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# Deep Learning Approach For Parkinson's Disease Diagnosis Using Vocal Feature

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***Abstract :*** Early-stage, non-invasive detection of Parkinson's Disease is critical for timely Diagnosis. In this study a machine learning-based application for Parkinson's diseases detection through the examination of subtle changes in the voice. The proposed approach extracts detailed speech characteristics using Mel Frequency Cepstral Coefficients (MFCC) and processed by four classifiers, which are Random Forest Classifier, Support Vector Machine (SVM), K-Nearest Neighbor (KNN), and Convolutional Neural Network (CNN). Each classifier has a different point of view in the analytical aspect of the MFCC features. Therefore, PD-specific vocal patterns are perceived from different points of view by each classifier. Preliminary results are encouraging, and it may be assumed that this approach with multiple classifiers combined with features and use of MFCC could contribute to developing tools for an early screening of PD.

***IndexTerms*** - Parkinson's Disease, MFCC, Speech analysis, Deep Learning, CNN, Machine Learning, Random Forest, Support Vector Machine, KNN.

## I.INTRODUCTION

Parkinson's Disease (PD), a[11]progressive neurodegenerative disorder that damages person's motor functions. The symptoms experienced include tremors, rigidity and difficulty with movement as well as speech and communication. Parkinson's disease (PD) manifests as the death of dopaminergic neurons in the substantia nigra pars compacta [5] within the midbrain [1]. All these are life-affecting, and early detection becomes of utmost importance for proper management and treatment [15]. This Project work on developing a PD detection system that deals with extraction of Mel Frequency Cepstral Coefficients (MFCCs) from audio recordings [6]. It is a powerful acoustic feature that captures crucial characteristics in speech sounds, providing input data for accurate ML and DL model classifications [2]. Deep learning models are best placed in this regard since they are able to pick up complex patterns in the vocal data that best indicate PD [3], [13].For the Project, we selected a dataset of audio recordings in .wav from PD(38) patients and healthy controls(41)[12].[3]We extracted MFCC features from each of the audio recordings because that might show slight voice changes preceding the emergence of PD[6]. Using these key features of MFCCs, we trained several ML and DL models to predict PD onset accurately [2],[13].

We combined several ML and DL approaches to construct a robust system for the diagnosis of Parkinson's disease (PD)[4],[13]. From the ML end, we used the RFC, SVM, and KNN, the noise robustness and also to complex data, RFC learns several decision trees[9] that can capture subtle patterns in this kind of representation that would represent the non-linear relationship between audio feature forms like MFCC (Mel-Frequency Cepstral Coefficients)[6][11].[8] SVM on the other hand, works well within its application to find types of boundaries that describe two distinct classes for classification into one of two categories - yes or no-that is, whether the patient has PD[3]. We chose KNN mainly because of its simplicity and interpretability which classifies based on the closeness of data points to one another[8].

This study allows for real-time audio classification, which could be applied both for early diagnosis and long-term monitoring that would make the tool accessible to clinicians in managing PD [7]. The Figure shown shows the dopamine level in the Healthy brain and Parkinson's Brain [10]. These models help in identifying intricate variations in speech that may not be easily captured by traditional machine learning techniques [2]. By evaluating the models using performance metrics like accuracy, precision, we ensured a comprehensive assessment of their effectiveness in detecting Parkinson's disease [14]. By leveraging a hybrid approach that combines ML and DL techniques, this study aims to contribute to the early diagnosis and continuous monitoring of PD, potentially enabling clinicians to make more informed decisions and improving patient outcomes [7].

