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DETECTION AND FORECASTING OF PARKINSON DISEASE PROGRESSION FROM SPEECH SIGNAL FEATURES USING MULTILAYER PERCEPTRON AND LSTM

Abstract *Accurate diagnosis of Parkinson's disease, especially in its early stages, can be a challenging task. The application of machine learning (ML) techniques has helped improve the diagnostic accuracy of Parkinson's disease (PD) detection but integration of diagnostic features in ML models for the prediction of disease progression has remained an unexplored research avenue. In this research work, Long Short Term Memory (LSTM) was trained using diagnostic features on Parkinson patients speech signals, to predict the disease progression while a Multilayer Perceptron (MLP) was trained on the same diagnostic features to detect PD. Diagnostic features were selected using two well known feature selection methods named Relief F and Sequential Forward Selection method. The integration of feature selection methods in LSTM model has resulted in PD progression forecast with an accuracy of 88.7%. Furthermore, with the application of input diagnostic features on MLP, PD stage was accurately detected with an accuracy of 98.63%, precision of 97.64% and recall of 98.8% showing model robustness and efficiency for its potential application in health care.*

Keywords Parkinson disease, machine learning, MLP, diagnostic features, LSTM

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1. Introduction

Parkinson disease (PD) is a progressive and degenerative illness that affects the nervous system and impairs movement control [5, 18]. It typically affects around one percentage of the population over the age of 60, with an occurrence rate of approximately 250 individuals per 100,000 people [8, 16]. While signs and symptoms can vary from one patient to another, common speech related symptoms for Parkinson's disease patients include reduced volume of speech, a monotonous pitch, changes in voice quality, and abnormally fast speech, often referred to as hypokinetic dysarthria. People with Parkinson's disease may not realize that they are speaking softly, so others often ask them to speak louder [8].

Approximately 90% of individuals with PD also experience some form of speech difficulty. This has led to a growing interest in utilizing voice measurements to detect and monitor the symptoms of PD. While physical conditions such as vocal nodules, vocal cord paralysis after a stroke or surgery, or contact ulcers on the vocal cords can contribute to voice disorders, these issues can also arise from vocal misuse, such as speaking too high or low in pitch, too softly or loudly, or with inadequate breath support, often due to postural problems [17]. Typically, predictions are based on clinical practices and neurological examinations, which involve assessing the patient in person using a novel scoring system known as Unified Parkinson's Disease Rating Scale (UPDRS). UPDRS stands as an invaluable tool in the realm of PD assessment, offering a comprehensive framework to evaluate a diverse array of symptoms. The UPDRS assessment consists of four parts: Part I evaluates non motor symptoms, Part II assesses activities of daily living, Part III evaluates motor symptoms, and Part IV examines treatment complications. There is an increasing acknowledgment of the importance of vocal signals within the domain of ML based voice analysis. Failing to detect PD in its early stages can lead to severe and even fatal consequences. Timely intervention is crucial for improving the quality of life for affected individuals [13]. The accurate and timely diagnosis of PD remains a challenge, necessitating innovative approaches to enhance diagnostic accuracy [10,18]. Machine learning (ML) approaches have demonstrated their reliability as a diagnostic tool, in the context of conventional approaches using chemical, physiological, or electrical inputs.

The objective of this research work is to investigate novel features from the speech samples and apply on deep learning models for Parkinson's disease stage diagnosis and progression prediction.

1.1. Related work

In recent years, extensive research has been conducted to diagnose PD using voice signals and various machine learning techniques. Lahmiri et al. [14] implemented a diverse set of eight feature selection techniques to reduce data set dimensionality including t test, entropy, ROC, Bhattacharyya statistics, Wilcoxon statistics, Fuzzy Mutual Information, Genetic Algorithm, and Recursive Feature Elimination with SVM Correlation Bias Reduction. The results exhibited high sensitivity and

