Realtime Parkinson Detection Using AI

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Abstract—

This project aims to develop a real-time Parkinson detection system utilizing artificial intelligence techniques. The system focuses on analyzing voice recordings to determine the presence of Parkinson's disease. By employing advanced AI algorithms, including machine learning and signal processing, the system can accurately detect subtle variations in vocal characteristics associated with Parkinson's. Real-time processing allows for immediate feedback, enabling timely intervention and support for individuals potentially affected by the disease. This innovative approach showcases the potential of AI in healthcare, particularly in early disease detection and management, ultimately improving patient outcomes and quality of life. Through machine learning techniques, the system distinguishes between healthy and Parkinson's affected voices with high accuracy. Real-time implementation enables early detection and intervention, potentially improving the quality of life for individuals with Parkinson's disease.

I. INTRODUCTION

Parkinson's disease (PD) is a progressive neurodegenerative disorder affecting millions worldwide. Early detection and intervention are crucial for effective management and improved patient outcomes. Traditional diagnostic methods often rely on clinical assessments, which can be time-consuming and subjective. Moreover, symptoms may not manifest visibly until the disease has advanced significantly.

In recent years, advancements in artificial intelligence (AI) have opened new avenues for the early detection and monitoring of diseases, including Parkinson's. One promising approach involves analyzing vocal characteristics, as changes in speech patterns are known to occur in individuals with PD. Voice-based detection systems offer the potential for non-invasive, cost-effective, and real-time screening, allowing for timely intervention and treatment.

This project proposes a novel real-time Parkinson detection system utilizing AI techniques to analyze voice recordings. By leveraging machine learning algorithms and signal processing methods, the system aims to identify subtle vocal cues associated with Parkinson's disease. The development of such a system holds great promise for enhancing early diagnosis and facilitating personalized treatment strategies.

A. *Related Work*

Several studies have explored the use of machine learning and signal processing techniques for Parkinson's disease detection. Previous research has investigated the efficacy of various feature extraction methods, including voice analysis, to discriminate between Parkinson's disease patients and healthy individuals. Additionally, advancements in deep learning algorithms have shown promise in improving the accuracy and robustness of detection models. Furthermore, efforts have been made to develop wearable devices and mobile applications for remote monitoring of Parkinson's disease symptoms, contributing to early diagnosis and personalized treatment strategies. However, challenges remain in achieving real-time detection accuracy, scalability, and integration of the system into clinical practice.

Moreover, research has explored the integration of multiple modalities for enhanced accuracy in diagnosis. Furthermore, efforts have been made to address the variability in Parkinson's disease symptoms and progression through longitudinal studies and data-driven approaches. Additionally, collaborations between interdisciplinary teams, including neurologists, engineers, and data scientists, have led to the development of novel methodologies and tools for Parkinson's disease detection and monitoring. Despite these advancements, there remains a need for standardized datasets, validation protocols, and regulatory frameworks to facilitate the translation of research findings into clinical practice effectively.

B. Challenge

Developing a real-time Parkinson's disease detection system using artificial intelligence (AI) poses several significant challenges. First and foremost, acquiring high-quality data for training and validation purposes is critical. However, obtaining large and diverse datasets with labeled samples can be challenging due to the variability in Parkinson's symptoms and the need for longitudinal data collection. Additionally, ensuring the privacy and ethical handling of patient data adds another layer of complexity.

Signal processing plays a crucial role in extracting relevant features from voice recordings for Parkinson's disease detection. However, the noisy and non-stationary nature of voice signals, coupled with inter-subject and intra-subject variability, presents challenges in designing robust feature extraction algorithms. Moreover, integrating multiple modalities, such as voice, gait, and handwriting, for improved accuracy requires addressing data fusion and synchronization issues.

Furthermore, designing machine learning models capable of real-time processing while maintaining high accuracy is a formidable challenge. Deploying complex algorithms on resource-constrained devices, such as smartphones or wearable devices, necessitates optimization for computational efficiency and memory constraints. Moreover, ensuring the reliability and interpretability of AI models in clinical settings is essential for gaining acceptance from healthcare professionals and regulatory authorities.

