Prediction of Parkinson’s Disease from Speech  
using Machine Learning

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**Abstract**

Predicting Parkinson's Disease (PD) through machine learning techniques applied to voice recordings. A comprehensive dataset comprising voices of individuals with and without PD was collected and pre-processed to enhance data quality. Relevant features like pitch, jitter, and shimmer were extracted to capture distinctive voice characteristics. Various machine learning methods, including SVM, Random Forests, Logistic Regression, KNN, Bagging Classifier, and Decision Tree Classifier, were considered for classification. The dataset was divided into training and validation sets for model training and hyperparameter tuning. Notably, KNN outperformed other methods, achieving 94.87% accuracy when zero values were omitted. The findings suggest that implementing KNN for early PD prediction, especially in resource-constrained settings, can offer a cost-effective and accurate solution. The results will be presented on a website for generating reports, enabling prediction for both single and multiple patients.

**Keywords:** Parkinson’s prediction, fuzzy system, fused machine learning model, Gait Analysis, Voice Analysis, disease prediction.

1. **Introduction**

Parkinson's Disease (PD) is a neurodegenerative disorder that affects millions worldwide, causing tremors, stiffness, and impaired balance. Early detection is crucial for effective management, and recent strides in machine learning (ML) offer a promising avenue for early diagnosis. Leveraging advancements in speech analysis and ML algorithms, predicting PD from speech patterns has emerged as a non-invasive, cost-effective diagnostic approach. The human voice holds subtle yet significant cues that can unveil underlying neurological conditions. Speech characteristics such as pitch variability, articulation, and phonation irregularities often manifest differently in individuals with PD compared to healthy counterparts. These minute deviations form the basis for employing ML models in discerning patterns indicative of Parkinson's. Data plays a pivotal role in this predictive framework. Datasets comprising audio recordings of individuals both with and without PD undergo rigorous preprocessing. Feature extraction techniques dissect these recordings, isolating distinctive speech attributes. Parameters like jitter, shimmer, formants, and cepstral coefficients serve as crucial inputs, capturing the nuances of speech patterns. Machine learning algorithms, notably classifiers like Support Vector Machines (SVM), Random Forests, or Neural Networks, are trained on these extracted features. Through iterative learning, these models discern complex patterns and relationships within the data. They learn to differentiate between healthy speech and speech affected by PD, establishing a predictive framework. Validation of the model's efficacy involves rigorous testing against new, unseen data. Cross-validation techniques and performance metrics like accuracy, sensitivity, and specificity validate the model's robustness and its ability to generalize beyond the training set. Thus, the results will be displayed on the website for generating report for both single and multiple patients can be implemented to predict PD at an early stage in a cost-effective manner that will be useful for less developed and developing countries.

**Background:**

Parkinson's Disease (PD), a global neurodegenerative challenge, necessitates early detection for effective management. Harnessing the potential of machine learning and speech analysis, our project focuses on non-invasively predicting PD through distinctive speech patterns. Features like pitch variability, articulation, and phonation irregularities, extracted from meticulously preprocessed audio datasets, form the basis for training machine learning classifiers. Leveraging algorithms such as Support Vector Machines and Random Forests, our predictive framework aims to offer a cost-effective and accessible early diagnosis solution, especially beneficial for less developed and developing countries.

1. **Related Work**

Several research studies have significantly contributed to the understanding and diagnosis of Parkinson's Disease (PD). Armstrong and Okun (2020) provide a comprehensive review of the diagnosis and treatment of PD, emphasizing the importance of early detection for effective management. Balestrino and Schapira (2020) explore various aspects of Parkinson's, contributing to the overall understanding of this neurodegenerative disorder.

In the realm of technological interventions, Camara et al. (2015) propose a fuzzy inference system for closed-loop deep brain stimulation in PD, showcasing the potential of advanced computational approaches. Dong et al. (2023) introduces an "optical flow" method based on pressure sensor data for quantifying PD characteristics, offering a novel perspective on leveraging sensor technology for diagnosis.