specificity in achieving accurate and reliable detection of Parkinson's disease. Braga & Ajith et al. [7] proposed early detection of PD, focusing on free speech recordings captured in uncontrolled background conditions and their detection mechanism integrated signal and speech processing techniques with ML algorithms. Despotovic et al [11] the study focused on enhancing feature selection efficiency in PD detection by combining Gaussian process with the Automatic Relevance Determination (ARD) feature selection technique. Haq et al. [12] proposed a PD prediction system utilizing a SVM as the predictive model. The authors incorporated an L1 Norm SVM for feature selection with cross validation technique, ensuring accurate classification of PD and healthy control subjects. Tuncer et al. [27] proposed a novel combination of Minimum Average Maximum tree and Singular Value Decomposition as a feature extraction technique for PD diagnosis. Rizvi, Danish et al. [20] investigated a predictive model for Parkinson's disease, employing a deep neural network (DNN) and a long short term memory (LSTM) network based approach with voice samples.Abd Hadeel Ahmed et al. [1] implemented a recurrent neural network with LSTM, integrating batch normalization and the adaptive moment estimation (ADAM) optimization algorithm to improve the PD classification performance. Rohit Lamba et al. [15] developed a hybrid model using machine learning techniques and feature extraction from PD and healthy patient voice data for disease detection.

1.2. Significance of the proposed research work

This research distinguishes itself from previous studies [14], [15], [7], [12], [20], [1] by exploring feature selection techniques combined with machine learning models for stage diagnosis and prediction of Parkinson's disease progression. In contrast to previous research studies which focused on disease detection only, the presented research work evaluates MLP, SVM, and LSTM with advanced feature selection methods like ReliefF and Sequential Forward Selection (SFS) on the Motor UPDRS to offer stage diagnosis and prediction both. The LSTM based Recurrent Neural Network model has not been examined using novel diagnostic features for PD forecasting. The remaining paper consists of three sections. In Section two, the proposed methodology and architecture of the machine learning models implemented in this research work are presented. In Section three, results are furnished and discussion is done whereas conclusion of the research work is given in Section four.

2. Methods/experimental

The work flow of the proposed research process is given in Figure 1. The research approach involves several sequential steps to develop a model to diagnose and predict the progression of PD. The first step is data acquisition, where the necessary data set is collected for analysis. Once the data are collected, a pre-processing technique, specifically normalization, is applied to standardize the data and remove any inconsistencies followed by class balancing using Synthetic Minority Oversampling Technique

(SMOTE). Next, feature extraction techniques, namely ReliefF and Sequential Forward Selection, are utilized to identify and select the most relevant features from the data set. These techniques aid in decreasing the dimensionality of the data, allowing a concentration on the most informative features. After feature extraction, efficient machine learning models including MLP and SVM were trained on the preprocessed dataset for the regression task to provide diagnosis of PD stages. LSTM was trained on the historical speech features of PD patients to forecast the disease progression. Training involves adjusting the model parameters for its performance optimization.

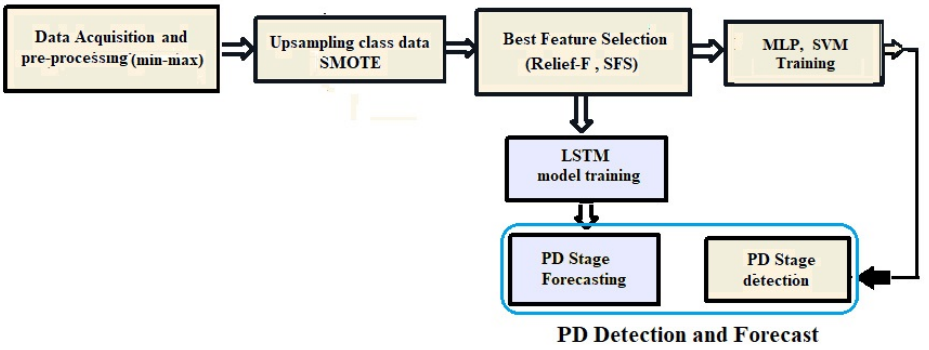

Figure 1. Work flow of the proposed research work

2.1. Data collection and analysis

The initial step of this study involves gathering voice data from a public database for analysis. The data collected includes the UPDRS assessment, which is a parameter used to evaluate motor symptoms of PD. Assessment is performed by a movement disorder specialist. The Parkinson telemonitoring voice data set from the UCI Machine Learning Repository [26] is used, which comprises voice measurements of 42 patients. Each patient has around 200 recordings. These participants were enrolled in a 6-month trial to evaluate a tele-monitoring device, which was designed to remotely monitor the progression of symptoms. The recordings were automatically captured within the patients' homes as part of the trial. This data set has multivariate characteristics and includes 5,875 instances. The data set provided is used predominantly for regression analysis purposes.

