Multimodal Detection and Analysis of Parkinson's Disease

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Abstract. Parkinson's disease (PD) is a central nervous system neurodegenerative condition that causes temporary or permanent loss of motor movements, speech, and mental processes. Parkinson's disease (PD) is distinguished by characterized by a wide spectrum of movement and non-movement symptoms that can affect function to varying degrees. Unfortunately, PD is difficult to diagnose because there are no conventional diagnostic tests or systems that can be relied upon for accurate results. While the Unified Parkinson's Disease Rating Scale (UPDRS) is recommended as a first-line for monitoring Parkinson's disease progression, it must be administered by a neurologist, therefore it's not a good tool for evaluating short-term variations in the disease state. For this reason, neurologists need to use automated diagnostic technologies to aid them. The study focuses on the development of a system for estimating the prevalence of a person's Parkinson's disease (PD) symptoms by remotely monitoring numerical interpretations of their regular motor movements as movement disorders escalate. The research has also focused on the identification of the vocal impairments in Parkinson's disease patients flowing speech or vowel rhythm. Parkinson's patients with a more severe form of the condition sketch spiral at a slower pace and with less pressure. Hence, the proposed method uses Composite Feature Score (CFS) of Motor Movements (M), Sketching (S) & Pen Pressure (P) and Vocal Impairments (V) features to evaluate the severity of Parkinson's disease (PD) with a need to find parameters that have a greater link so that they can be taken into account for an appropriate diagnosis. Diverse multi-feature processing techniques have been utilized in the study to extract and compute valuable features to develop accurate scores for evaluating PD decision-support systems.

Keywords: Parkinson's disease (PD), Automated Diagnostic Technology, Composite Feature Score (CFS), Motor Movements (M), Sketching (S), Pen pressure (P), Vocal Impairments (V)

1 Introduction

Parkinson's disease (PD) is an escalating neurodegenerative disease associated with a wide range of movement and non-movement symptoms [1]. The rising frequency of Parkinson's disease (PD) [2] and the wavering life expectancy of

PD patients due to pharmaceutical or surgical treatments need the development of precise and dependable remote medicine systems for PD evaluation of patients. In Parkinson's disease (PD), the central nervous system's motor impulses, communication, cognitive processes, and other important functions are lost partially or completely [3, 4] and the dopamine-producing neurons in the brain are lost. One percent of population over the age of 50 suffer from Parkinson's disease [5, 6]. Since this ratio is likely to proliferate as people age, it's a risk factor for PD [7]. It's possible to alleviate some PD symptoms with medication, and surgical treatment, which can help increase the life expectancy of PD patients. It degeneration the central nervous system and presents a decrease in mobility, including tremors and stiffness. Speech symptoms include dysarthria (inability to articulate sounds), hypophonia (low volume), and monotone speech (reduced pitch range). Cognitive deficits and emotional changes are also possible, and dementia risk is elevated.

Parkinson's disease is traditionally diagnosed by assessing a patient's neurological history and evaluating their motor skills in various scenarios. It's generally difficult to diagnose PD because there is no conclusive diagnostic procedure for it, especially in the beginning when motor symptoms are not very significant. In order to keep track of the disease's course over time, patients must make frequent clinic appointments. Numerous multiple evaluation approaches are used to predict the presence of PD, including the Unified Parkinson's Disease Rating Scale (UPDRS), the Parkinson's Disease, and the Quality of Life Questionnaire. As a result, UPDRS is the most widely utilized approach [8,9]. But these methods have been proven to waste a lot of time and effort. An effective screening approach, especially one that does not involve a visit to the clinic, would be advantageous. As a result of machine-based solutions and medical decision-making in recent decades has benefited greatly from enhanced support.

In order to complete a specific task, the human motor system depends on a sequence of the stereotyped pattern of motor movement [10], such as hand swinging during walking. Distinctive movement patterns and the transitions between motions can be used to detect indicators of Parkinson's disease. PD patients can only be assessed utilizing a restricted number of methods. On average, clinicians evaluate patients once or twice a year under the supervision of a medical professional, utilizing the Movement Disorder Society's Unified Parkinson's Disease Rating Scale (or MDS-UPDRS). The prediction of these kinds of evaluations is often influenced by patient-reported characteristics and physician's perceptions of motor impairment [11]. Signals from an accelerometer are converted into numerical numbers. They are part of the learned motor repertoire, which includes subsets that are similar to different motions. Motor Movement (M) data from PD patients receiving a conventional neurological exam, healthy individuals through a similar protocol, and those living independently with Parkinson's disease are used to train machine learning algorithms. This enables to objectively monitor and evaluate Parkinson's disease progression and mobility quality in Parkinson's patients in an unsupervised context.

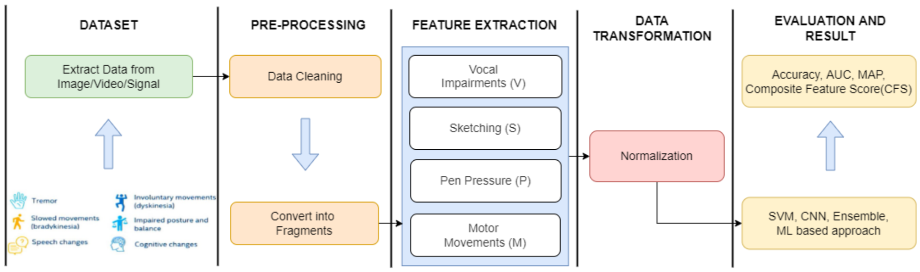


Fig. 1. The overview of methodology for detection analysis of Parkinson's Disease.

Tremor and postural instability are hallmarks of Parkinson disease. Patients handwriting and sketching skills are affected, and in the initial stage micrographia has been used to diagnose Parkinson's disease. In spite of the fact that language skills and education have an impact on a person's handwriting, researchers have shown that sketching a spiral shape is a non-invasive and unbiased measurement [12]. The relationship between handwriting and spiral sketching has been demonstrated in the initial stage of PD [13]. Writing or sketching is not without its limitations, however, as it requires a professional to evaluate the sketches, particularly in the initial stages of condition. Machine-based assessment of writing and sketching (S) feature is now possible with the availability of machine learning algorithms that can record hand-drawn sketches. For real-time and trustworthy handwriting analysis, these remote based monitoring are appropriate for extracting various behaviour of handwriting [14]. Clinical decision-making highly depends on factors such as tremor intensity which can be determined via spiral drawing kinematics. Finding demonstrates it is able to distinguish between between a control condition and PD in addition to inferior and superior tremors [15]. In addition to the sketching feature, PD patients pen-pressure (P) has been found to be lower than that of normal condition patients when sketching [16].