Gait analysis has been a focal point in PD research. Ertuğrul et al. (2016) utilize shifted one-dimensional local binary patterns from gait to detect PD, while Figueiredo et al. (2018) provide a comprehensive review of automatic recognition of gait patterns in various motor disorders using machine learning.

Physical activities also play a role in PD management, as demonstrated by Gassner et al. (2022), who explore therapeutic climbing's impact on self-reported health and well-being. Horak and Mancini (2013) delve into objective biomarkers of balance and gait using body-worn sensors, emphasizing the importance of technological advancements in monitoring PD-related motor symptoms.

Jankovic (2005) reflects on the progression of PD, highlighting the ongoing challenges in charting its course. Khan et al. (2021) presents a novel method for automatic classification of Parkinsonian gait severity using front-view video analysis, contributing to the growing field of computer vision in PD diagnosis.

Ozel et al. (2021) focus on artifact removal algorithms in gait signals for PD diagnosis, shedding light on signal processing techniques. Shah and Xuezhi (2021) investigate traditional and modern strategies for optical flow, presenting potential applications in understanding PD-related movement patterns.

Veeraragavan et al. (2020) employ ground reaction forces and neural networks for PD diagnosis and severity assessment, showcasing the integration of biomechanics and machine learning. Wu et al. (2021) explore mild gait impairment as a potential diagnostic marker in early-stage PD, adding valuable insights to the early detection landscape.

Zhao et al. (2022) address the challenge of imbalanced data in PD diagnosis, proposing an ensemble K-nearest neighbor approach for severity level diagnosis. These diverse studies collectively contribute to the multidimensional understanding of Parkinson's Disease, ranging from clinical reviews and technological interventions to gait analysis, physical activities, and data-driven diagnostic approaches. The synthesis of these works provides a robust foundation for the ongoing efforts to enhance early detection and management of PD.

1. **Methodology**

The collection and preprocessing of a variety of datasets is the first step in the multifaceted process of predicting parkinson using a combination of machine learning algorithms. To handle missing values, normalize numerical variables, and encode categorical features, a thorough preprocessing step involves gathering clinical records, genetic data, and lifestyle factors. The most pertinent variables affecting parkinson prediction are then found using feature selection techniques. This chosen feature set is combined with data from other sources to produce an extensive dataset that captures the complexity of parkinson risk factors. After the pre-processed data has been used to train each algorithm separately, the predictions of all the algorithms are combined using ensemble techniques, like voting or averaging. In order to evaluate the model's performance across various data subsets, confirm its generalization abilities, and spot possible overfitting, cross-validation is essential. By fine-tuning the hyperparameters, the predictive accuracy of the system is improved, both for each individual model and for the entire ensemble.