Table 1 presents comprehensive information regarding the attributes of the data. Seventy percent of the data from each PD stage, amounting to 4114 instances, is used for training purposes, while thirty percent, consisting of 1761 instances from each stage is allocated for testing purposes. Among the speech signal attributes, motor-UPDRS and Total UPDRS are the output variables, with the chosen speech features acting as input to the machine learning model. Figure 2 illustrates the distribution of data among these stages, reflecting the allocation of individual data points. These stages are commonly employed in clinical evaluations to classify the patients diagnosed with PD [25].

Table 1
Data set attribute information

Subject Number	An integer serving as a unique identifier for each subject
Age	The age of the subject
Sex	The gender of the subject,
Test time	The duration since the subject's recruitment in the trial (in seconds)
Motor UPDRS (output)	The clinician's Motor UPDRS score
Total UPDRS (output)	The clinician's Total UPDRS score
Jitter: Discrete Difference Pitch(DDP)	Measures quantifying the variations in frequency
Jitter (%)	
Jitter: Relative Average Perturbation (RAP)	
Jitter: (Absolute)	
Jitter: Pitch Period Perturbation Quotient 5 (PPQ5)	
Shimmer: Discrete Difference Amplitude(DDA)	Measures quantifying the variations in amplitude
Shimmer: Decibel (DB)	
Shimmer: Amplitude Perturbation Quotient 5(APQ5)	
Shimmer: Amplitude Perturbation Quotient 11(APQ11)	
Shimmer: Amplitude Perturbation Quotient 3 (APQ3)	
Normalized High-frequency Power Ratio (NHR)	Measures representing the ratio of noise to total components in voice
Harmonic to Noise Ratio (HNR)	
Recurrence Plot Density Entropy (RPDE)	dynamical complexity measure
Detrended Fluctuation Analysis (DFA)	A signal fractal scaling exponent
Pitch Period Entropy (PPE)	A nonlinear measure of fundamental frequency variation

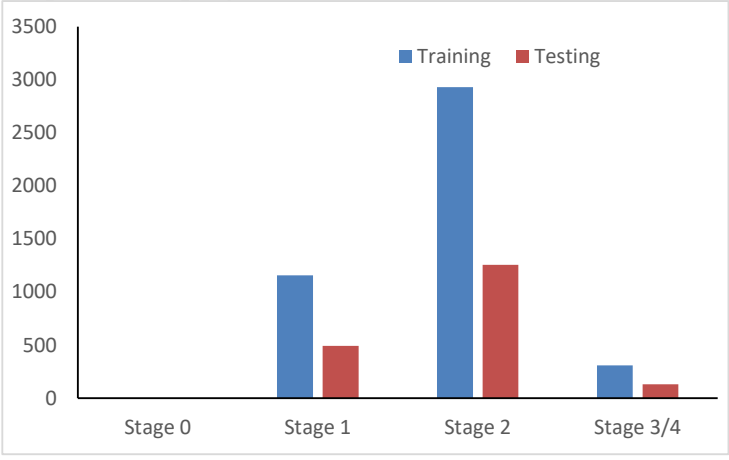

Figure 2. Group-wise Distribution of Experimental Data set

2.2. Data pre-processing with SMOTE and data normalization

The class imbalance in the UCI experimental data set was addressed using Synthetic Minority Oversampling Technique (SMOTE) to create new instances of minority class samples. It starts by selecting a sample and its nearest neighbors, and then constructs synthetic samples by interpolating between the selected sample and its neighbors. Using SMOTE, the number of stage 3 and 4 samples were increased significantly, expanding the data set from 41 to 341 instances.