Speech has been demonstrated to fluctuate between PD patients and non-patients, numerous studies have shown a decline in speech [17]. Decreased loudness, lowered diversity in intensity and pitch, reduced harmonic overtones and nasal congestion, and inaccurate articulation are all features of speech that can be used to evaluate a patient's lengthy progression of the disease. Hence, vocal impairments (V) features of the patient can be employed as a diagnostic tool in a decision support system. Due to the fact that it is a non-invasive procedure and the speech data can be obtained quickly, it is a common pick. Speech samples have been utilized in a number of studies to help diagnose PD [18, 19]. The Figure 1 illustrates the overall framework of the project. The block diagram of the entire methodology is explained. Firstly data is extracted from data sources for both spiral sketching & pen pressure and the vocal impairments, then the data is preprocessed, cleaned and converted into fragments with different features are extracted from the fragmented features. The data included information and features from these four different features. This data is then normalized and used for training on different models as mentioned in the section evaluation and results. The model that gave the best results was used for evaluation purposes.

The primary focus of the research is to develop a trustworthy computer-based multi-feature evaluation of treatment outcomes. The features of Motor Movements (M), Sketching (S) & Pen Pressure (P), and Vocal Impairments (V) were investigated to differentiate between normal individuals and Parkinson's patients with varying degrees of severity, and a new Composite Feature Score (CFS) has been proposed with a significant correlation with treatment response. Individual features were identified in previous research, but the conjunction of these features had not been evaluated. The paper is presented in section as follows: related work is described in section 2. The description of the dataset used and data-preprocessing is presented in section 3. With two subsections, the overall proposed methodology is presented in section 4. The section 5 has a detailed experimental implementation, as well as the evaluations, conclusions, and interpretation. The research work is concluded with a conclusion and future scope in section 6.

2 Related Work

Detection of Parkinson's disease using existing systems which use various machine learning algorithms. Some even have multiple algorithms. They use features like speech, MRI scans, or Handwriting data. These systems have some drawbacks. Each system uses just one type of feature. This results in relatively low accuracy. Furthermore, one feature usually isn't enough to determine whether a person has Parkinson's. We aim to build a system that uses multiple features such as pen pressure, vocal impairments, and movements integrated into a single system which will help us to achieve better accuracy in detecting Parkinson's disease and also to analyze the severity of spread. The research work [20] investigated the achievability of utilizing speech to identify changes in drug states, based on the assumption that minor changes in voice and content connected to dopaminergic levels might be detected. For 25 PWP, they estimated acoustic and prosodic features for three speech tasks (image description, reverse counting, and diadochokinetic rate), evaluating 'True' and 'False' DRT for each. For the photo description challenge, they also created semantic features. They also discovered that DRT affected speech pace. Their findings imply that automatic speech analysis can detect variations in the DRT cycle. The proposed methodology, which comprises a combination of the k-means clustering-based feature weighting (KMCFW) algorithm and a complex-valued artificial neural network, is the paper's main novelty (CVANN) [21]. For the diagnosis of Parkinson's disease, researchers employed a Parkinson's dataset that included features extracted from speech and sound recordings. The weighting of PD attributes is done using the KMCFW approach. The new features are encoded in a complicated numerical format. The CVANN receives these feature values as an input. The suggested system's efficiency and efficacy were carefully validated against the PD dataset using five distinct evaluation methodologies.

This study recommended the use of the Composite Index of Speed and Pen-pressure (CISP) of sketching as a feature for measuring the severity of PD in the research work. [6] The speed, pen-pressure, and CISP of sketching a spiral are all adversely connected with the severity of PD, according to this study. While the severity of the condition had a substantial impact on these three characteristics, the CISP of sketching had the largest link. The difference in CISP between Severity Level (SL) 1 and 3 was statistically significant, but not for speed or pen-pressure. CISP, on the other hand, was unable to distinguish between SL1 and SL2 or SL2 and SL3. Tsanas et al. [22] used signal processing techniques to estimate the unified Parkinson's disease rating scale (UPDRS) using linear and non-linear regression on voice recordings from 42 people with early-stage Parkinson's disease. The researchers discovered a 7-point discrepancy in accuracy between clinical and non-clinical UPDRS assessments. The research work [11] demonstrates how the stationary representation of movement syllables captures the entire quality of motor action. Both in clinical settings where scripted actions are performed and in unconstrained normal life, the proposed technique distinguishes motor impairment accompanying various PD-associated states. The suggested approach was specifically evaluated on movement abnormalities associated with Parkinson's disease, but we see no reason why it couldn't be applied to other neurological conditions with distinct movement characteristics. Seven characteristic parameters were collected from spiral drawing experiment hand movement in [23] [24] The characteristic value was interpolated linearly. In this publication, the researchers found a few good predictors of Parkinson's disease.

For enhancing PD diagnosis, a new classification technique based on support vector machine (SVM) selected features to train rotation forest (RF) ensemble classifiers is given [25]. The dataset contains voice measures from 31 people, 23 of whom have Parkinson's disease, and each record is defined by 22 attributes. The diagnosis model starts by using a linear SVM to pick the top ten features out of a total of 22. Six alternative classifiers are trained using the subset of features in the second step of the classification model. The accuracy of classifiers is then improved in the third stage by employing the RF ensemble classification approach. The classification accuracy (ACC), Kappa Error (KE), and Area under the Receiver Operating Characteristic (ROC) Curve are three metrics used to evaluate the results of the tests (AUC). After all, using the RF ensemble classification strategy considerably improved PD diagnosis in 5 of the 6 classifiers. In the RF ensemble of the IBk (a K-Nearest Neighbor variation) algorithm, they achieved about 97% accuracy, which is quite good for Parkinson's disease diagnosis. Therefore research aims to the development of a new hybrid features remote diagnostic method that can be used to solve the PD diagnosis dilemma. The novelty of the research work lies in the proposed approach that involves a combination of the feature score obtained from movement, speech samples, sound samples, and notepaper samples for the remote diagnosis of Parkinson's Disease.

3 Dataset Source and Data-Preprocessing

3.1 PD and Control Handwriting Dataset [26]

The dataset used for the Sketching (S) & Pen Pressure (P) consists of 15 healthy people and 62 Parkinson's Patients from the Department of Neurology at Istanbul University's Cerrahpasa Faculty of Medicine. Three distinctive tests were developed by collecting three types of handwriting records from all subjects (Stability Test on Certain Point, Static and Dynamic Spiral Test) through graphics tablet in the research work. The Static Spiral Test (SST), has been utilized in clinical research for a variety of objectives including evaluating tremors, examining movement function, and interpreting Parkinson's disease. In this test, the program displays three wound Archimedean spirals on the graphics tablet, and patients are asked to retrace the same spiral as many times as they can with the digital pen. The above-mentioned traits, as well as other data used to identify the patient, are registered in the database during the test. The Dynamic Spiral Test (DST) is the second test. The Archimedean spiral blinks in other words become visible at certain time intervals. The patients are constrained to remember the pattern and keep drawing. Because retracing the Archimedean spiral is strenuous in this situation, the goal of this test is to see how the patient's drawing performance and pause times have changed. The majority of the patients continued to draw as a result of this test, however, every patient failed to remember the pattern. The Stability Test on a Specific Point (STCP) is the third test. The patients are instructed to hold the digital pen on a red point in the middle of the screen for a set amount of time without touching the screen. The goal of this test is to figure out how stable the patient's hands are or how much tremor the patient has.