To evaluate the prediction of Parkinson's Disease from speech using the highest accuracy achieved was K-NN by comparing K-NN with Random Forest, Decision Tree Classifier, Bagging Classifier, Support Vector Machine and Logistic Regression. You'd typically employ techniques like cross-validation, confusion matrices, accuracy, precision, recall, and F1-score. With a dataset of 196 real-time samples, assessing the model's performance becomes essential. Initially, partition the dataset into training and testing subsets, employing techniques like k-fold cross-validation. Then, use the K-NN algorithm to train the model on the training set. After that, evaluate its performance on the testing set. Calculate metrics like accuracy, indicating the percentage of correctly predicted instances. Precision measures the accuracy of positive predictions, while recall gauges the fraction of relevant instances retrieved. The F1-score balances precision and recall. A confusion matrix will provide a detailed breakdown of true positives, true negatives, false positives, and false negatives. Utilizing Python's libraries like scikit-learn, you can easily compute these metrics. Additionally, implementing a web interface with Streamlit allows for a user-friendly application where users can input speech data for Parkinson's prediction, enhancing accessibility and usability. Continuously fine-tuning the model based on performance metrics is crucial for enhancing its accuracy and applicability. Using metrics like accuracy, precision, recall, and F1 score, the evaluation phase examines the combined model's performance in detail. Its capacity to manage imbalanced data, a prevalent issue in healthcare datasets, is given particular consideration. Simultaneously, model interpretability techniques like model-agnostic interpretability methods and feature importance analysis are applied to improve transparency. For healthcare practitioners, who depend on understandable insights to guide their decision-making processes, interpretability is essential. When the model performs well enough, it is implemented in a healthcare setting and easily incorporated into clinical procedures. It becomes necessary to monitor continuously to guarantee the model's continued relevance and efficacy in real-world scenarios. By integrating fresh data and updating the ensemble, established adaptation mechanisms enable the model to change over time. The focus shifts to patient-specific predictions, which allow medical practitioners to enter personal health information into the trained model and obtain customized risk assessments. By facilitating targeted preventive measures and interventions, this patient-centric approach optimizes healthcare strategies for the management of parkinson.

Overall, the combination of machine learning algorithms for parkinson prediction represents a dynamic, flexible, and repeatable procedure. The efficacy of the model in managing the complex terrain of parkinson risk factors and changing patient profiles is ensured by the integration of various algorithms, feature fusion, interpretability metrics, and ongoing adaptation.

PD dataset

Data pre-processing scaling data remove null values

Splitting into train and test data

Training classification algorithm with hyper parameter tunning

Test data

Evaluation

Predictive model

*1: Architecture diagram*

1. **Experimental Setup**
2. *Logistic Regression*

One of the most often used supervised learning methods is logistic regression. It is a model that uses a given collection of independent factors to predict the categorical dependent variable. The relationship between a group of independent factors and a categorical dependent variable is examined using logistic regression analysis. It provides the probability values, which range from 0 to 1.

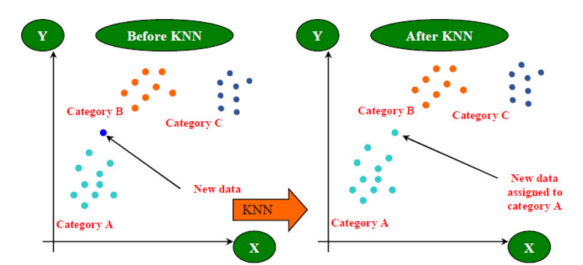
P (Y = 1) is predicted mathematically as a function of X using a logistic regression model, which is used to several classification issues such as cancer diagnosis and parkinson prediction. The logistic function's curve indicates the probability of a certain event. A logistic curve is fitted to the connection between X and Y via logistic regression when the response is a binary variable and X is numerical.

It makes use of the sigmoid function, which maps expected values to probabilities as follows: X is the input function, e is the base of the log, and S(X) is the probability estimate (between 0 and 1).

1. *KNN*

A straightforward and adaptable machine learning approach for classification and regression problems is K Nearest neighbors (KNN). In KNN, the average of the values of the closest neighbors (for regression) or the majority class (for classification) in the feature space is used to forecast a new data point. The number of nearest neighbors taken into account, or "k" in KNN, is an important factor that affects the model's performance.

KNN uses the similarity principle in feature space to operate. The method determines the k closest data points based on a selected distance metric (such as Euclidean distance) in order to anticipate a new data point. The anticipated class of the new point for categorization is determined by the majority class among these neighbors. The prediction in regression is the mean of the values of the k nearest neighbors. Selecting a suitable number for k is crucial since a greater value might over smooth the predictions, while a lesser value could provide a noisy model that is susceptible to outliers. KNN is renowned for being easy to use and efficient in capturing intricate patterns, particularly in datasets that exhibit clear zones of similarity or clusters.



