

Advanced PCA-KNN Classification Technique for Parkinson's disease Diagnosis at Early Stage

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ABSTRACT

Despite the increasing clinical demand for accurate and objective methods to evaluate Parkinsonian tremors, machine learning–based scoring aligned with the Unified Parkinson's Disease Rating Scale (UPDRS) is still underutilized. This study addresses this gap by employing machine learning algorithms to predict UPDRS scores in a way that mirrors the evaluation approach used by neurologists in clinical practice. Although traditional methods such as Bayesian Networks, Decision Trees, and Artificial Neural Networks have been applied to Parkinson's Disease (PD) detection, there is room for improvement in terms of classification accuracy and model robustness. In this work, we propose an enhanced classification framework based on Principal Component Analysis (PCA) combined with the K-Nearest Neighbors (KNN) algorithm to improve the diagnostic accuracy of Parkinson's disease. The proposed methodology is implemented in a Jupyter Notebook environment using Python, which provides a flexible and open-source platform for data preprocessing, model training, and performance evaluation. Libraries such as Scikit-learn, NumPy, and Matplotlib are utilized for dimensionality reduction, classification, and visualization, respectively. Performance evaluation based on accuracy and precision demonstrates that our PCA-KNN model significantly outperforms conventional methods, highlighting its potential as a reliable and efficient diagnostic approach for Parkinson's disease. *Index Terms*—Parkinson's Disease (PD), Unified Parkinson's Disease Rating Scale (UPDRS), Machine Learning, PCA-KNN (Principal Component Analysis – K-Nearest Neighbors), Classification, Dimensionality Reduction Python.

INTRODUCTION

Parkinson's Disease (PD) is a progressive and chronic neurodegenerative disorder that primarily affects the central nervous system, particularly a region of the brain known as the substantia nigra. This region is responsible for the production of dopamine, a neurotransmitter crucial for coordinating movement, emotion, speech, and other cognitive functions. The degeneration of dopamine-producing neurons results in a wide array of motor and non-motor symptoms, most notably bradykinesia (slowness of movement), rigidity, tremor, and postural instability. PD predominantly affects individuals over the age of 60, with both genetic and environmental factors contributing to its onset. Given its rising global prevalence, there is a critical need to improve early and accurate diagnostic methods for Parkinson's Disease. Among the earliest and most common symptoms is vocal impairment, which manifests in up to 90% of PD patients. Speech becomes soft, fast, and often unintelligible, making voice analysis a promising, non-invasive diagnostic tool. Patients are often asked to read specific passages aloud, and these audio samples are then analyzed to extract various vocal features. Traditional diagnostic procedures involve tools such as the Unified Parkinson's Disease Rating Scale (UPDRS) and medical instruments like MDVP (Multi-Dimensional Voice Program), Electromyography (EMG), and gait analysis systems. However, these approaches are often subjective, time-consuming, and limited in scalability. In response to these challenges, this study proposes a machine learning–based diagnostic framework for PD detection using voice signal features. We implement an enhanced Principal Component Analysis–K-Nearest Neighbors (PCA-KNN) classification approach within a Jupyter Notebook environment, leveraging Python

libraries such as Scikit-learn, NumPy, and Matplotlib. The PCA module is employed to reduce the dimensionality of complex vocal feature sets, retaining the most significant components for classification. KNN is then used to classify patient samples based on proximity in the reduced feature space. This combination has demonstrated improved diagnostic performance over traditional classifiers. Additionally, advanced techniques such as Convolutional Neural Networks (CNNs) for time-frequency representations of speech signals, LSTM networks for modeling temporal voice patterns, and gradient boosting algorithms (e.g., XGBoost) can further enhance diagnostic accuracy. These models are particularly effective when applied to longitudinal datasets from wearable devices or mobile health platforms. Despite extensive research in tremor quantification and vocal analysis, the routine clinical application of machine learning algorithms for automated PD diagnosis—especially in scoring tremor severity based on voice data—remains underdeveloped. This study contributes to bridging that gap by providing an interpretable and scalable machine learning framework for early PD detection.