Additionally, establishing robust validation protocols and benchmarking standards for evaluating the performance of Parkinson's disease detection systems is essential. Incorporating clinical expertise and patient feedback into the validation process helps ensure the clinical relevance and usability of the developed solutions. Moreover, navigating regulatory requirements and obtaining approval for medical devices and AI-based diagnostics adds another layer of complexity to the development process.

II. Analysis

Figure 1 the process outlined above provides a structured framework for building a real-time Parkinson's disease detection model using machine learning techniques. By importing necessary dependencies, collecting and analyzing relevant data, and preprocessing it to prepare for model training, we lay the foundation for effective detection. Utilizing a support vector machine model, we train our system to recognize patterns in voice recordings indicative of Parkinson's disease.

Through rigorous evaluation, we ensure the model's accuracy and reliability, crucial for its practical application in real-world scenarios. Finally, by integrating the trained model into a predictive system, we create a tool capable of providing timely feedback on Parkinson's disease presence based on voice analysis.

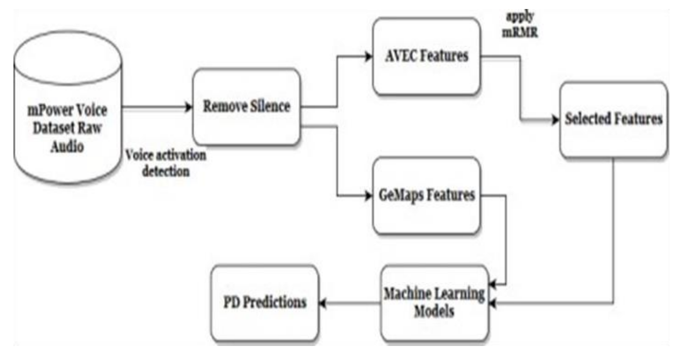


Fig. 1. SUPPORT VECTOR MACHINE

The initial step involves "Importing the dependencies," where we bring in essential libraries and modules needed for various tasks like data analysis, preprocessing, and model training. This includes popular tools like pandas, scikit-learn, and numpy.

Moving on to "Data collection and analysis," we start by gathering relevant datasets containing voice recordings along with labels indicating Parkinson's disease presence or absence. Once collected, we thoroughly examine the data to understand its structure, distribution, and any potential patterns that could aid in detection.

Following this is the "Data preprocessing" stage, which comprises several key processes. Initially, we separate the data into features (representing voice characteristics) and targets (indicating disease status). Subsequently, we split the dataset into training and test sets to evaluate the model's performance. Additionally, we may apply data standardization techniques to ensure consistency and enhance the model's accuracy.

Next is "Model training," where we employ a support vector machine (SVM) model on the preprocessed data. SVM is a supervised learning algorithm commonly used for classification tasks, making it suitable for detecting

Parkinson's disease based on voice features.

Once the model is trained, we proceed to "Model evaluation," where its performance is assessed using metrics such as accuracy score. This score provides insights into the model's ability to accurately classify instances of Parkinson's disease versus healthy individuals based on voice recordings.

Finally, in "Building a predictive model," we utilize the trained SVM model to make predictions on new, unseen data. This predictive model can then be integrated into a real-time system capable of analyzing voice recordings in real-time, offering timely feedback on the likelihood of Parkinson's disease presence.

Reports the feature selection results for each binary and multiclass classification carried out in the current study. For the sake of brevity, we reported the 5 top-ranked parameters for each feature selection method.

Results are reported for each binary and multiclass analysis performed.

Rank	Mid-Advanced PD vs. HC
1	MFCC_std_8thDelta_delta
2	WavDec_det_TKEO_mean_1_coef
3	MFCC_mean_deltaDeltaLogEnergy
4	himmer__F0_abs_dif
…	…
255	Shimmer__F0_TKEO_prc75

III. SOLUTION

A. Process

The process begins with the collection of Parkinson's data, which includes voice recordings from individuals with and without Parkinson's disease. This dataset serves as the foundation for training the machine learning model.