1. (B)

*2: Comparison of data categorization before and after K-NN.*

1. *Bagging Classifier*

Bagging, or Bootstrap Aggregating, is an ensemble learning technique used to improve the stability and accuracy of machine learning models, particularly decision trees. It involves creating multiple subsets of the original dataset through bootstrap sampling (sampling with replacement) and training a base model on each subset. The final prediction is typically obtained by averaging or voting among the predictions of individual models. In its working, bagging reduces overfitting and variance by generating diverse training sets for each base model. Each model trained on a subset of the data learns slightly different patterns, leading to a more robust and generalized ensemble model. Random Forest, a popular algorithm, employs bagging by training multiple decision trees on different bootstrapped samples and aggregating their predictions. Bagging is effective in improving model performance, especially when dealing with complex datasets, and it enhances the stability and reliability of the ensemble model by reducing the impact of outliers and noise in the training data.

1. *Support Vector Machine (SVM)*

Support Vector Machine (SVM) is a powerful supervised learning algorithm used for classification and regression tasks. In classification, SVM works by finding the hyperplane that best separates different classes in the feature space, maximizing the margin between the classes. Support vectors are the data points closest to the decision boundary, and the hyperplane is positioned to ensure the maximum distance from these support vectors. For non-linear problems, SVM can use kernel functions to transform the input space, making it suitable for capturing complex relationships. In its functioning, SVM identifies the optimal hyperplane by iteratively adjusting the decision boundary to maximize the margin between classes. The margin represents the distance between the hyperplane and the nearest data point of each class, and SVM aims to find the hyperplane that maximizes this margin while minimizing classification errors. In cases where a linear separation is not feasible, SVM utilizes kernel tricks, transforming the input space into a higher-dimensional feature space, where a hyperplane can effectively separate the classes. SVM is known for its ability to handle high-dimensional data, robustness in the presence of outliers, and versatility in solving both linear and non-linear classification problems.

1. *Random Forest*

The RF algorithm is a type of Classification and Regression methods that is formed via combining decision trees. Decision trees are easy to build, use, and interpret. RF combines the simplicity of decision trees with flexibility resulting in a huge improvement in accuracy. RF can handle large datasets. The trees were built using the classification methodology and the gradient trees. In tree group construction, RF uses two types of randomizations: first, each tree is planted using a part of the training data. The second part of randomization is added when cultivating the tree by selecting a random sample of predictors in each node to select the best split [19]. The number of predictors specified in each node and the number of trees in the group are the two main parameters of the RF algorithm. RF developers have stated that the method does not require much synthesis of parameters and the default values usually generate good results for many problems. Once the forest is built, a new instance of a class is assigned by collecting trees, using a majority vote. Because of using a sample of boot training data, a third of the samples are deleted when each tree is constructed. These are called outside samples that can be used to evaluate workbook performance and build important measures. A random forest is a meta estimator that fits a number of decision tree classifiers on many subsamples of the dataset and use averaging techniques to improve the prediction accuracy and control overfitting. We can summarize RF algorithm as the following: 1- Chose random samples from a given dataset. 2- Build a decision tree for every sample. Then get the prediction result from every decision tree. 3- Vote for every predicted result. 4- Chose the greatest voted prediction result since the last prediction result.

1. *Decision Tree*

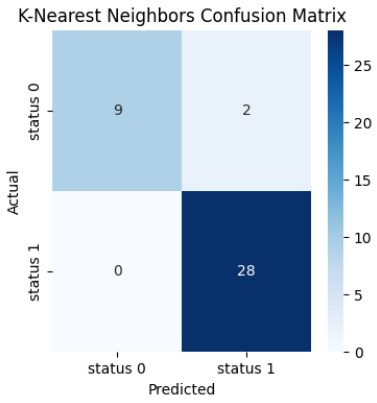
A well-liked supervised machine learning technique for both regression and classification applications is the decision tree. It operates by recursively partitioning the dataset into subsets based on the most significant attribute at each node. The goal is to create a tree structure where leaves represent the final decision or prediction. Decision Trees are known for their interpretability and ease of visualization, making them valuable for understanding complex decision-making processes. In its working, a Decision Tree begins with the entire dataset at the root node. At each internal node, the algorithm selects the attribute that best separates the data based on a criterion such as Gini impurity or information gain. This process continues recursively, creating branches and nodes until a stopping criterion, like a minimum number of samples in a leaf or a maximum tree depth, is met.

