification problem the confusion matrix represents the number of correctly and incorrectly classified instances per class. True positive (t_p): Accurately classified number of PD patients; True negative (t_n): Accurately classified number of healthy individuals; False positive (f_p): Incorrectly classified number of healthy people as PD patients; False negative (f_n): Incorrectly classified number of PD patients as healthy people.

$$Accuracy\ (Acc) = \frac{t_p + t_n}{t_p + t_n + f_p + f_n} \qquad (10) \qquad Precision = \frac{t_p}{t_p + f_p} \qquad (11)$$

$$Recall = \frac{t_p}{t_p + f_n} \qquad (12) \qquad F1 - score = \frac{2 * Precision * Recall}{Precision + Recall} \qquad (13)$$

TABLE II. CALCULATION RESULTS OBTAINED USING MUTUAL INFORMATION GAIN (TOP 10% FEATURES)

Classifier	Accuracy	Precision	Recall	F1-score
Decision Tree	83.9%	0.82	0.87	0.84
Support Vector Machine	87.1%	0.88	0.88	0.88
Naïve Bayes	83.9%	0.82	0.88	0.88
KNN	80.6%	0.77	0.87	0.81

TABLE III. CALCULATION RESULTS OBTAINED USING MUTUAL RECURSIVE FEATURE ELIMINATION (TOP 10% FEATURES

Classifier	Accuracy	Precision	Recall	F1-score
Decision Tree	87.1%	0.875	0.875	0.875
Support Vector Machine	90.3%	0.93	0.87	0.89
Naïve Bayes	93.5%0	0.93	0.93	0.93
KNN	83.9%	0.82	0.87	0.84

TABLE IV CALCULATION RESULTS OBTAINED USING A HYBRID MIG-RFE FEATURE SELECTION ALGORITHM (TOP 10% FEATURES)

Classifier	Accuracy	Precision	Recall	F1-score
Decision Tree	90.3%	0.88	0.93	0.90
Support Vector Machine	93.5%	0.93	0.93	0.93
Naïve Bayes	**96.82%**	**1.00**	**0.93**	**0.96**
KNN	87.1%	0.83	0.93	0.87

In this study, a hybrid MIG-RFE feature selection method is proposed and it can be seen that the suggested feature selection technique improved the performance of the Naïve Bayes classifier, with an accuracy of 96.82 percent. A comparison is drawn of the designed system with recently published researches as shown in Table V. It can be seen that, our approach provided better accuracy then some of the previous works.

TABLE V COMPARISON WITH THE PREVIOUS WORK ON SAME DATASET

Paper	Methodology	Accuracy
[29] Saljuqi.et.al	Sparse Matching Pursuit +PCA	93%
[30] Xia.et.al	Cross Fuzzy Entropy +SVM	96.77%
[31] Ye.et.al	Adaptive Fuzzy Neuro Inference System + PSO	90.32%
Proposed Work	**MIG-RFE +Naïve Bayes**	**96.82%**

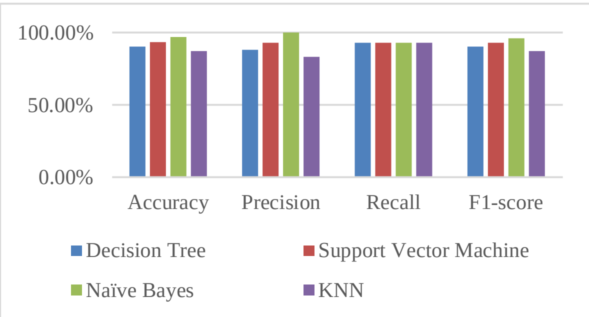

Figure.4. Experimental results of Proposed MIG-RFE approach

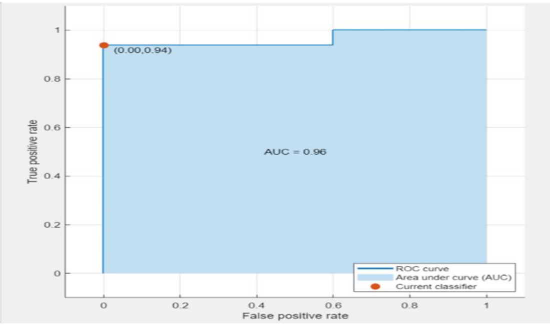

Figure.5. ROC curve of Naïve Bayes Classifier.