Table 1. Features of Vocal Sketching (S) and Pen Pressure (P)

	Features
Sketching (S)	Horizontal and Vertical Velocity Horizontal and Vertical Acceleration Horizontal and Vertical Jerk Magnitude (Velocity, Acceleration, Jerk) Number of Changes in Velocity Direction (NCV) Number of Changes in Acceleration Direction (NCA) Relative NCV and NCA
Pen Pressure (P)	In-Air Time On-Surface Time Number of Strokes Stroke Speed

The X_m and Y_m coordinates, Pressure (P_m), and Timestamp (t) for the three tests mentioned are initially parameters. They are examined in terms of Test ID for computing Sketching and Pen Pressure features. The feature computation involves the sketching features which are computed using the kinematic formulation. The features include Horizontal, Vertical, and Magnitude (Velocity, Acceleration, and Jerk). Number of Changes in Velocity Direction (NCV) and Acceleration Direction (NCA) calculated utilizing the number of relative extremum on mean for velocity and acceleration, Relative NCV and NCA. Therefore, the time duration is considered in the iteration of $(t+1)$ while calculating the magnitudes for sketching of spiral by considering the $X_m(t)$ and $Y_m(t)$ coordinates at time t.
Magnitude of Velocity -

$$V_m = \sqrt{[X_m(t+1) - X_m(t)]^2 + [Y_m(t+1) - Y_m(t)]^2} \tag{1}$$

Magnitude of Acceleration -

$$A_m = \sqrt{[V_x(t+1) - V_x(t)]^2 + [V_y(t+1) - V_y(t)]^2} \tag{2}$$

Magnitude of Jerk -

$$J_m = \sqrt{[A_x(t+1) - A_x(t)]^2 + [A_y(t+1) - A_y(t)]^2} \tag{3}$$

Further, the extraction and computation of pen pressure is the threshold value of the pressure ($P_{threshold}, 1 < P_{threshold} < 1024$) such In-Air Time ($P_m > P_{threshold}$) and On-Surface Time ($P_m < P_{threshold}$). Next, the number of strokes is calculated by utilizing the On-Surface Time, and Strokes Speed is computed by is dividing the stroke distance by the time duration of the stroke [27]. The attribute information is represented in Table 1

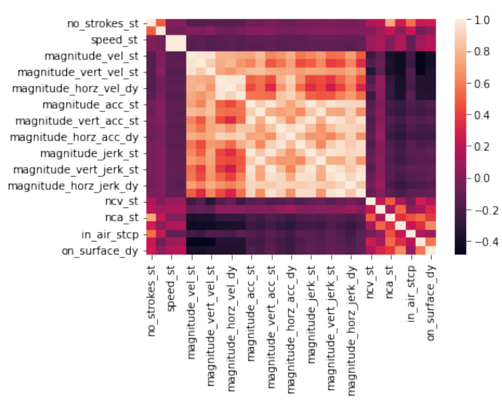


Fig. 2. Correlation matrix of the dataset features for Sketching(S) & Pen Pressure(P).

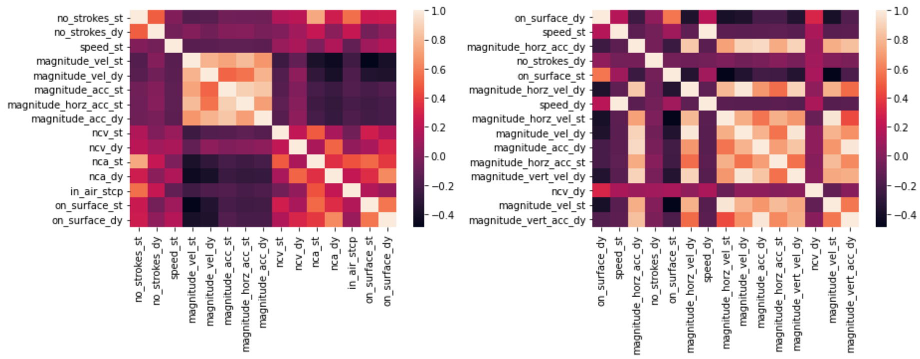


Fig. 3. Correlation matrix of the selected features for Sketching(S) & Pen Pressure(P) using Correlation and P-value (left) and Relevance Minimum Redundancy (mRMR) (right) technique.

Feature selection techniques were applied to the above-mentioned attributes. Therefore, out of the initial 29 features related to the above-mentioned attributes were processed, 15 different features were extracted using the Correlation and P-value technique and the Maximum Relevance Minimum Redundancy technique. In the Correlation and P-value technique, the p-value is calculated for each attribute. These measured p-values and the correlation can be used to decide whether to keep a feature or not. Minimum redundancy feature selection is a method for reliably identifying features phenotypes and narrowing down their significance using an algorithm called minimum redundancy feature selection. The correlation between the Sketching & Pen Pressure features are depicted in the correlation matrix in Figure 2. The correlation between the selected Sketching & Pen Pressure features using Correlation and P-value (left) and Maximum Relevance Minimum Redundancy (mRMR) (right) technique are depicted in the correlation matrix in the Figure 3 respectively.

3.2 Parkinson Speech Dataset With Multiple Types Of Sound Recordings Data Set [28]

The dataset used for the Vocal Impairments (V) in the research was developed by Professor Max Little of the University of Oxford by recording the speech signals, in partnership with the National Center for Voice and Speech in Denver, Colorado. This dataset contains a variety of biological voice measurements from 31 individuals, 23 Patients with Parkinson's (PwP). Each column in the table represents a different voice measure, and each row represents one of the 195 voice recordings by these people. Table 2 lists the features that were left following feature selection and were used in this study. As a result, 26 features were initially processed, 11 different features were extracted using the Correlation and P-value technique and the Maximum Relevance Minimum Redundancy technique and are shown in Table 3 and 4 respectively.