Followed by class balancing, the data was normalized using minmax and z score normalization and tested on the proposed model. The minmax normalization technique exhibited higher accuracy than the z-score normalization method. Furthermore, the preprocessing step involves removing missing values and outliers from the data.

2.3. Feature selection methods

For the diagnosis of Parkinson's disease, two well-known feature selection algorithms, the ReliefF algorithm and the Sequential Forward Selection algorithm were implemented. In the available literature [22–24], these two algorithms have shown to effectively identify and choose the most pertinent features for medical images and data classification. Thus it can be perceived to contribute to the precise and efficient diagnosis and predict the progression of PD. The ReliefF evaluates the relevance of features by considering their ability to discriminate between different classes. It measures the importance of each feature based on the difference between the feature values of the nearest instances of the same and different classes. By assigning weights to the features based on their significance, the algorithm identifies the most discriminative ones, which are crucial for accurate classification.

Table 2
List of selected features using SFS and ReliefF algorithm

S no.	SFS algorithm	ReliefF algorithm
1	Total UPDRS	Test time
2	Subject Number	Total UPDRS
3	Age	Subject Number
4	Test Time	Age
5	Sex	NHR
6	Jitter (%)	Sex
7	Jitter (Abs)	Jitter (Abs)
8	Jitter: DDP	DFA
9	Shimmer: APQ5	Jitter: RAP
10	Jitter: PPQ5	Jitter: DDP

Sequential Forward Selection (SFS) is a feature selection technique that aims to build an optimal subset of features by iteratively adding one feature at a time. It starts with an empty set of features and incrementally selects the most informative feature in each iteration that maximizes the improvement in model performance. This process continues until a specified number of features or a predefined performance criterion is met. SFS explores the space of feature combinations, potentially discovering synergistic effects between features that contribute to better classification performance [6].

The ten highest ranked features using ReliefF and SFS techniques are reported in Table 2. There are seven features that are common in the top-ranked features obtained using both types of feature selection methods.

2.4. Building machine learning models

Machine learning algorithms can help uncover hidden patterns and understand the intricate interactions that contribute to PD.

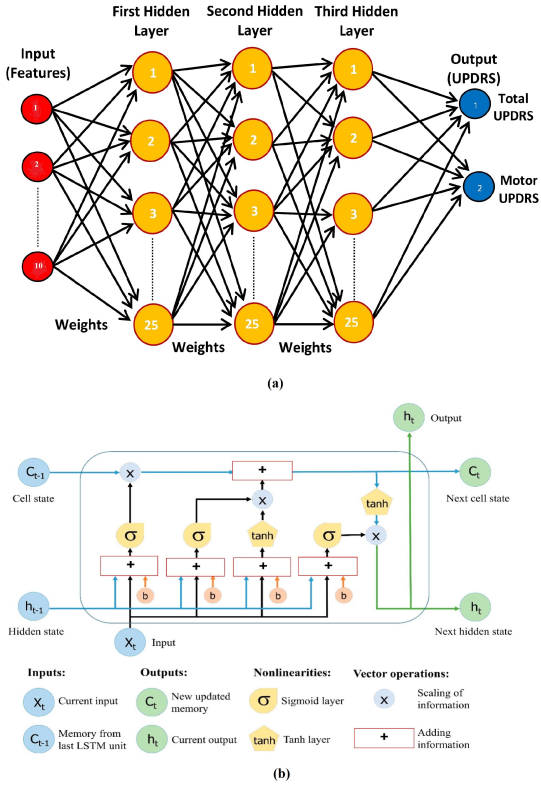

Figure 3. Proposed architecture of machine learning models including (a) MLP (b) LSTM

Among several machine learning models, the application of MLP has been very effective in the diagnosis of many diseases using speech and image data as the input [21]. The architecture of LSTM allows forecasting of diseases using historical/ time series patients data [20]. Based on the aforementioned reasons, MLP and LSTM were chosen in the proposed study for detection and forecasting of PD progression.