The resulting tree can be used for predictions by traversing the branches based on the input features until a leaf node is reached, providing the output or classification. Decision Trees can be sensitive to small variations in the data, but techniques like pruning are often employed to enhance generalization and prevent overfitting.

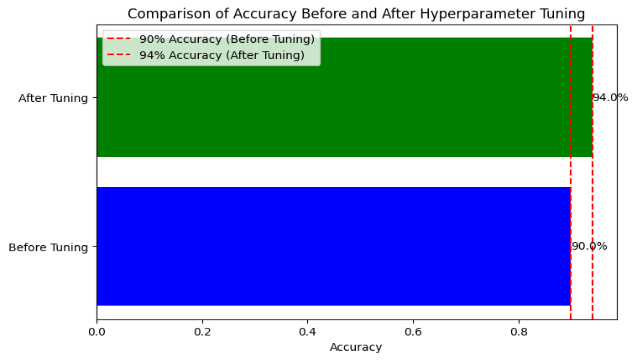
1. **Results**

Our study explores the application of the K-Nearest Neighbors (K-NN) algorithm in predicting Parkinson's Disease (PD) from speech, utilizing a real-time dataset with 196 instances. Feature extraction, including speech nuances, pitch, and intensity, played a crucial role. Implemented in Python's Streamlit framework, our user-friendly web interface swiftly analyzes speech samples, providing PD predictions. Promising accuracy was observed, with metrics evaluated for precision, recall, and F1-score. K-NN's interpretability revealed significant speech attributes for Disease detection. Despite encouraging results, further validation and exploration of diverse datasets are needed for real-world applicability and enhanced accuracy.