Table 2. Features of Vocal Impairements(V)

Features	**Group**
Average Fundamental Frequency (MDVP:Fo) Highest Fundamental Frequency (MDVP:Fhi) Lowest Fundamental Frequency (MDVP:Flo) Jitter (local), Jitter (absolute), Jitter (ddp)	Frequency Parameters
Amplitude Perturbation Quotient (MDVP:APQ) Relative Average Perturbation (MDVP:RAP) Pitch Period Perturbation Quotient (MDVP:PPQ) spread1, spread2 (Quantification)	Perturbation Parameters
Noise-to-harmonic, Harmonic-to-noise Autocorrelation	Harmonic Parameters
Shimmer (local), Shimmer (local, dB) Shimmer (apq3), Shimmer (apq5), Shimmer (apq11) Shimmer (dda)	Amplitude Parameters
Recurrence Period Density Entropy (RPDE) Detrended Fluctuation Analysis (DFA) Correlation Dimension (D2) Pitch Period Entropy (PPE)	Miscellaneous Parameters

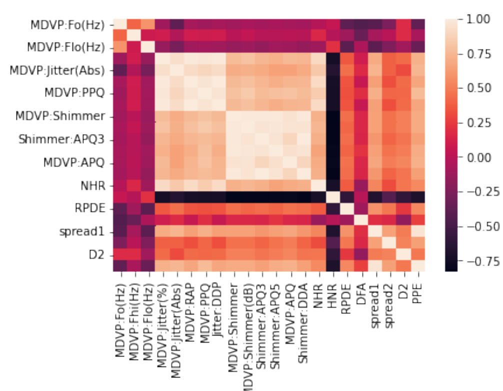


Fig. 4. Correlation matrix of the dataset features for Vocal Impairments (V).

Table 3. Features extracted using Features Technique 1 - Correlation and P-value.

Features	**Group**
Average Fundamental Frequency (MDVP: Fo) Highest Fundamental Frequency (MDVP:Fhi) Lowest Fundamental Frequency (MDVP:Flo) Jitter (local)(MDVP: Jitter(%)) spread1, spread2 (Quantification)	Frequency Parameters
Shimmer (local)	Perturbation Parameters
Harmonic-to-noise	Harmonic Parameters
Detrended Fluctuation Analysis (DFA) Correlation Dimension (D2) Recurrence Period Density Entropy (RPDE)	Miscellaneous Parameters

Table 4. Features extracted using Feature Technique 2 - Maximum Relevance Minimum Redundancy (mRMR)

Features	**Group**
Average Fundamental Frequency (MDVP: Fo) Highest Fundamental Frequency (MDVP:Fhi) Lowest Fundamental Frequency (MDVP:Flo) spread1, spread2 (Quantification)	Frequency Parameters
Amplitude Perturbation Quotient (MDVP:APQ)	Perturbation Parameters
Harmonic-to-noise	Harmonic Parameters
Shimmer (local)	Amplitude Parameters
Detrended fluctuation analysis (DFA) Correlation dimension (D2) Pitch Period Entropy (PPE)	Miscellaneous Parameters

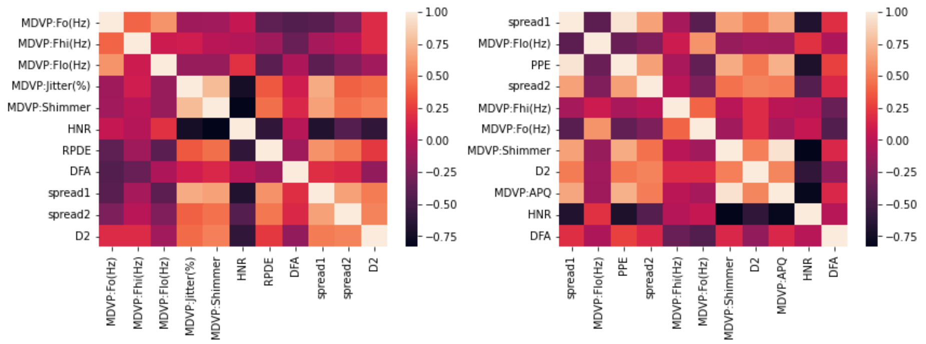


Fig. 5. Correlation matrix of the selected features for Vocal Impairments (V) using Correlation and P-value (left) and Maximum Relevance Minimum Redundancy (mRMR) (right) technique.

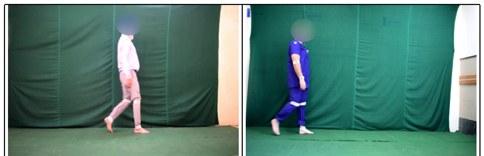
The correlation between the vocal impairments features is depicted in the correlation matrix in Figure 4. The correlation between the selected vocal impairments features using the Correlation and P-value technique (left) and the correlation using the Maximum Relevance Minimum Redundancy (mRMR) technique (right) is depicted in the correlation matrix in Figure 5 respectively. The primary goal of the vocal impairments data is to distinguish healthy persons from those with Parkinson's disease patients.

3.3 Motor Movement Dataset (KOA-PD-NM) [29, 30]

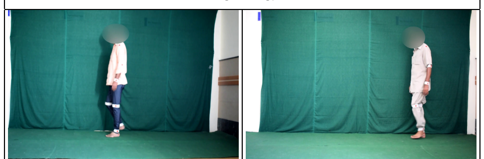
This dataset includes the demographic information of Knee Osteoarthritis (KOA), Parkinson's disease (PD), and healthy/ normal (NM) subjects. Total 16 Parkinson's Disease (PD), and 30 Normal/Healthy (NM) patients are included in the gait video collection, with two sequences (left to right and right to left) for each subject in the frontal plane. The single NIKON DSLR 5300 camera was placed 8 meters distant from the walking mat in the hospital area, and a set of 6 red-colored passive reflective markers were mounted to the subject's body joints to gather the dataset (each video in MOV format).

The research work utilizes the Normal/Healthy (NM) and Parkinson's Disease (PD) video from the KOA-PD-NM dataset. Primarily the kinematic features are detected and computed frame by frame from the normal and Parkinson video input. The key points (x-y coordinates) are extracted for each frame, and thereafter evaluate kinematic features using a bottom-up technique and developing a feature set with coordinates, velocity, and acceleration features. The information about a sample frame from each category of the used dataset in the research work is presented in Table 5.

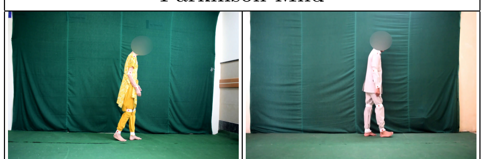
Table 5. Table illustrate a sample frame from each category of motor movement dataset in the research work.