2.4.1. MultiLayer perceptron

A multilayer perceptron (MLP) is a feed-forward computational model [21] that comprises perception units called neurons arranged in layers, including an input layer, one or more hidden layers, and an output layer. The number of nodes in the hidden layer(s) can be adjusted. The MLP learns from the data by adjusting the weights and biases associated with the connections between neurons. This learning process is achieved through an iterative optimization technique called backpropagation, where the model updates these parameters to minimize the difference between predicted and actual target values. Each neuron applies an activation function that introduces non-linearity to the model's computations. Regularization techniques such as L1 or L2 regularization can be applied to prevent overfitting. Training a MLP involves providing labeled data sets for supervised learning. The network learns from these examples and becomes capable of processing unknown inputs more accurately [2]. In Fig. 3(a), the proposed framework of an MLP is demonstrated which comprises multiple layers, each with a designated function. These layers collaborate to convert input data into meaningful output predictions.

2.4.2. Support Vector Machine

Support Vector Machine (SVM) is a classification model used to detect a disease. It is a powerful ML model and its purpose is to identify an optimal hyperplane that distinctly separates data points belonging to different classes or, in the case of regression, that best fits the input data. Within SVM, data points are encoded as vectors in a high-dimensional space. The goal is to locate the hyperplane that most effectively segregates the data points into distinct classes or approximates the regression line. The optimal hyperplane, known as the decision boundary, guarantees the maximum margin, signifying the distance between the hyperplane and the nearest data points in each class or the deviations from the exact regression line [24]

2.4.3. Long Short-Term Memory (LSTM)

A Long Short-Term Memory (LSTM) model is a type of Recurrent Neural Network and is capable of learning long-term dependencies and sequential patterns, and enhances prediction accuracy [20]. The LSTM in the presented research work was employed for forecasting PD stage 2 and stage 3 based on stage 1 and stage 2 data respectively.

The model consists of sequence input layer, an LSTM layer with a specified number of hidden units, a fully connected layer, and a regression layer. The LSTM

layer is configured with *tanh* activation for the memory cell known as state activation, and it is configured with sigmoid activations for the input, forget, and output gates known as Gate activation. The LSTM functioning involves initialization with the LSTM initializing with a memory cell and a hidden state. For each time step, the LSTM receives an input and the previous hidden state. The input is used to compute values for the input, forget, and output gates. These values are passed through sigmoid activation functions to produce gate values between 0 and 1. The cell state is updated using the input and forget gates to decide what information to store or discard. The hidden state is updated based on the cell state and the output gate. The updated hidden state is used for making predictions. The output is produced based on the hidden state and can be used for tasks such as classification or regression. The proposed LSTM framework used in the research work is illustrated in Fig. 3(b).

2.4.4. Parameter tuning of ML models

During the research work, several adjustments were made to the MLP, SVM and LSTM models to optimize their performance and the tuned parameters for each of the models are reported in Table 3.

The MLP comprises three fully connected layers, each containing 25 nodes. The Rectified Linear Unit (ReLU) activation function was applied as the activation function. To prevent the training algorithm from running indefinitely, an iteration limit of 1000 was set. In this study, no regularization is applied to the network as the regularization strength (Lambda) was set to 0 and a 10 fold cross-validation had been employed to evaluate model performance. The Limited-memory Broyden-Fletcher-Goldfarb Shanno (LBFGS) algorithm was used as an optimization technique designed for unconstrained optimization problems. It falls within the category of quasi-Newton methods and is notably effective for addressing problems characterized by a substantial number of variables.

A Gaussian Radial Basis Function (RBF) kernel function is used in the SVM implementation, which is capable of handling nonlinear relationships by mapping input features into higher dimensional space. The Kernel Scale is set to 2 after testing with 0, 1, 2, 3 and 4. The epsilon value is set to 'Automatic' and is primarily relevant in SVM regression tasks and defines the width of the epsilon insensitive zone. Data standardization (Normalization) and Sequential Minimal Optimization (SMO) is applied which efficiently solve the quadratic programming (QP) problem that arises during the training of SVM. A 10-fold cross validation was employed to evaluate the SVM performance .