Next, the collected data undergoes preprocessing. This involves cleaning the data, extracting relevant features from the voice recordings, and formatting it for analysis. Data preprocessing ensures that the input data is in a suitable format for the machine learning algorithm to process effectively.

Following preprocessing, the dataset is divided into two subsets: the training set and the test set. This step, known as the train-test split, involves randomly partitioning the data to allocate a portion for training the model and another portion for evaluating its performance.

On one hand, the training set (A) is used to train the Support Vector Machine (SVM) classifier. The SVM algorithm learns from the features and labels in the training data to identify patterns associated with Parkinson's disease presence or absence in voice recordings.

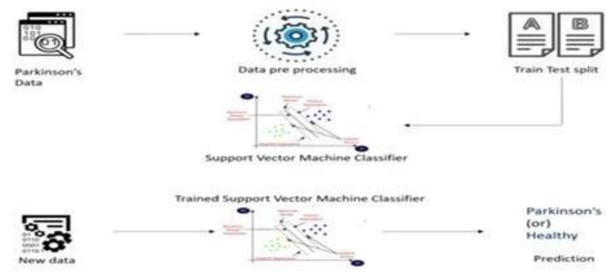


Fig. 2. PROCESS

On the other hand, new data is introduced into the process. This data comprises voice recordings from individuals not included in the training set. The trained SVM classifier is then applied to this new data to make predictions regarding Parkinson's disease presence or absence.

Ultimately, based on the learned patterns, the SVM classifier outputs predictions categorizing the individuals from the new data as either "Parkinson's" or "Healthy." This prediction is based on the analysis of their voice characteristics compared to the patterns learned during model training.

B. Data Set

The diagram outlines a comprehensive pipeline for training a Support Vector Machine (SVM) model with Principal Component Analysis (PCA) integration. Firstly, the process commences with the Problem Data, encompassing the raw data set with feature vectors and their respective labels. Following this, the pipeline proceeds to the phase of Determining the Number of Features, where the optimal feature set is selected, either through manual curation or employing feature selection algorithms.

Next, the Train Data subset is generated from the Problem Data, ensuring it aligns with the desired feature count and serves as the input for training the SVM model. Simultaneously, the Test Data subset is isolated for later evaluation, ensuring it remains independent from the training process. Subsequently, PCA is applied to the Train Data, a pivotal step in dimensionality reduction aimed at retaining maximal variance while reducing the feature space.

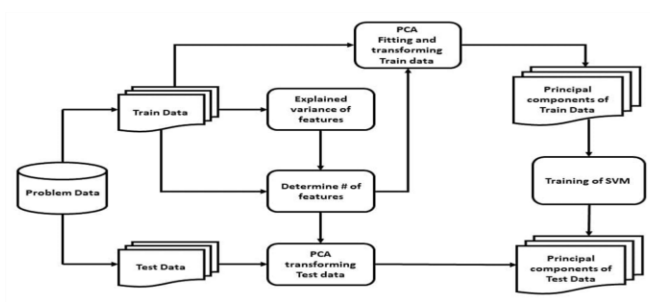


Fig. 3. DATA SET

Analyzing the Explained Variance of Features offers insights into the significance of individual features, aiding in understanding their impact on model performance. The resulting Principal Components of Train Data represent the transformed, lower-dimensional features derived from PCA. These components are then utilized in Training the SVM model, which learns to classify data points based on the reduced feature space.

Similarly, the Test Data undergoes PCA transformation using the same parameters as the Train Data to generate Principal Components of Test Data. These transformed features serve as the input for evaluating the SVM model's performance. Finally, the Evaluation stage quantifies the model's efficacy using various metrics such as accuracy, precision, and recall, thereby gauging its ability to generalize to unseen data and effectively classify instances. Overall, this pipeline encapsulates a systematic approach to SVM training augmented with PCA, optimizing feature representation and enhancing model performance.