Normal



Parkinson-Mild



Parkinson-Severe

4 Methodology

The primary goal of the methodology is to provide the minimum need to clinicians to rate the severity of the different symptoms that today are being done manually using machine learning algorithms and data that is collected from movement, speech and sound samples, and notepaper samples and being able to translate that into a reliable composite score. The proposed research, instead of examining the effectiveness of every feature and processing approach individually, evaluates the composite features score and also performs a feature selection, and derives numerous features and processing strategies into a single feature parameter. The work utilizes various feature subset classification in the research. There are two important reasons for using the proposed method. First, the study intends to examine and showcase the evaluation of every feature parameter in identifying normal participants from Parkinson's disease patients using several classifiers. Second, because the composite feature set is the unique utilized feature set, it is examined as a separate group and evaluates the effectiveness of every selected feature in the particular model.

4.1 Sketching(S) & Pen Pressure(P) and Vocal Impairments(V)

In the methodology, initially using the Minimum Redundancy Maximum Relevance [32] and Correlation and P-value filter techniques, the features are ranked based on their relevance with the classification model and redundancy with other

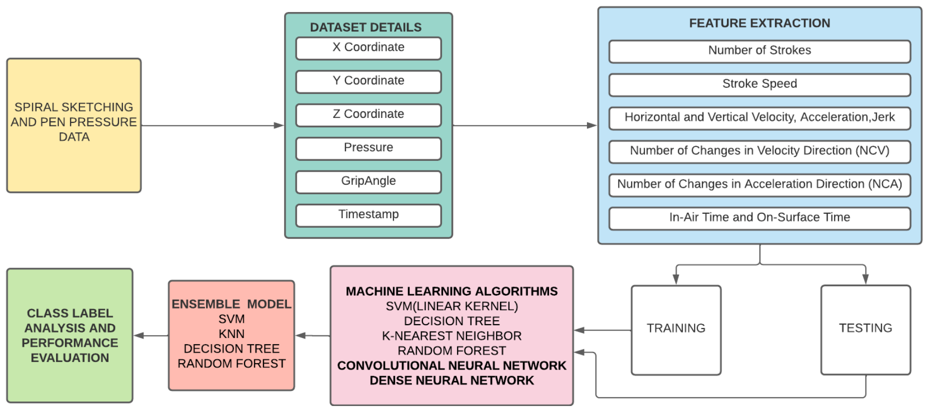


Fig. 6. The overall architecture diagram for Sketching (S) & Pen Pressure (P) feature.

features and report the results produced using the highest-ranked features. The overall architectural diagram for the module sketching and pen pressure feature is shown in Figure 6 were initially the dataset containing the coordinates, pen pressure, grip angle, and timestamp feature, then the velocity and acceleration features are computed from the initial features and the data is segregated into training and testing sets. Further various machine learning techniques like Support vector machines (SVM) with linear kernels, an instance-based learning algorithm (k-Nearest Neighbour), a decision-tree-based learning algorithm (Random Forest) are used individually and also comprise the ensembles [31].

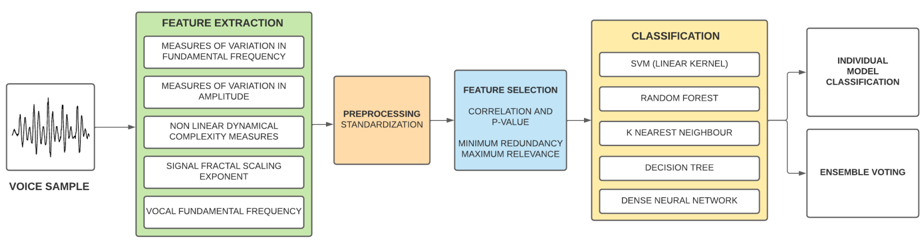


Fig. 7. The overall architecture diagram for Vocal Impairments (V) feature.

The architectural diagrams for the vocal impairments feature where features are extracted from features and the data is preprocessed and the feature selection technique is applied is represented in Figure 7. Numerous machine learning algorithms are implemented and the comparative result is calculated for individual model classification and also ensemble voting. The evaluation of sketching and signal processing methods employing ensemble learning techniques, which incorporate the predictions of four machine learning algorithms, is another significant contribution of the research. The research proposes to mitigate the impact of classifiers in the evaluation of feature extraction techniques, as well as the variation of the ultimate classification techniques, by integrating the predictions of various classifiers.

Fig. 8. The architectural framework of Dense Neural Networks.

For sketching & pen pressure, the Convolutional Neural Network (CNN) has been implemented to showcase the comparative result. The neural network is used to classify the data into two classes is provided with the spiral waveforms images of Parkinson's and normal individuals which have been resized to 224x224 dimensions. The CNN architecture implemented is constructed using five blocks of consecutive convolution and pooling layers. Every five blocks constructed, has a total of thirteen convolutional layers with kernels, five max-pooling layers, fully connected layers, and a layer with a sigmoid activation function to predict the output (VGGNet architecture). The second deep learning technique for the sketching & pen pressure, vocal impairments, and motor movements is the Dense Neural Network (DNN). DNNs are made up of neurons, that are fundamental components that are linked by interconnecting interconnection and have a weight that is compounded by the information transferred through the structure. The six layers dense neural network framework is developed with five dense layers with ReLu activation function and an output layer with two neurons and softmax activation function for prediction of Parkinson positive and negative as shown in Figure 8. The input layer is made up of neurons that represent sketching & pen pressure extracted feature, various sound parameters for vocal impairments, and extracted keypoints and motion keypoints for motor movements.

4.2 Motor Movements (M)

The research work proposes the methodology to compute the motor movements of the individuals in the video dataset using kinematic features and detect the normal and Parkinson mild and server-class based on the computed features using machine learning and deep learning techniques. The framework primarily collects the information from the video input, including key points (x-y coordinates), and thereafter evaluates kinematic features frame by frame using a bottom-up technique. In order to determine the 2-D skeleton of the person in the frame, the proposed methodology applied model [33] effectively. To understand the importance of body motion and the motion keypoints associated with individuals in the frame, the method uses a non-parametric formulation. Frame per frame, the framework collected 18 keypoints (x-y coordinates) from the videos. The kinematic keypoints are computed to parameterize the motion in order to understand more effectively (velocity and acceleration). These 18 kinematic keypoints (velocity and acceleration) and 18 body position keypoints are captured. Because of the invisibility and overlap of human joints, the pose-estimation algorithm was unable to detect and some of the keypoints were missed by the method, and the uncaptured keypoints were indicated by a zero. Hence the missing keypoints were substituted with zero and were addressed in data pre-processing. The frames with more than five missing keypoints are not useful for training.