The Sequential LSTM based Regression Neural Network employs Sequence Input Layer, LSTM Layer, Fully Connected Layer, and Regression Output Layer with each having configuration of 1×1. The state activation function is set to the hyperbolic tangent function (tanh) with values between -1 and 1. The gate activation functions (Input Gate, Forget Gate, and Output Gate) are set to the sigmoid function with the Adam optimizer chosen as the optimization training algorithm. The maximum

Table 3
Parameter tuning of ML models

MLP	
Layer Configuration	3 Fully Connected Layers
Number of Nodes	First Layer: 25 Second Layer: 25 Third Layer: 25
Activation Function	ReLU
Iteration Limit	1000
Regularization Strength	0
Data Standardization	Applied
Learning Rate	0.1
Optimizer	LBFGS
Cross-validation	10-fold
SVM Model Details	
Model Type	Gaussian SVM
Kernel Function	Gaussian
Kernel Scale	2
Box Constraint (C)	Automatic
Epsilon Value	Automatic
Data Standardization	Applied
Optimizer	SMO
Cross-validation	10-fold
LSTM Model	
Model Type	Sequential LSTM
Layer Configuration	Sequence Input Layer (1x1) LSTM Layer (1x1) Fully Connected Layer (1x1) Regression Output Layer (1x1)
State Activation Function	Tanh
Gate Activation Function	Sigmoid
Optimizer	Adam
Maximum Epochs	1000
Validation Frequency	50
Number of Hidden Units	150
Learning Rate	0.001

number of training epochs is set to 1000 and validation is performed every 50 iterations or mini-batches. The number of hidden units is 150 with the learning rate fixed at 0.001 throughout the training.

2.4.5. Performance Evaluation Metric

To assess the prediction performance of each method; MSE and R Squared were used. MSE provides insights into the magnitude of errors, and R-squared, on the

Table 4
ML Models Performance for PD stage Detection

Article(year)	**Technique**		**Outcome**	
	MSE	R-Squared	MSE	R-Squared
Without Feature Selection				
Training	0.0590	1.00	2.361	0.97
Test	1.1847	0.98	5.286	0.91
ReliefF				
Training	0.0311	1.00	0.8193	0.99
Test	0.9745	0.98	3.3467	0.94
Sequential Feature Selection (SFS)				
Training	0.0358	1.00	0.8428	0.99
Test	0.6275	0.99	2.6863	0.95

other hand, indicates the goodness of fit of the model by revealing how well the independent variables demonstrate the variability in the dependent variable [9]. The formulae to compute R-squared and MSE are given below:

$$Rsquared = 1 - \frac{(SmS_{res})}{(SmS_{totl})} \tag{1}$$

Where SmS_{res} is the sum of squared differences between the predicted and actual values of y and SmS_{totl} represents the sum of the squared differences between the actual values of y and their mean. Formula:

$$MSE = \frac{1}{n} * \sum (y - y_{predicted})^2 \tag{2}$$

Where n is the number of observations, y is the true value of the dependent variable and $y_{predicted}$ represents the predicted value of dependent variable.

3. Results and discussion

The experimental findings and discussion of the proposed machine learning approach are presented into two parts : first for PD stage detection; and then for PD stage forecast.

3.1. PD Detection

A detailed comparison of the performance of machine learning models (MLP and SVM) for PD detection using diagnostic features from ReliefF and SFS algorithms is reported in Table 4.

The ReliefF algorithm and the MLP model produced an MSE of 0.9745 on the test data with an R Squared value of 0.98. For the ReliefF SVM model, the MSE