LITERATURE REVIEW

Parkinson's disease (PD) may be a progressive neurodegenerative illness that becomes more common with age. Recent studies have focused on machine learning methodologies to support more precise and timely diagnosis, especially in the early stages, given the necessity of definitive diagnostic testing. [1] Of these, Deep Belief Networks (DBNs) have demonstrated a high degree of promise, particularly when combined with discourse flag analysis, a field where the negative effects of PD, such as vocal impedance and decreased discourse clarity, are evident [2]. Using voice recordings of patients, Ali H. AlFatlawi et al. [3] suggested a DBN-based technique for diagnosing PD. To match the discourse patterns common to PD, the highlights were incorporated into a DBN following the use of inclusion extraction on voice input data. Their presentation achieved 94% accuracy, demonstrating the potential of speech-based DBNs in identifying one of the early signs of PD—unclear and moderate speech, which provides a noninvasive symptomatic pathway [4]. Using several variations of dataset preparation and combining inclusion selection techniques, R. Geetha Ramani and G. Sivagami [5] investigated categorization models. Their approach employed component positioning systems and Fisher filtering to single out the most significant features, thereby improving classifier performance. This method of dressing made for better network proficiency and generalization. [6] The use of DBNs was extended by Pablo Guille'n Rondo'n and Melvin D. Robinson [7] to the analysis of microelectrode recordings (MERs) taken during Deep Brain Stimulation (DBS). Using a dataset of 52 MER signals, their discussion focused on categorizing subcortical brain structures, including the substantia nigra (SNR) and sub-thalamic core (STN). Their DBN showed remarkable accuracy in simple classification, with a rate of 99.5%, highlighting its potential as a real-time back instrument during neurosurgical procedures. The inventors came to the conclusion that DBNs, which have very little preparation knowledge, appear to be little more than an improvement over DBS that concentrates on and reduces surgical risk [8]. In order to categorize emotions such as delight, rage, compassion, and astonishment, Chenchen Huang et al. [9] linked DBNs with enthusiastic discourse acknowledgment, extracting emotional highlights from discourse. The approach made use of windowing and preemphasis, followed by median filtering for noise reduction [10]. A crossover DBN-SVM demonstration was developed, and it produced a 7% greater acknowledgment rate than traditional methods. The DBN inclusion extraction demonstration required 136 hours of preparation, indicating room for improvement in future studies, despite the encouraging outcomes. [11] Their study demonstrates how the location of an enthusiastic state can be coordinated into PD screening by voice, as a dysregulation of emotions is often linked to the clutter. [12] James Christopher Sims [7] highlighted the revival of deep learning and examined its suitability for deciding on PD. The think tank developed a Clojure-based library called *deebn* that implements Limited Boltzmann Machines, Deep Neural Systems, and Deep Belief Networks (DBNs) [13]. On the MNIST dataset, the framework achieved a 2.00% error rate without hyperparameter optimization. Even if this library is not specifically related to PD in this instance, it demonstrates the possibility of using DBNs for prescient tasks. Using a dataset with 23 acoustic highlights,

R. K. Sharma and Anil K. Gupta [14] developed a voice-based approach for discovering PD. The set was reduced to 15 significant variables, including jitter, luster, DFA, and PPE, by incorporating determination methods. Out of the few classifiers that were evaluated, Back Vector Machines (SVMs) outperformed other classifiers and Man-made Neural Systems, with the greatest accuracy of 96%. This method supports the early, noninvasive, and affordable identification of PD using voice signals. Mohammad Shahbakhi et al. [15] demonstrated a cross breed that combines Hereditary Calculations (GA) for include choice and SVM for