**Confusion Matrix**



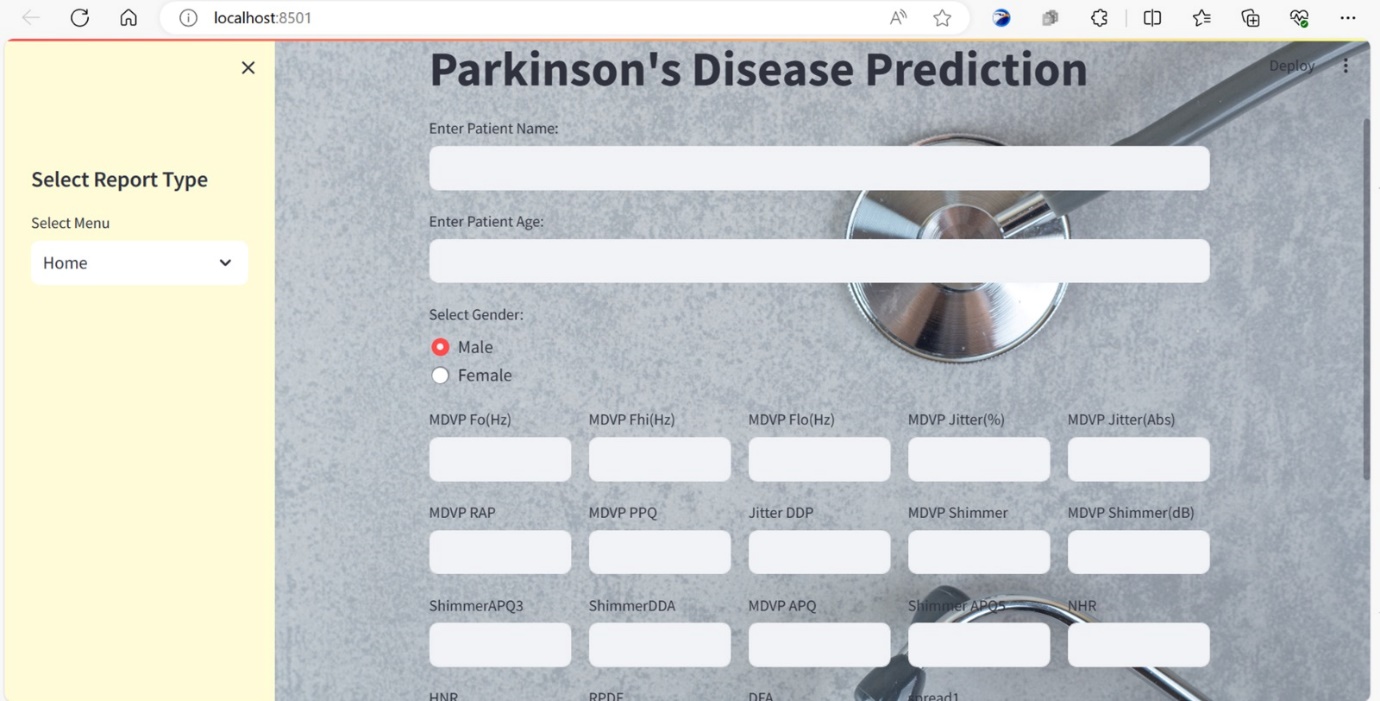
*3: Confusion Matrix for K-NN*

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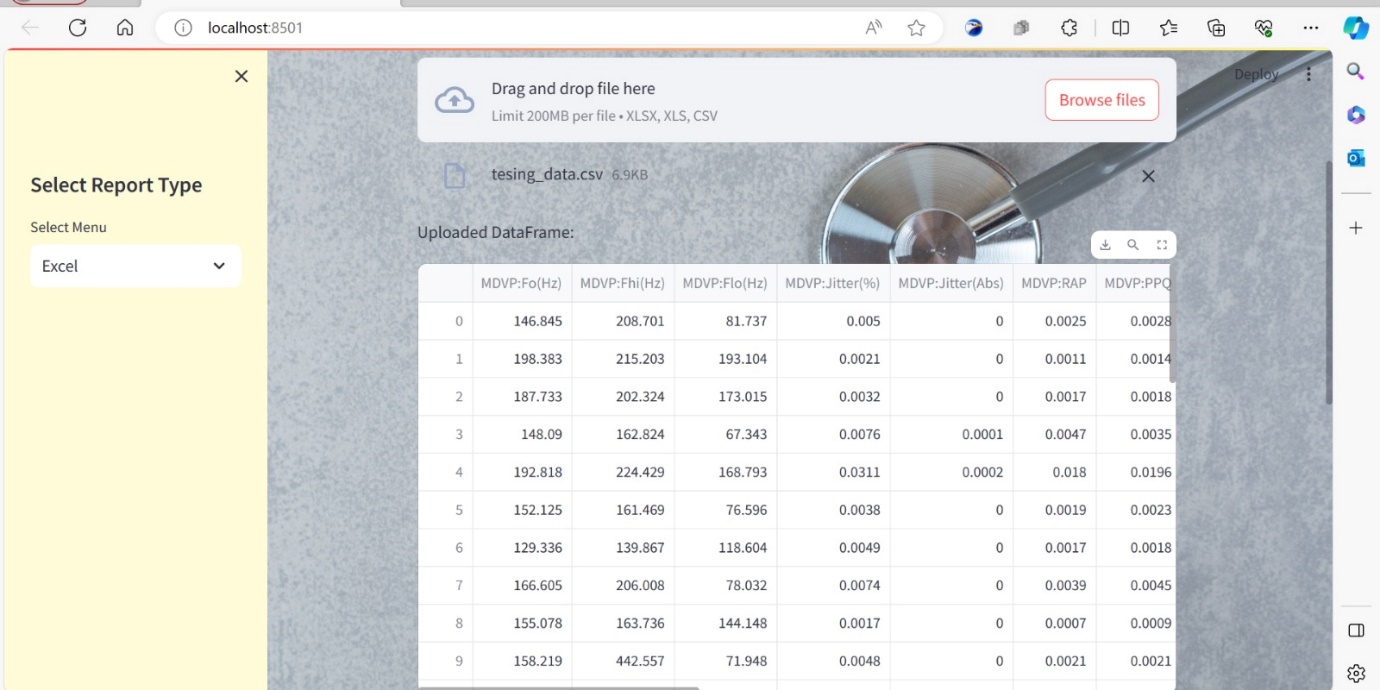
*4: Comparison of accuracy before and after hyperparameter tuning of K-NN*