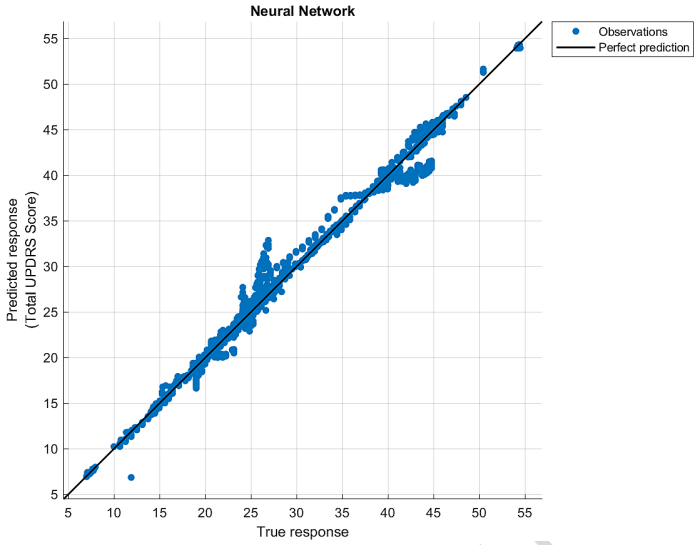

Figure 4. True Responses vs. Predicted Response of MLP−SFS Model

was 3.3467 and the R-Squared value was 0.94. The performance of the models for the training data was significantly better for all the scenarios presented.

The SFS algorithm with the MLP resulted in an MSE of 0.6275 and an R-Squared value of 0.99 for the test data. For the SFS algorithm and Gaussian SVM, MSE was 2.6863 and the R-Squared value was 0.95. For comparison, both MLP and SVM were evaluated for PD detection without feature selection and considering all speech features as input. The MSE value and the R-Squared value were higher in both scenarios than the values obtained when the input was selected features.

Notably, the MLP when used in combination with SFS feature selection method, emerged as the model with highest performance. Fig. 4 illustrates the comparison between true responses and predicted responses of the final model, which was built using the SFS feature selection method in conjunction with MLP model. A close alignment between the points on the plot suggests that the model is accurate in its predictions, while deviations may indicate areas where the model can be improved. This outcome underscores the effectiveness of MLP in capturing the underlying patterns in the data, particularly when paired with feature selection methods like SFS.

Selecting MLP SFS model as the better model for the classification of PD stages, the confusion matrix for the classification of PD stages is shown in Fig. 5. All instances of stage 2 are correctly classified. However, 20 instances of stage 1 are classified as stage 2 and 4 instances of stage 3 are classified as stage 2. These results emphasize the importance of feature selection techniques for model accuracy improvement. The MLP−SFS combination is promising for precise disease management, and

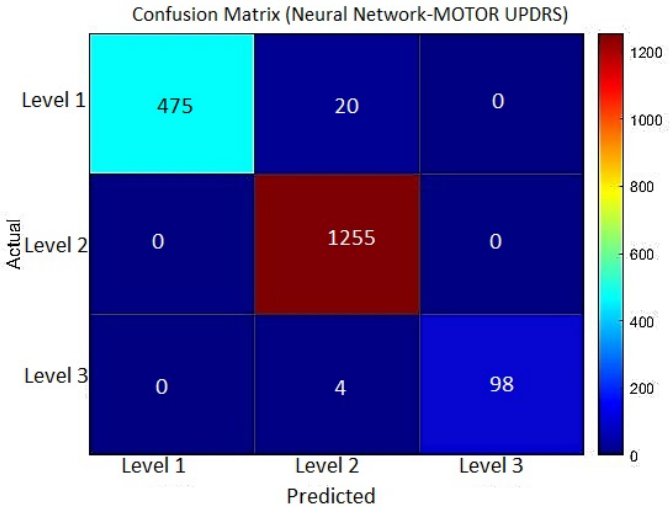

Figure 5. Confusion Matrix of PD stage classification using MLP SFS Model

these findings provide a strong basis for further research and clinical tools to improve Parkinson's disease assessment and management.

3.2. PD stage forecasting

Table 5 provides insights into the results of LSTM Forecast for stage 2 and stage 3 respectively. The training was conducted for 1000 epochs, with updates after each iteration. The results are presented at selected iterations (e.g., 50, 100, 150, 200, etc.). The Root Mean Squared Error (RMSE) serves as a metric for the model accuracy assessment and the validation loss values signify the disparity between predicted and actual values, with lower values indicating a reduction in the gap between predicted and actual values throughout the training process.

The stage 2 prediction over multiple epochs exhibits decreasing trend in error and loss metric suggests effective learning over time. The final RMSE is reported as 0.88, and MSE is 0.77, which indicates good model's performance. The stage 3 forecast model incorporating information from stages 1 and 2 achieves an MSE of 3.16 and an RMSE of 1.78 respectively, offering a detailed assessment of accuracy parameter.