C. *Information*

The objective of the support vector machine algorithm is to find the hyperplane in a N dimensional space(N – the number of frames)that distinctly classifies the data points.

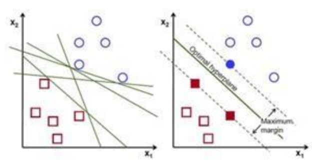


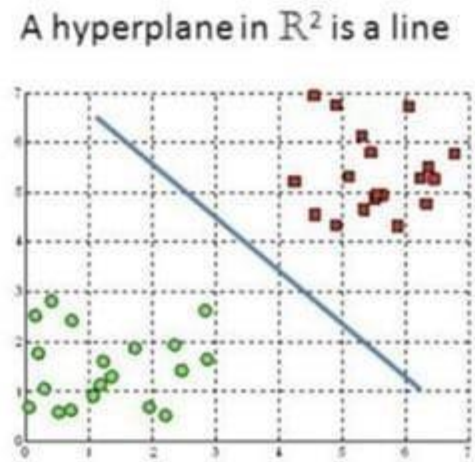
Fig. 1. N – LINES FORMATION

The Support Vector Machine (SVM) algorithm aims to identify a hyperplane within an N-dimensional space, where N represents the number of features, that effectively separates data points belonging to different classes. This hyperplane acts as a decision boundary, maximizing the margin between the classes, thereby ensuring a clear distinction between them. SVM accomplishes this by identifying support vectors, which are the data points closest to the decision boundary. By optimizing the position of the hyperplane with respect to these support vectors, SVM strives to achieve the best possible classification performance, ultimately enabling accurate and robust classification of data points in high-dimensional spaces.

D. *HYPER PLANES AND SUPPORT VECTOR*

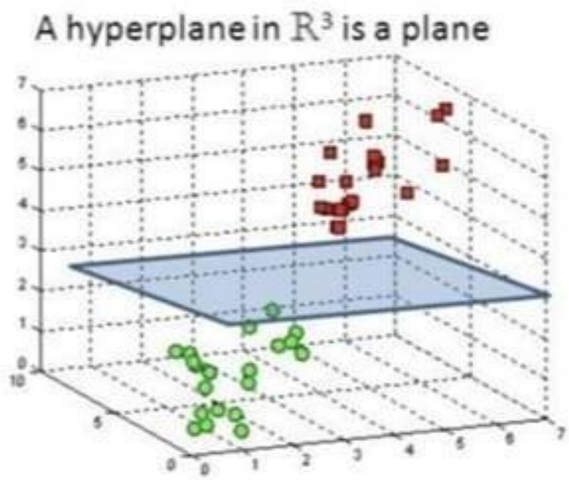
To separate the two classes of data points, there are many possible hyperplanes that could be chosen. Our objective is to find a plane that has the maximum margin, i.e the maximum distance between data points of both classes. Maximizing the margin distance provides some reinforcement so that future data points can be classified with more confidence.

Hyperplanes are decision boundaries that help classify the data points. Data points falling on either side of the hyperplane can be attributed to different classes. Also, the dimension of the hyperplane depends upon the number of features. If the number of input features is 2, then the hyperplane is just a line. If the number of input features is 3, then the hyperplane becomes a two-dimensional plane. It becomes difficult to imagine when the number of features exceeds 3.



The concept of maximizing the margin in Support Vector Machine (SVM) classification is fundamental to its objective of finding an optimal decision boundary. By selecting the hyperplane with the maximum margin, SVM aims to create a robust classification model that generalizes well to unseen data. This margin represents the distance between the closest data points of each class to the decision boundary, effectively acting as a buffer zone that enhances the classifier's ability to classify future data points with confidence.