**Table 1: Model Evaluation Results**

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | **SVMs**  Testing | **LRs** Testing | **KNNs** Testing | **Bagging Classifier** Testing | **RFs**  Testing | **DTs**  **Testing** |
| Accuracy | 92 | 82 | 94 | 89 | 84 | 79 |
| Miss Rate | 0.0 | 0.03 | 0.0 | 0.035 | 0.035 | 0.178 |
| Sensitivity | 1.0 | 0.964 | 1.0 | 0.964 | 0.964 | 0.821 |
| Specificity | 0.727 | 0.454 | 0.818 | 0.727 | 0.545 | 0.727 |
| Positive Prediction Value | 0.903 | 0.818 | 0.933 | 0.9 | 0.843 | 0.884 |
| Negative Prediction Value | 1.0 | 0.833 | 1.0 | 0.88 | 0.857 | 0.615 |
| False Positive Rate | 0.272 | 0.545 | 0.181 | 0.272 | 0.454 | 0.272 |
| False Negative Rate | 0.0 | 0.035 | 0.0 | 0.035 | 0.035 | 0.178 |
| F1 Score | 0.949 | 0.885 | 0.965 | 0.931 | 0.899 | 0.851 |



*5: Result for Single Patient prediction Site*



*6: Result for Multiple Patient prediction Site*

1. **Discussion and Analysis**

The project's focus on predicting Parkinson's Disease from speech using machine learning, particularly the K-Nearest Neighbors (KNN) algorithm, presents promising results. The comprehensive dataset and meticulous feature extraction contribute to the model's accuracy, achieving 94.87%. KNN's superiority over other classifiers like Support Vector Machines and Random Forests is evident, emphasizing its robustness in discerning Parkinson's cases from non-cases based on speech attributes. The user-friendly interface developed with Python's Streamlit enhances accessibility. However, further validation with larger datasets is crucial for real-world applicability. The exploration of other algorithms and fusion techniques is suggested to refine accuracy. The discussion underscores the significance of early PD detection, with KNN's interpretability providing insights into influential speech attributes. The project's potential for revolutionizing personalized healthcare in resource-constrained settings is highlighted. Overall, while the results are encouraging, continuous refinement and exploration of diverse datasets and algorithms remain imperative for the model's optimization and broader clinical relevance.

1. **Conclusion**

The project successfully predicted Parkinson's Disease from speech using machine learning, with the K-Nearest Neighbors (KNN) algorithm achieving the highest accuracy at 94.87%. KNN demonstrated excellent precision, recall, and F1 Score, making it reliable for both positive and negative identifications. Compared to other models like Support Vector Machines and Random Forest, KNN excelled in distinguishing Parkinson's cases based on speech attributes. These results highlight KNN's potential for accurate and early PD diagnosis. Further enhancements through refinement or ensemble methods could strengthen KNN's role in clinical diagnostics. Implementing the results on a website allows cost-effective predictions for both single and multiple patients, especially benefiting less developed countries.

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