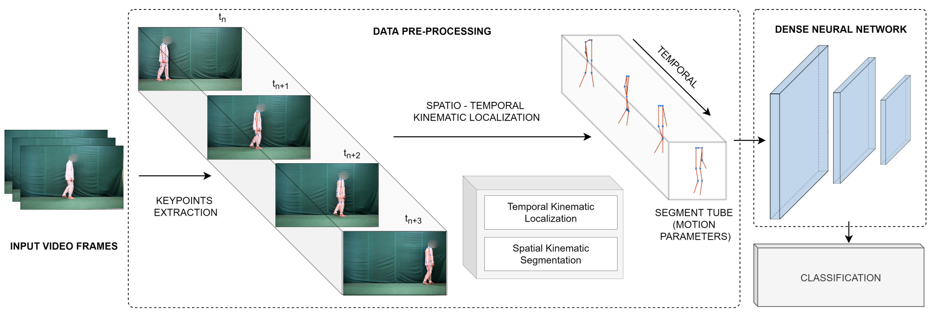


Fig. 9. The overall architecture diagram for the Motor Movement (M) features.

Let x_n and y_n be the coordinates of the n^{th} frame captured at time t_n. The time period between two consecutive frames t_d is computed by subtracting the captured time of frame $frame_n$ and the successive frame $frame_{n+1}$. The x and y subscript represents the velocity and acceleration in x and y direction respectively.

$$t_d = t_{n+1} - t_n \tag{4}$$

The difference between successive frames is used to determine the velocity of the keypoints in the underlying conceptual framework.

$$V_x = \frac{x_{n+1} - x_n}{t_d} \tag{5}$$

$$V_y = \frac{y_{n+1} - y_n}{t_d} \tag{6}$$

The magnitude of velocity has been computed as follows-

$$V_n = \sqrt{V_x^2 + V_y^2} \tag{7}$$

The difference in velocity of keypoints in successive frames is used to determine acceleration.

$$a_x = \frac{(V_x)_{n+1} - (V_x)_n}{t_d} \tag{8}$$

$$a_y = \frac{(V_y)_{n+1} - (V_y)_n}{t_d} \tag{9}$$

The magnitude of acceleration has been computed as follows-

$$a_n = \sqrt{a_x^2 + a_y^2} \tag{10}$$

Every frame is labeled with the class that corresponded to it, as well as the 18 body keypoints, to generate a feature set with a total of 72 features including 36 kinematic keypoints. Different structural placements demonstrate distinct characteristics. Therefore as result, a particular joint keypoint can be postulated as human movement. The kinematic keypoints (velocity and acceleration) are computed as described above after the missing keypoints are managed. The extracted 72 feature set is used for training and testing the machine learning and deep learning model which is discussed in the previous subsection.

5 Result Analysis and Evaluation Measures

The proposed method uses Composite Feature Score (CFS) of motor movements (M), sketching (S), pen pressure (P), and vocal impairments (V) features to evaluate the severity of Parkinson's disease (PD). Diverse multi-feature processing techniques have been utilized in the study to extract valuable parameters for Parkinson's disease evaluation, and the computed features are input into different machine learning and deep learning algorithms to develop accurate scores for decision-support systems. The machine learning approaches are used to model the retrieved features.

The proposed work implements the correlation and p-value technique and minimum redundancy-maximum relevance (mRMR) [32] knowledge feature selection technique to select the appropriate and suitable features as well as to collect a precise and efficient PD recognition framework by minimizing the computationally challenge to a minimum threshold with high interdependence. The mRMR technique is based on limiting redundancy among high-ranking parameters in order to maximize their concurrent interdependence on the dependent variable. For pre-processing steps, the mRMR algorithm has indeed been extensively used for a wide range of machine learning tasks. The research also uses mRMR to examine the effect of subsets of features and develop a collection of features to distinguish between Parkinson's disease patients and healthy people. The analysis of the experiment is performed using NVIDIA GeForce GTX 1650 with a 4.5 GHz Intel Core processor and 16GB DDR4 RAM.

5.1 Sketching(S) & Pen Pressure(P)

Multiple independent classification techniques are used in ensemble classification, and the classification outputs are integrated using a combined approach. Theoretical and empirical research on ensemble learning indicated that to generate more accurate measurement results, the ensemble members must be heterogeneous and precise. Based on the research findings, the research uses a variety of learning algorithms in an ensemble model, including SVM with linear kernels, K-Nearest Neighbour, Decision-tree, and Random Forest. For ordinal scoring, the predictions of individual classifiers are combined using the hierarchical stacked model approach. Table 6 represents the performance evaluation of the proposed work with different classifiers and feature selection techniques for sketching & pen pressure with accuracy, precision, and recall parameters. The precision, recall, F1 score, and accuracy metrics are used to demonstrate the evaluation performance for sketching & pen pressure depicted in Table 6.

Table 6. Performance evaluation of proposed work with different classifiers and feature selection techniques for Sketching & Pen Pressure.

Feature Set	**Model Name**	**Precision**	**Recall**	**F1-Score**	**Accuracy**
Baseline Features	SVM (Linear kernel)	0.7638	0.8333	0.7971	0.8194
	K Nearest Neighbor	0.7361	0.8983	0.8091	0.8611
	Random Forest	0.7916	0.9324	0.8837	0.8737
	Decision Tree	0.7916	0.8124	0.8837	0.9123
	Ensemble	0.8754	0.8401	0.7832	0.8464
Correlation & P-value	SVM (Linear kernel)	0.7345	0.8546	0.7913	0.8198
	K Nearest Neighbor	0.7334	0.8876	0.8294	0.8614
	Random Forest	0.8716	0.9745	0.9437	0.9834
	Decision Tree	0.8716	0.9124	0.9837	0.9624
	Ensemble	0.7216	0.8212	0.7823	0.7875
Maximum Relevance Minimum Redundancy (mRMR)	SVM (Linear kernel)	0.7044	0.8345	0.7568	0.7638
	K Nearest Neighbor	0.7232	0.8864	0.8086	0.8472
	Random Forest	0.8713	0.9642	0.9473	0.9834
	Decision Tree	0.8826	0.9424	0.9073	0.9623
	Ensemble	0.8734	0.8412	0.8232	0.8635

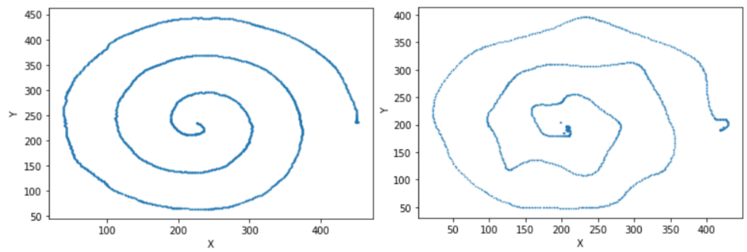


Fig. 10. Illustration of spiral sketched by the normal individual (left) and Parkinson's patient (right).