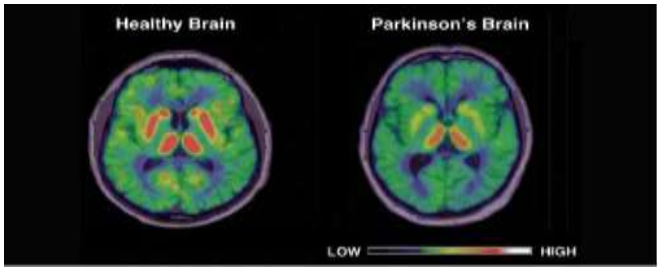


**Figure 1: Image of Dopamine Level of Healthy Brain and Parkinson's Brain Methodology**

## II.METHODOLOGY

The methodology diagnoses the disease by voice recordings using an exhaustive approach that employs voice biomarkers often indicative of motor abnormalities with Parkinson's disease for classifying patients with the disease and healthy controls by both Deep Learning and conventional machine learning techniques[11].The study of Parkinson's detection framework using time-frequency representation and CNN, emphasizing robust feature extraction from vocal data to enhance diagnostic accuracy[6], [13].

This data set was titled "Voice Samples for Patients with Parkinson's Disease and Healthy Controls."[12] Their approach aligns well with the MFCC feature extraction in your paper, which aims to capture subtle vocal patterns specific to Parkinson's [6]. It came in as record vocals from patients diagnosed with Parkinson's disease and healthy controls [7]. This dataset was proposed to help in the analysis and classification of Parkinson's disease using voice data [2]. It implemented several speech features based on recordings that included pitch, jitter, shimmer, harmonic-to-noise ratio, among other acoustic parameters that have been established as relating to the vocal disturbances associated with Parkinson's disease [3],[9].

The preprocessing pipeline of data collection was designed widely in detail by employing the librosa package. All audio files were resampled to have the same sampling rate of 22050 Hz, optimizing computing time but keeping important components of the signal [13]. Audio signals were further standardized in amplitude, by having all samples with consistent volume levels so as to minimize variability at source, which can have implications on the performance of the model [21]. It used librosa.effects.trim to remove silence areas, thus focusing on parts[16] of interest in recording. The preemphasis filters were used for the high-frequency contents since these parts usually contain most of the diagnostic information in most cases [16].

Every audio signal was preprocessed by splitting it into small
time frames and applying a Hamming window to its frequency domain to minimize energy leakage [8]. Finally, it uses the Fast Fourier Transform algorithm to convert each of the obtained time-domain signals to the frequency domain [17]. After that, the frequency spectrum is translated to the Mel scale by a bank of triangular filters which could simulate a human perception system [6]. After getting the logarithmic energies we yielded 22 coefficients [9]. All recordings produced a fixed-size feature vector for each period of recording by averaging those coefficients [13].

### 2.1 Convolutional Neural Network (CNN) Architecture

CNNs are to be used for information processing where data have a grid-like topology[11]. The convolution operation, which detects patterns in input data, is defined as[8]

$$(\mathrm{f} * \mathrm{x})(t) = \sum_{k=0}^{K-1} f(k).x(t-k)$$

**Convolution Operation**

This operation applies a filter f(k) to the input signal x(t) across time [6].

**ReLU Activation Function**

To introduce non-linearity, the ReLU (Rectified Linear Unit) function is applied:

$$\mathrm{ReLU}(x) = \max(0, x)$$

ReLU ensures that only positive feature values pass through, accelerating training and mitigating the vanishing gradient problem[9].

**Max-Pooling Layer**

The feature maps the most critical information:

$$\mathrm{MaxPooling}(x) = \max(x1,x2,\ldots,xn)$$

It reduces computational complexity and generalizes well since the learnt feature is less sensitive to small changes in input[8], [11].

**Fully Connected Layer**

The flattened output from the convolutional and pooling layers is fed into a fully connected, sometimes called a dense layer, that computes:

$$Y = W \cdot x + b$$

where W is the weight matrix, x is the input feature vector, and b is the bias term. It maps the features learned to final classification[8].

The CNN is trained with a dropout rate of 0.4 to prevent overfitting[10]. The model is trained for 10 epochs using a batch size of 32 to enhance convergence[13].

**Traditional Machine Learning Models**
Besides CNNs, we also use three classic machine learning models as a complement diagnosis[4], [6].