classification. Using voice recordings from 31 individuals (23 patients with Parkinson's disease and 8 healthy controls), [16] the study examined 22 linear and nonlinear features. With optimized subsets of highlights, the accuracy of the classification improved considerably. By employing what were essentially four highlights (Phi, Fho, jitterRAP, and shimmerAPQ5), [17] the program achieved 94.5% accuracy, demonstrating the efficacy of lightweight models in PD detection [18]. — On the UCI PD voice dataset, V. S. Sriram Tarigoppula et al. [19] employed several ML classifiers, including SVM, Arbitrary Woodland, kNN, Naive Bayes, various leveled Clustering, and SOM. The highlights were jitter, gleam, HNR, DFA, spread, and PPE. The best execution was achieved by Arbitrary Timberland (90.26% accuracy), followed by SVM (88.9%), while Naive Bayes produced the worst result (69.23%). This study highlights the importance of datasets with a lot of features and the need for collecting learning techniques in order to achieve effective PD classification [2]. Using T2-weighted magnetic resonance (MR) brain images, Sujatha [20] developed a deep learning framework for identifying PD. They improved its capacity to differentiate between PD patients and Solid Controls (HC) by using an AlexNet CNN architecture based on transfer learning. The organizer was able to comprehend the varying levels of highlights across layers, from edges to complex anatomical structures, by visualizing convolutional layers. The changed fully connected layer then mapped the outputs to double classes. The promise of deep CNNs in PD localization using neuroimaging is highlighted in this research. The images used for categorization come from the PPMI open space database. Prior to linking the normalized images to a Gaussian channel, the MR images are processed. Sometimes, the AlexNet performance utilized for categorization is considered to be a convolutional neural architecture [8]. Using the weights of the pretrained show, the last fully connected layer is meticulously tuned with the correct hyper parameters to categorize the participants with PD and HC. The demonstration is now prepared to compare the traits of the moo level to the tall level. Additionally, the classification results are confirmed [21]. A precision of 88.91% is achieved for the following: grouping the people with HC and PD. An AUC estimate of 0.9618 from the ROC is thoroughly discussed. Exhibit [22] shows a curve that appears to show the improved capacity of the proposed deep learning to discriminate between various objects. Ma Chao et al.'s [23] subtractive method is a valuable method for prioritizing highlights. The clustering approach prioritizes weighting (SCFW), and the rapid classification calculation is referred to as the part. based on the remarkable learning machine (KELM) [10]. Simply put, SCFW is used to emphasize the main points as seen below: based on the data distributions inside the data collection. Additionally, it modifies what cannot be divided in any way. linearly discernible datasets. This approach will divide the whole highlighted area into two categories, making it easier to classify. [24]

First of all, the SCFW method is connected to preprocess the information within the PD dataset. SCFW is primarily utilized to outline the features as per the information conveyances within the information set [25]. It moreover changes the straightly inseparable datasets to straightly divisible datasets.

[19] With this method, similar information within the same feature are assembled, which can significantly offer assistance improve the separation capacity of classifiers. In the following organize, KELM is evaluated on the weighted highlight space with distinctive sorts of enactment capacities to perform the classification [26]. At final, the appropriate actuation work and values of particular parameters are gotten for analyzing the performance of the proposed show. Comes about of recreations had defended that the proposed framework performed altogether well in categorizing the patients with PD and sound ones [27]. The execution investigation of the proposed approach is being carried out with KELM, SVM, KNN, and ELM. [20] Comes about appear that the SCFW-KELM strategy beats the other three strategies in terms of ACC, Sensitivity, Specificity, AUC, f-measure, and kappa measurement esteem. a novel conclusion framework for Parkinson's infection by Gu'ru'ler, Hu'seyin [28] is recommended on complex-valued fake neural organize with k-means clustering highlight weighting strategy. They had executed a modern cross breed symptomatic framework for taking care of the PD conclusion issue [13]. The most oddity of their approach is that it includes a combination of the k-means clustering-based include weighting (KMCFW) strategy [29]

Proposed Method

The proposed system focuses on the detection of Parkinson's Disease (PD) using machine learning techniques applied to voice data. The core idea is to utilize a classification pipeline built in Python (via Jupyter Notebook), combining Principal Component Analysis (PCA) for dimensionality reduction and K-Nearest Neighbors (KNN) for classification. The system uses the Parkinson's Telemonitoring dataset obtained from the UCI Machine