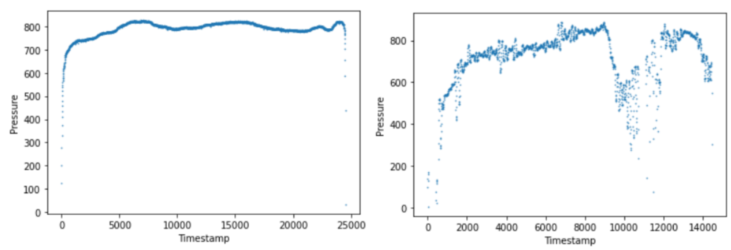


Fig. 11. Pen pressure graph of the normal patient (left) and Parkinson's patient (right) with respect to time.

Figure 10 represent the spiral sketched for the spiral sketching test of the Parkinson's (right) and normal (left) patients. The right spiral sketched in Figure 10 represents the Parkinson's patient with increasing severity. Figure 11 represent the pen pressure graph against the time of the normal (left) and Parkinson's (right) patient. Figure 12 and Figure 13 represents accuracy and loss graphs of accuracy and loss for sketching & pen pressure with respect to the number of epochs for training and testing datasets using the proposed Convolutional Neural Network and Dense Neural Network methodology respectively.

5.2 Vocal Impairments(V)

The proposed model is implemented using various models, which are trained for obtaining the optimum training and testing accuracies for the vocal impairments dataset. An Ensemble model combining four base models viz. K-Nearest Neighbour classifier, decision tree classifier, random forest, and the SVM classification model are proposed in order to produce one optimal predictive model. Therefore, the vocal impairment dataset has been trained on different machine learning models along with the dense neural network. The classification metrics for the training and testing accuracy for sketching & pen pressure and vocal impairments using Convolutional Neural Network and Dense Neural Network are mentioned in Table 7.

Table 7. Performance evaluation for modules Sketching(S) & Pen Pressure(P) And Vocal Impairments(V) using DNN And CNN

Methods	**Dense Neural Network (DNN)**		**Convolutional Neural Network (CNN)**	
	Accuracy (%)		Accuracy (%)	
	Training	Testing	Training	Testing
Sketching(S) and Pen Pressure(P)	88.68	83.34	93.38	92.16
Vocal Impairments(V)	96.5	92.68	-	-

Table 8. Performance evaluation of proposed work with different classifiers and feature selection techniques for Vocal Impairments.

Feature Set	**Model Name**	**Precision**	**Recall**	**F1-Score**	**Accuracy**
Baseline Features	SVM (Linear kernel)	0.7334	0.9167	0.8148	0.8968
	K Nearest Neighbor	0.7333	0.9167	0.8148	0.9222
	Random Forest	0.7451	0.9954	0.8448	0.9986
	Decision Tree	0.7345	0.9958	0.8342	0.9972
	Ensemble	0.7454	0.9964	0.8452	0.9018
Correlation & P-value	SVM (Linear kernel)	0.7085	0.8732	0.7823	0.8628
	K Nearest Neighbor	0.7257	0.9278	0.8418	0.9256
	Random Forest	0.8824	0.9438	0.9548	0.9868
	Decision Tree	0.7435	0.9234	0.8542	0.9428
	Ensemble	0.7428	0.9045	0.8542	0.9198
Maximum Relevance Minimum Redundancy (mRMR)	SVM (Linear kernel)	0.7686	0.8732	0.7923	0.8668
	K Nearest Neighbor	0.7143	0.9367	0.8648	0.9268
	Random Forest0	0.7834	0.9632	0.8824	0.9878
	Decision Tree	0.8428	0.9654	0.9234	0.9743
	Ensemble	0.8454	0.9296	0.9045	0.9364

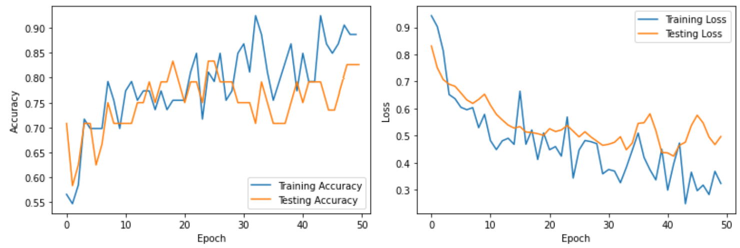


Fig. 12. Graphs of accuracy and loss for Sketching(S) & Pen Pressure(P) on training and testing datasets using Dense Neural Network.

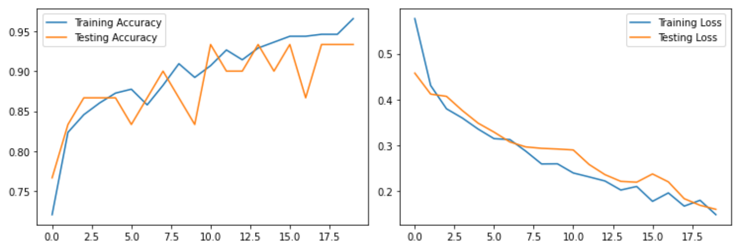


Fig. 13. Graphs of accuracy and loss for Sketching(S) & Pen Pressure(P) on training and testing datasets using Convolutional Neural Network.

Figure 14 represents accuracy and loss graphs of accuracy and loss for vocal impairments with respect to the number of epochs for training and testing datasets using the proposed Dense Neural Network methodology. Table 8 represents the performance evaluation of the proposed work with different classifiers and feature selection techniques for vocal impairments. The evaluation parameters used to demonstrate the performance are precision, recall, F1 score, and accuracy metrics as depicted in Table 6.

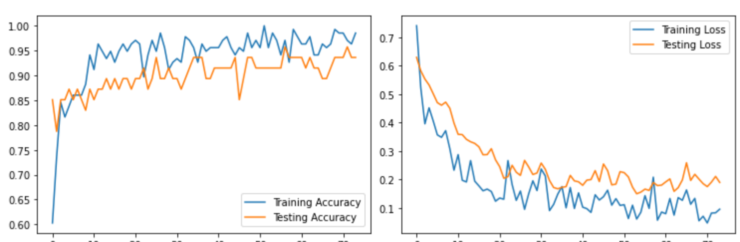


Fig. 14. Graphs of accuracy and loss for Vocal Impairments(V) on training and testing datasets using Dense Neural Network.

5.3 Motor Movements(M)

The research work has used four different models to classify the proposed motor movement dataset into three categories namely Normal, Mild Parkinson, and Severe Parkinson. The comparative result for the applied models included Dense Neural Network (DNN), SVM using poly and RBF kernel, and Random Forest classifier in terms of Precision, Recall, F1-Score, and classification accuracy is shown in Table 9. Figure 15 display the epochs vs. accuracy and epochs vs. a loss of the dense neural network model's classification process, respectively.