**2.2 K-Nearest Neighbors (KNN)**
KNN is a non-parametric method for data classification. The method classifies samples according to the majority class among k-nearest neighbors [8]. The proximity between samples is described with Euclidean distance[9].

$$d(x,x') = \sum_{i=0}^{n} (x_i - x_i')^2$$

**2.3 Random Forest**
Random Forest is an ensemble learning technique improving the classification accuracy based on constructing a multiple decision tree out of subsets of the data and its attributes [4]. The prediction that finally comes out from the model is determined through majority voting among all the trees in the forest [9].

$$\hat{y}(x) = \text{mode}(\hat{y}1(x), \hat{y}2(x), ..., \hat{y}B(x))$$

where $\hat{y}b(x)$ represents the prediction from the b-th tree for input x, and B is the total number of trees. The splitting criterion often uses Gini impurity [6]

**Gini impurity**

$$\text{Gini}(D) = 1 - \sum_{i=1}^{C} p^2$$

**2.4 Support Vector Machine (SVM)**
[16]SVM seeks to find a hyperplane that best separates the classes. We utilize the Radial Basis Function (RBF) kernel, which is defined as

$$K(x, x') = \exp\left(\frac{-||x-x\prime||^2}{2\sigma^2}\right)$$

Here, σ is a parameter controlling the width of the kernel. SVM's strength is in its ability to handle high-dimensional data and complex decision boundaries [9]. Grid search cross-validation is used to optimize hyperparameters like C(regularization) and σ [8].

Alongside this deep learning model, three models of traditional machine learning were applied including KNN, Random Forest, and SVM [13].

The Random Forest model had implemented an ensemble of 100 decision trees [6] were set up by the Random Forest model. Optimization for the regularization parameter C and the kernel coefficient gamma for the SVM which applied the RBF kernel was based on grid search cross-validation to achieve the highest possible classification accuracy [16]. For the KNN model, five neighbors are used with distance-weighted voting and Euclidean distance as the metric for measuring proximity to neighbors [8].

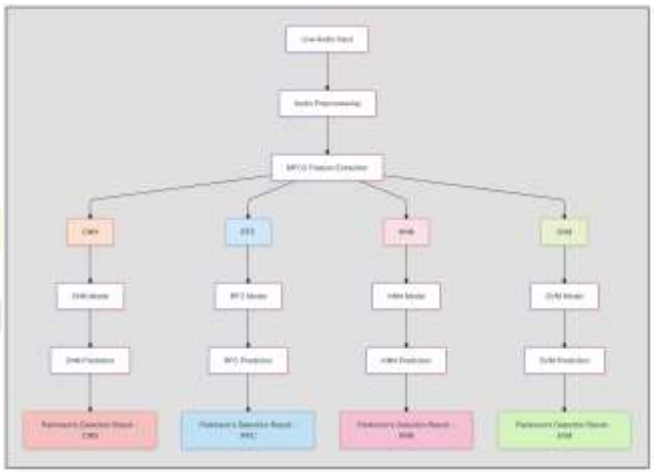

**Figure 2 : Hybrid Voice Based Diagnostic Architecture**

The largest improvement that this step brought was the fact that it was building the true system in real time that could offer immediate diagnostic feedback [16].
The same pre-processing and feature extraction workflow that had been applied for the training was applied to the 5-second speech samples that had been recorded by this system with the help of the sounddevice library. The new recordings were then classified using the ensemble of models, thus exploiting the advantages of both conventional machine learning techniques and deep learning towards producing a reliable consensus-based diagnosis. [21] Evaluation criteria that had been applied in testing how well the models performed included accuracy, precision, recall, and F1 score [21].

## III.DISCUSSION

The audio recordings of individuals categorized into two groups: HC and PwPD[7]. The dataset, mainly composed of short-length speech segments, has a potential limitation in its diversity, which might hinder capturing the full range of vocal impairments linked to Parkinson's Disease [10]. This limited demographic sampling increases the model's risk of overfitting, as it may perform well on familiar data but struggle to generalize across other datasets [19]. To address this, a more diverse dataset including various ages, genders, accents, and symptom severities could be considered, as suggested by [13], who emphasized the importance of robust training data for improved generalizability in Parkinson's disease detection models