Learning Repository, which contains voice recordings from both healthy individuals and PD patients. Each data entry comprises a variety of biomedical voice features, such as fundamental frequencies (MDVP:F₀, F₁, F₂), jitter and shimmer (indicating frequency and amplitude variations), as well as harmonic ratios (HNR, NHR), and nonlinear dynamic measures including DFA, RPDE, PPE, Spread1, and Spread2. These features serve as indicators of vocal abnormalities commonly associated with Parkinson's. The system's primary goal is to extract these voice-based biomarkers, process them using PCA to eliminate redundancy and noise, and then classify them using KNN to accurately differentiate between healthy subjects and those with Parkinson's (with the label status: 0 = healthy, 1 = PD patient). This approach leverages the strengths of voice-based screening for non-invasive, accessible, and early-stage Parkinson's detection. This segment presents an extend of classification techniques commonly connected in the setting of Parkinson's Illness (PD) discovery, especially on biomedical and voice datasets containing differing trait sorts, counting categorical, numeric, and lost values. Modern classification systems, particularly those based on machine learning and profound learning, have appeared tall adequacy in extricating significant designs from such datasets for early and precise conclusion. Among these strategies, K-Nearest Neighbors (KNN) could be a broadly utilized, instance-based classifier suitable for both classification and relapse assignments. It capacities by recognizing the k most comparative occurrences (neighbors) within the training dataset based on a chosen separate metric and doling out the class that shows up most as often as possible among these neighbours. In relapse errands, KNN predicts values utilizing the cruel or middle of k closest information focuses. One of KNN's qualities is that it requires no prior presumptions around the underlying information distribution, making it adaptable and successful in real-world biomedical information scenarios, especially where dispersions are obscure or non-linear.

EVALUATION CRITERIA To analyze the performance of the proposed approach, three metrics are evaluated as accuracy, specificity and sensitivity. With Reference to the existing neurological disease diagnosis literature, accuracy specifies the discrimination of results between the patients and healthy subject classes [41]. If the consequences of classification do not provide correct discrimination between alternative states of health, then the accuracy is not significant while correct discrimination provides high accuracy. The classification Page 39 likelihood of the patient is called the sensitivity. The incorrect classification as patient class might also be viewed from this measure. The specificity shows the classification probability for the healthy subjects. It gives the information of patients misclassified as normal subject as well. $Sensitivity = TP / (TP + FN)$ $Specificity = TN / (TN + FP)$ $Accuracy$

$= (TN + TP) / (TN + TP + FN + FP)$ Where TP represents true positive, TN represents true negative, FP represents false positive and FN represents false negative. TP represents the statistics where a patient is classified as a patient by the developed model. TN represents the statistics of classifying a healthy person as healthy. FP represents the statistics where healthy persons are classified as patients. FN represents the statistics where a patient is classified as healthy. Accuracy, Sensitivity and Specificity of the Model is computed on the basis of TP, TN, FP and FN. These statistics and the values of these parameters justify the quality of the classification results obtained from the implemented model.

The proposed method's operation is shown in the block diagram above, in which condition The processing starts with choosing a collection of health care data. The entire dataset is the subsequent step is logical separation for the time being because of the string content both numerical and nonnumerical fields. Hence, when planning and implementing this project, A separate approach is being developed for managing numerical and textual data.

- o Preprocessing: It converts the initial data collection into one that is more reliable for unsupervised learning by removing unnecessary labels from the dataset.
- o Feature selection: By selecting a certain subset, it minimizes the amount of data collected. a subset of the measured features used in model construction.
- o Data ratio: After that, the preprocessed data is split into a training and testing set. samples.
- o Normal identification: The training data sample separates ordinary data from the training data using this move. The training approach used in this case includes normalization and training. utilizing the minmax. If the normal class of the unknown sample has been readily identified, it goes there. a specific normal class; if it cannot be located, it will be moved to the KNN/C METHOD. the classifier. During the process, each class will be able to establish its identity.