V. CONCLUSION

PD is a chronic disorder that worsens with time. Proper therapy and medicine can enhance the lives of Parkinson patient, which is feasible only with early detection. The primary emphasis of this research is a PD diagnostic system based on gait signals. Feature selection is critical for constructing ML models. Using the feature selection approach in an efficient manner can improve the classification accuracy and the performance of the model with the lesser number of features. This paper proposes a hybrid MIG-RFE feature selection algorithm based on MIG and RFE. The dataset used in this study consists of total 31 subjects from which 15 are PD patients and the remaining belongs to the healthy group. After data preprocessing, eight statistical features are extracted from thirteen different time series gait data. Top 10% significant features are chosen using MI and RFE. This resulted in total of 20 features. Then union of the selected features is obtained giving 14 features and classified by ML classifiers. Accuracy, precision, recall and F1-score are among the performance matrices evaluated to compute the performance of model. The k-fold (k=10) cross-validation approach was used for validation of the results. With an accuracy of 96.82%, the suggested approach surpasses the other ML and DL models. For future, the authors intend to work on finding the severity of PD disease utilizing standardized score defined by UPRDS. Due to limitation of dataset, the authors also plan to work on multiple datasets and employ recent deep learning techniques.

REFERENCES

[1] Zhao, Huan, et al. "Wearable sensors and features for diagnosis of neurodegenerative diseases: A systematic review." Digital Health 9 (2023): 20552076231173569.

[2] Lamba, Rohit, Tarun Gulati, and Anurag Jain. "A hybrid feature selection approach for Parkinson’s detection based on mutual information gain and recursive feature elimination." Arabian Journal for Science and Engineering 47.8 (2022): 10263-10276.

[3] Mohammadi, Ashena Gorgan, et al. "Parkinson's disease diagnosis: The effect of autoencoders on extracting features from vocal characteristics." Array 11 (2021): 100079.

[4] Shetty, Sachin, and Y. S. Rao. "SVM based machine learning approach to identify Parkinson's disease using gait analysis." 2016 International conference on inventive computation technologies (ICICT). Vol. 2. IEEE, 2016.

[5] Balaji, E., et al. "Automatic and non-invasive Parkinson’s disease diagnosis and severity rating using LSTM network." Applied Soft Computing 108 (2021): 107463.

[6] Bhat, Shreya, et al. "Parkinson's disease: Cause factors, measurable indicators, and early diagnosis." Computers in biology and medicine 102 (2018): 234-241.

[7] Morris, Meg E., et al. "Constraints on the kinetic, kinematic and spatiotemporal parameters of gait in Parkinson's disease." Human Movement Science 18.2-3 (1999): 461-483.

[8] Roiz, Roberta de Melo, et al. "Gait analysis comparing Parkinson's disease with healthy elderly subjects." Arquivos de neuro-psiquiatria 68 (2010): 81-86.

[9] Lamba, Rohit, et al. "A systematic approach to diagnose Parkinson’s disease through kinematic features extracted from handwritten drawings." Journal of Reliable Intelligent Environments (2021): 1-10.

[10] Gunduz, Hakan. "Deep learning-based Parkinson’s disease classification using vocal feature sets." IEEE Access 7 (2019): 115540-115551.

[11] Goyal, Jinee, Padmavati Khandnor, and Trilok Chand Aseri. "Analysis of Parkinson's disease diagnosis using a combination of Genetic Algorithm and Recursive Feature Elimination." 2020 Fourth World Conference on Smart Trends in Systems, Security and Sustainability (WorldS4). IEEE, 2020.