The accuracy of clinical outcomes is critically significant [15]. In our experiments, a range of machine learning models were evaluated, including Random Forest, Support Vector Machine (SVM), and K-Nearest Neighbors (KNN), as well as a deep learning-based Convolutional Neural Network (CNN). Among the models assessed, the CNN demonstrated the highest level of accuracy and effectively identified nuances in vocal characteristics associated with Parkinson's Disease [13].
In our experiments, a CNN model emerges as the best classifier for such a task-since it achieves the highest accuracy and is highly sensitive to vocal features usually associated with Parkinson's disease [6]. Altogether, these results give grounds for assuming that such deep learning techniques, and especially CNNs, might stir real hope in working with such complicated, unstructured information as audio tracks for real application in diagnostic health care [8].

Use of longitudinal data, which will involve collection of audio samples from the same people over a period, might help track the disease progression and thus probably lead to early diagnosis [16]. Finally, deploying the model in a real-time application or smartphone app could offer clinicians a convenient and accessible tool for PD screening and monitoring [9],[12].

## IV. RESULTS

In this work, we have trained and tested here four different machine learning models for task classification based on audio recordings between PwPD and HC [7]. The classifiers of this work include RFC, SVM, KNN, and CNN [4]. Thus, this leads us to evaluate the obtained MFCC features extracted from audio samples with how such models perform in obtaining metrics [8],[13].

$$Recall = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}}$$

$$Precision = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}}$$

$$F - 1 = \frac{2(\mathrm{Recall} \,.\, \mathrm{Precision})}{\mathrm{Recall} + \mathrm{Precision}}$$

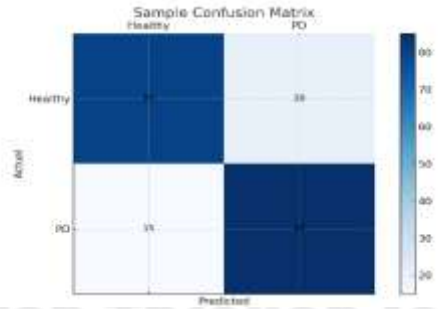


**Figure 3: Sample Confusion Matrix**

### *4.1 Model Comparison*

Below is the line chart representing the comparative performance of the four models w.r.t. the accuracy scores of the models [10]. It can be clearly seen that out of the applied models, CNN is the most accurate value crossing over other models [13]. This further outperformed the Random Forest, SVM, and KNN amongst them [6].