Hyperplanes serve as the decision boundaries that separate different classes of data points in SVM. These hyperplanes are geometric constructs that divide the feature space into distinct regions corresponding to different class labels. The dimensionality of the hyperplane corresponds to the number of features in the dataset. For instance, in a two-dimensional feature space, the hyperplane is simply a line. In a three-dimensional space, it becomes a two-dimensional plane. However, as the number of features increases beyond three, visualizing the hyperplane becomes increasingly challenging due to the higher-dimensional nature of the space.



Most SVM achieves its classification task by positioning the hyperplane to maximize the margin while ensuring correct classification of training data. This optimization process involves identifying the support vectors, which are the data points closest to the decision boundary. By leveraging these support vectors, SVM constructs a decision boundary that effectively separates the classes and maximizes the margin, thereby enhancing the classifier's ability to generalize to unseen data.

E. Discussion

Results show that traditional machine learning approaches can discriminate with high accuracy between the voices of the patients affected by Parkinson’s disease and of healthy controls, even if the patients are only in the early stage of the disease. Moreover, it is possible to distinguish the voices of the mid-advanced stage patients before and after the therapy. The accuracies of the multiclass classifications are not as good as the ones of the binary classifications, but the results obtained are in line with the expectations.

The average accuracy reached for the binary classifications which involve all the possible PD states considered in this study (healthy, early, mid-advanced ON and OFF L-Dopa) is 82.25%, calculated on the basis of the best performing models.Overall, these results show how traditional ML methodologies still hold a relevant place for highly complex tasks such as voice analysis with low-cardinality datasets; on a side note, as limited as the study population might be, this remains a work involving one the biggest datasets for PD detection to-date. ML algorithms can still provide significant results, sometimes improving the state-of-the-art diagnosis, if carefully fine-tuned and applied to the correct features.

IV. Outlook and Conclusion

Looking ahead, the development of real-time Parkinson's disease detection systems utilizing artificial intelligence represents a promising frontier in healthcare technology. These systems have the potential to revolutionize the early diagnosis and management of Parkinson's disease, offering timely interventions and personalized treatment strategies. By leveraging advanced machine learning algorithms and signal processing techniques, we can harness the power of voice analysis to detect subtle changes indicative of Parkinson's disease presence.

Furthermore, the integration of real-time detection systems into existing healthcare infrastructure holds immense potential for improving patient outcomes and reducing healthcare burdens. With the ability to analyze voice recordings in real-time, these systems can provide immediate feedback to healthcare providers, enabling early intervention and proactive management of Parkinson's disease symptoms. Moreover, the accessibility and non-invasiveness of voice-based detection make it a promising approach for widespread adoption and use in various clinical settings.

The development of real-time Parkinson's disease detection systems using artificial intelligence represents a significant step forward in improving the diagnosis and treatment of this debilitating condition. By harnessing the power of AI and voice analysis, we can empower healthcare professionals with tools to detect Parkinson's disease earlier, leading to better patient outcomes and improved quality of life. As we continue to advance in this field, collaboration between researchers, clinicians, and technology experts will be essential in translating these innovations into tangible benefits for individuals affected by Parkinson's disease.

V.FUTURE WORK

In the realm of future work, there are several avenues for advancing real-time Parkinson's disease detection using artificial intelligence and voice analysis. One promising direction involves the integration of multimodal data sources, such as voice recordings, wearable sensor data, and digital biomarkers, to enhance the accuracy and reliability of detection systems. By combining multiple modalities, we can capture a more comprehensive picture of Parkinson's disease symptoms and progression, enabling more personalized and precise diagnostic algorithms.

Further research is warranted in the development of deep learning architectures tailored specifically for voice-based Parkinson's disease detection. Deep learning models, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have shown promise in analyzing complex patterns in voice data and extracting informative features. Exploring novel architectures and training strategies could lead to even more robust and efficient detection systems capable of real-time analysis.

Overall, future work in real-time Parkinson's disease detection should focus on interdisciplinary collaboration, innovative technology development, and rigorous validation in clinical settings. By harnessing the potential of emerging technologies and addressing existing challenges, we can continue to improve early diagnosis, personalized treatment, and patient outcomes for individuals affected by Parkinson's disease.

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