Table 9. Performance evaluation of proposed work with different classifiers for motor Movements

Model Name	Precision	Recall	F1 score	Accuracy
Dense Neural Network	0.9882	0.9912	0.9867	0.9820
SVM (poly kernel)	0.9072	0.9737	0.9653	0.9765
SVM (RBF kernel)	0.9163	0.8655	0.9279	0.9354
Random Forest	0.9552	0.9737	0.9653	0.9782

Furthermore, the ROC curve for Dense Neural Network, Random Forest model, and SVM with poly, RBF kernel model for Normal, Mild and Severe Parkinson Patients are shown in Figure 16 each class. The ROC curve is used to assess the performance of the proposed method. The AUC value for the proposed models for different classes is shown and ranged from 0.85 to 0.99, while the AUC value range for DNN is 0.98 to 0.99 indicating that the Dense Neural Network correlates well enough for classification.

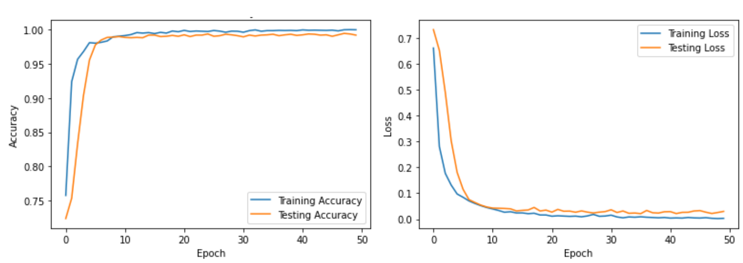


Fig. 15. Graph of Epochs vs. Accuracy and Epochs vs. Loss for the motor movement classification using dense neural network model.

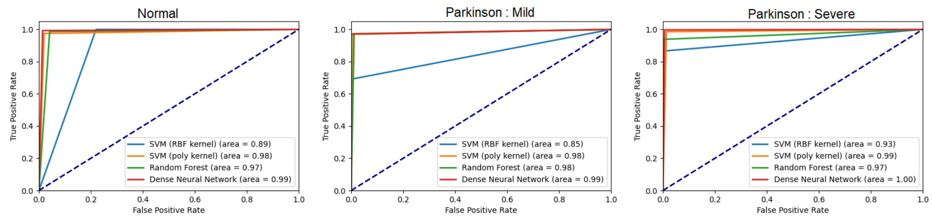


Fig. 16. ROC curves for different models in comparison with Normal, Mild and Severe Parkinson Patients.

5.4 Composite Feature Score (CFS)

The Composite Feature Score of sketching (S), pen pressure (P), and vocal impairments (V) feature to examine the severity of Parkinson's disease (PD) is proposed. Initially, the composite score for the vocal impairments and sketching & pen pressure for a particular patient is calculated using the harmonic mean of the predicted class probability. The harmonic mean is considered because the class probability values are distinct measurements and it is used to determine divisor and multiplicative connections between the values. The harmonic mean provides every parameter the same significance, without providing higher weight to particular class values, and normalizes the probability values while equating the composite score.

Let $f_{pr}(x)$ be the predict probability function of the vocal impairments and sketching & pen pressure classifier and $f_{class}(x)$ be the predict class function of motor movement, where x is the input parameter. Let S_{vocal}, I_{spiral}, and V_{motor} be the input data of the vocal impairments, sketching & pen pressure, and motor movements respectively. Let the composite score $K_{v.sp}(-1 < K_{v.sp} < 1)$ for the vocal impairments $(V(\alpha)_p)$ and sketching & pen pressure $(SP(\beta)_p)$ for patient p is calculated as described $(0 < V(\alpha), SP(\beta) < 1)$ -

$$V(\alpha)_p = f_{pr}(S_{vocal}) \tag{11}$$

$$SP(\beta)_p = f_{pr}(I_{spiral}) \tag{12}$$

$$(K_{v \cdot sp})_p = \frac{2 \times V(\alpha)_p \times SP(\beta)_p}{V(\alpha)_p + SP(\beta)_p} \tag{13}$$

Next, for the motor movement the prediction of the Normal, Parkinson-Mild and Parkinson-Severe class is represented by $M(\delta)_p$, where $M(\delta)_p \in \{Normal - 0, Parkinson\ Mild - 1, Parkinson\ Severe - 2\}$

$$M(\delta)_p = f_{class}(V_{motor}) \tag{14}$$

Furthermore, the integer value of the $K_{v \cdot sp}$ and $M(\delta)$ is calculated by multiplying by λ in order to define the range to examine the level of severity. If the class prediction of both vocal impairments and sketching & pen pressure is the Person with Parkinson (PwP) then the value of $\lambda = -1$ else the value of $\lambda = 1$. Therefore, the value of the composite feature score for particular patient p is calculated using formula-

$$(V_{cfs})_p = \frac{\lambda}{2}((K_{v \cdot sp})_p + M(\delta)_p) \tag{15}$$

Table 10. The table demonstrates the level of severity with the composite feature score.

$V(\alpha)$	$SP(\beta)$	$M(\delta)$	V_{cfs}
Normal	Normal	0 Normal	$0 < V_{cfs} < 1$
PwP	PwP	1 Parkinson Mild	$-1 < V_{cfs} < 0$
PwP	PwP	2 Parkinson Severe	$-2 < V_{cfs} < -1$

The Table 10 demonstrates the calculation of composite feature score and the level of severity range for Parkinson's patient and normal individual with different motor movement class.

6 Conclusion

Parkinson's disease (PD) is a progressive neurological disorder described by a broad spectrum of movement and non-movement parameters. The characteristic progression of Parkinson's disease is varying; however, it is frequently faster in individuals with Postural instability and gait disorders. Because the definitive diagnostic tests for Parkinson's disease are not available, practitioners must have a good understanding of its clinical presentations in order to distinguish it from other conditions. The research reveals how an automatic detection technology can support a neurologist diagnose Parkinson's disease. The proposed system, termed motor movements (M), sketching (S), pen pressure (P), and vocal impairments (V), incorporates an effective features weighting approach, which is the research key novelty. While the severity of the disease had a substantial impact on these four features, the association was evaluated using the Composite Feature Score (CFS). A Parkinson's dataset utilized in this work included features extracted from movement, paper-notepad, spoken, and sound samples. The proposed method incorporates a data pre-processing technique with the purpose of eliminating the heterogeneity in features in the Parkinson's disease dataset to increase the classifier's prediction value. Four separate performance evaluation features were used to evaluate the hybrid feature method. Accuracy, precision, recall, and f1-score value are the evaluation measures used in the research. Everything points to the notion that the proposed method using complex-valued features can be proved to have a favorable impact in giving an accurate examination of Parkinson's disease. It is expected that such superior predictive accuracy rates could be achieved in a number of treatment examination circumstances.

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