The LSTM model demonstrates accurate forecasting capabilities throughout PD stage 2 and PD stage 3. The convergence of training and validation metric indicates that the model is stabilizing and making accurate predictions. The test data analysis shows that 1560 samples were accurately forecast within the specified PD stage 2 range. Furthermore, 2625 samples were correctly forecast, albeit with a slight deviation from the disease stage 2 range, falling into the stage 1 range. Similar anomalies are observed for PD stage 3 forecasting, where, due to the lower number of test samples, PD stage 3 faces comparable challenges.

Table 5
LSTM Forecast Performance of PD stages

PD stage 2 Forecast			PD stage 3 Forecast		
Epoch	**Validation RMSE**	**Validation Loss**	**Epoch**	**Validation RMSE**	**Validation Loss**
1	12.00	71.9485	1	21.77	236.8813
100	2.67	3.5727	100	7.51	28.1740
200	1.75	1.5258	200	3.42	5.8389
400	0.96	0.4565	400	2.00	2.0040
600	0.97	0.4681	600	1.97	1.9437
800	0.89	0.3991	800	1.62	1.3103
1000	0.88	0.3950	1000	1.78	1.5793

3.2.1. Proposed model comparison with state of the art

Finally, the result of the proposed method is compared with significant research methods presented using the same UCI Parkinson data set. Table 6 draws a comparison of the results of this research with three other prominent works in terms of accuracy and output. The proposed work is novel as the other three methods have only PD detection models using ML methods, while the proposed method also performs PD stage forecasting. Fatlawi et al [3], Rasheed et al. [19] and Alshammri et al. [4] obtained accuracy of 94%, 97.50% and 98.31% in PD detection using Data Belief Networks(DBN), Back propogation Variable Adaptive Momentum (BPVAM) and Multilayer Perceptron (MLP) whereas the proposed MLP SFS model achieved an accuracy of 98.63%, recall of 98.83% and precision of 97.35% exceeding the performance of the previous research methods. In addition, the presented LSTM with SFS secured an 88.7% accuracy in PD forecasting which can be improved further by providing more samples of stage 3. The comparison shows superior performance of the presented work .

Considering the UCI Machine Learning Repository database used in the research work, the database is well known and have been used in many past PD related research studies. However, inclusion of more patients data in the study can improve the training of ML models.

4. Conclusion

This research work provides valuable insights into the application of machine learning models along with feature selection methods for assessing the diagnosis and progression of Parkinson's disease through the prediction of Motor UPDRS scores. Noteworthy is the proven robustness and promise of the MLP model, especially when combined with the SFS feature selecting technique. Furthermore, the study highlights the success of an LSTM in accurately forecasting stage 2 and stage 3 data. The commendable RMSE values underscore the effectiveness of the RNN LSTM model in making precise and reliable predictions. These findings carry significant implications

Table 6
Comparison of Proposed Model with State of the Art Techniques

Article(year)	**Technique**	**Outcome**	**Performance**
Fatlawi et al.(2016)	DBN	PD detection	Acc. =94%
Rasheed et al.(2020)	BPVAM PCA	PD detection	Acc. =97.50%
Alshammri et al.(2023)	MLP	PD detection	Acc. =98.31%
Proposed method	SFS MLP, SFS LSTM	PD detection PD forecasting	Acc.= 98.63% Acc. =88%

for advancing the understanding of Parkinson's disease and its progression, facilitating early detection, and tailoring treatment strategies for improving the quality of life for individuals living with Parkinson's disease. However, collection of larger and more diverse data sets to improve the precision and applicability of machine learning models is desired. Exploring alternative feature extraction techniques, such as Perception Linear Predictive Coefficients (PLP) or wavelet transforms, is proposed to assess their potential for enhancing model performance. Another avenue is the integration of speech analysis with other biomarkers, including genetic data and neuroimaging, to create more accurate and reliable machine learning models for Parkinson's disease diagnosis and progression monitoring.

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