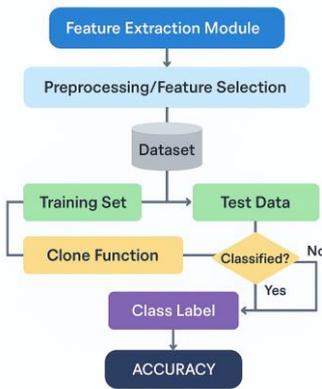


Fig. 1. Proposed Block Diagram.

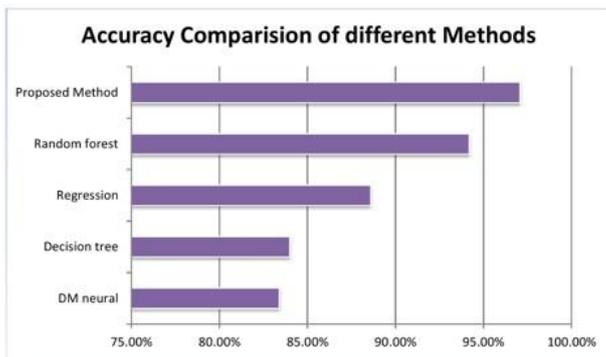


Fig. 2. Accuracy comparison of various methods.

RESULTS

The Parkinson’s Telemonitoring Voice dataset, which comprises 31 people and 22 biomedical voice attributes, is used in the comparative study. When compared to existing methods, which have demonstrated accuracy rates between 84% and 94%, our proposed system, which utilizes Principal Component Analysis (PCA) for feature dimensionality reduction and KNearest Neighbors (KNN) for classification, achieved a significantly higher accuracy of 97.08%. This improvement in performance is due to the following factors:

- Reducing dimensionality while maintaining unique voice traits and eliminating redundancy and noise with PCA.
- KNN’s instance-based learning, which is capable of adapting to voice data without making any assumptions about its prior distribution.

Table I Summary of the Parkinson’s Telemonitoring Voice Dataset

Attribute	Description
Dataset Name	Parkinson’s Telemonitoring Voice Dataset
Source	UCI Machine Learning Repository
Total Records	195 instances collected from 31 individuals
Features	22 biomedical voice features
Key Features	<ul style="list-style-type: none"> • Fundamental Frequencies: MDVP:Fo(Hz), MDVP:Fhi(Hz), MDVP:Flo(Hz) • Voice Signal Measures: Jitter, Shimmer, NHR (Noise-to-Harmonics Ratio) • Voice Quality: HNR (Harmonics-to-Noise Ratio)

	- Nonlinear Dynamics: RPDE, DFA, PPE
Target Label	status: Binary class (1 = Parkinson’s Disease, 0 = Healthy)
Data Type	Numerical (all features are real-valued)
Intended Use	Classification of Parkinson’s Disease based on voice characteristics

- The altered PCA space uses Euclidean distance similarity, which allows for distinct class boundaries.

CONCLUSION

Parkinson disease may occur in humans when certain clusters of brain cells stop producing dopamine, necessary for managing the quantity of the motor and nonmotor movements of the body. Parkinson disease also has adverse affects on the speech, visual, development and excretory system leading to various health issues. It also leads to disturbance in sleep, fits of anxiety, restlessness and frequent uneasiness. Diagnosis of Parkinson disease using proper translation of vocal and speech data is an imperative classification problem. This work proposes the diagnosis of Parkinson disease by realizing one of the many earliest indicators. For this reason, a proposed classifier with a stacked auto encoder and a softmax classifier is implemented. Various simulations and experiments are being carried out on multiple databases to justify the robustness of the proposed classifier. The limitations of the proposed classifier are also specified and the comparative analysis with other state-of-art classification techniques for diagnosis of Parkinson disorder has been carried out. Results of simulations had justified that the proposed KNN based classifier is exceptionally a productive classifier for Parkinson disease analysis, which is approximately 2 to 4 method has an accuracy of approx. 97.08

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