[12] Daliri, Mohammad Reza. "Chi-square distance kernel of the gaits for the diagnosis of Parkinson's disease." Biomedical Signal Processing and Control 8.1 (2013): 66-70.

[13] Alam, Md Nafiul, et al. "Vertical ground reaction force marker for Parkinson’s disease." PloS one 12.5 (2017): e0175951.

[14] Lee, Sang-Hong, and Joon S. Lim. "Parkinson’s disease classification using gait characteristics and wavelet-based feature extraction." Expert Systems with Applications 39.8 (2012): 7338-7344.

[15] Ertuğrul, Ömer Faruk, et al. "Detection of Parkinson's disease by shifted one dimensional local binary patterns from gait." Expert Systems with Applications 56 (2016): 156-163.

[16] Khoury, Nicolas, et al. "Data-driven based approach to aid Parkinson’s disease diagnosis." Sensors 19.2 (2019): 242.

[17] Veeraragavan, Srivardhini, et al. "Parkinson’s disease diagnosis and severity assessment using ground reaction forces and neural networks." Frontiers in physiology 11 (2020): 587057.

[18] Zhao, Aite, et al. "A hybrid spatio-temporal model for detection and severity rating of Parkinson’s disease from gait data." Neurocomputing 315 (2018): 1-8.

[19] Liu, Xu, et al. "A dual-branch model for diagnosis of Parkinson’s disease based on the independent and joint features of the left and right gait." Applied Intelligence (2021): 1-12.

[20] Ashour, Amira S., et al. "Long short-term memory-based patient-dependent model for FOG detection in Parkinson's disease." Pattern recognition letters 131 (2020): 23-29.

[21] Goldberger, Ary L., et al. "PhysioBank, PhysioToolkit, and PhysioNet: components of a new research resource for complex physiologic signals." circulation 101.23 (2000): e215-e220.

[22] Hausdorff, Jeffrey M., et al. "Gait variability and basal ganglia disorders: stride-to-stride variations of gait cycle timing in Parkinson's disease and Huntington's disease." Movement disorders 13.3 (1998): 428-437.

[23] Remeseiro, Beatriz, and Veronica Bolon-Canedo. "A review of feature selection methods in medical applications." Computers in biology and medicine 112 (2019): 103375.

[24] Yin, Zhong, et al. "Cross-subject EEG feature selection for emotion recognition using transfer recursive feature elimination." Frontiers in neurorobotics 11 (2017): 19.

[25] Ghane, Mostafa, et al. "Enhanced decision tree induction using evolutionary techniques for Parkinson's disease classification." Biocybernetics and Biomedical Engineering 42.3 (2022): 902-920

[26] Vapnik Vladimir, N. "The Nature of Statistical Lemming Theory [M]." New York: Spring-Verlag 286 (1995).

[27] Ghanad, Navid Khozein, and Saheb Ahmadi. "Combination of PSO algorithm and naive Bayesian classification for Parkinson disease diagnosis." Advances in Computer Science: an International Journal 4.4 (2015): 119-125.

[28] P. Hall, U. B. Park, and R. J. Samworth, “Choice of neighbor order in nearest-neighbor classification,” Annals Stat., Vol. 36, pp. 2135–52, 2008.

[29] Saljuqi, Masume, and Peyvand Ghaderyan. "A novel method based on matching pursuit decomposition of gait signals for Parkinson’s disease, Amyotrophic lateral sclerosis and Huntington’s disease detection." Neuroscience Letters 761 (2021): 136107.

[30] Xia, Yi, et al. "Symmetry analysis of gait between left and right limb using cross-fuzzy entropy." Computational and mathematical methods in medicine 2016 (2016).

[31] Ye, Qiang, Yi Xia, and Zhiming Yao. "Classification of gait patterns in patients with neurodegenerative disease using adaptive neuro-fuzzy inference system." Computational and mathematical methods in medicine 2018 (2018).