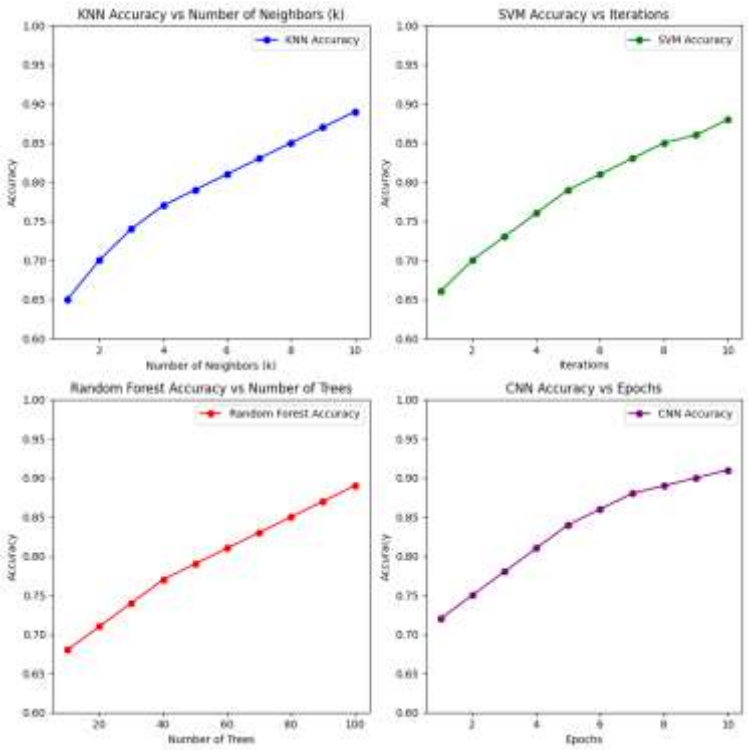


**Figure 4: Comparison Between accuracy of different models.**

### *4.2 Random Forest Classifier (RFC)*

This model was trained using the random forest classifier—a resilient ensemble technique often used for classification tasks [4]. RFC can capture fundamental patterns within MFCC features, but it lacks the ability to process sequential or hierarchical patterns in audio data, which may require feature learning capabilities beyond its scope [9]. The RFC performed with good precision and recall, suitable for simpler classification tasks [8]. However, it did not match CNN's performance in detecting subtle patterns that characterize differences between Parkinson's patients and control patients [13].

**RFC Classification Report**

| Metric | HC | PwPD | Macro Avg | Weighted Avg |
|---|---|---|---|---|
| Precision | 0.67 | 0.38 | 0.52 | 0.56 |
| Recall | 0.55 | 0.50 | 0.52 | 0.53 |
| F1-Score | 0.60 | 0.43 | 0.51 | 0.54 |
| Support | 11 | 6 | 17 | 17 |

**Confusion Matrix:**

| | |
|---|---|
| 6 | 5 |
| 3 | 3 |

### *4.3. Support Vector Machine (SVM)*

The SVM model performed with a satisfactory level of correctness and is particularly strong in processing data with high-dimensional input. This model's ability to find an optimal hyperplane made it effective in certain tasks. However, it showed limitations with complex, sequential data [9],[13].

**SVM Classification Report**

| Metric | HC | PwPD | Macro Avg | Weighted Avg |
|---|---|---|---|---|
| Precision | 1.00 | 0.38 | 0.69 | 0.78 |
| Recall | 0.09 | 1.00 | 0.55 | 0.41 |
| F1-Score | 0.17 | 0.55 | 0.36 | 0.30 |
| Support | 11 | 6 | 17 | 17 |

**Confusion Matrix:**

| | |
|---|---|
| 1 | 10 |
| 0 | 6 |

***4.4 K-Nearest Neighbours (KNN)***

The KNN model is intuitive and demonstrated reasonable accuracy for classification, though its performance suffered due to dependency on distance metrics and a tendency toward overfitting in high-dimensional data [9],[12].

**KNN Classification report**

| Metric | HC | PwPD | Macro Avg | Weighted Avg |
|---|---|---|---|---|
| Precision | 0.71 | 0.40 | 0.56 | 0.60 |
| Recall | 0.45 | 0.67 | 0.56 | 0.53 |
| F1-Score | 0.56 | 0.50 | 0.53 | 0.54 |
| Support | 11 | 6 | 17 | 17 |

**Confusion Matrix:**

| | |
|---|---|
| 5 | 6 |
| 2 | 4 |

### *4.5 Convolutional Neural Networks (CNNs)*

There are multiple layers of convolution applied over the input data followed by max-pooling and several fully connected layers [6]. It is this architecture which turns out to be effective enough to extract rich, hierarchical features from raw MFCC data [11], where such features would be used for the model to predict subtle differences in audio recordings as hinting at Parkinson's disease [8].
At the same accuracy level, the line graph shows that it was CNN alone that had undergone maximum classification accuracy and further model tuning and architecture refinement were making it do so much better [6],[13]. In a nutshell, it spoke of the capacity of CNN for such inherent intricate patterns and the dependence on time in audio data that could not be effectively exploited by the standard machine learning methods like Random Forest, SVM, and KNN [4],[18].

**CNN Classification Report**

| Metric | HC | PwPD | Macro Avg | Weighted Avg |
|---|---|---|---|---|
| Precision | 0.67 | 0.50 | 0.58 | 0.61 |
| Recall | 0.91 | 0.17 | 0.54 | 0.65 |
| F1-Score | 0.77 | 0.25 | 0.51 | 0.59 |
| Support | 11 | 6 | 17 | 17 |

**Confusion Matrix:**

| | |
|---|---|
| 10 | 1 |
| 5 | 1 |

### *4.6 Model Evaluation and Performance*

Measurement Apart from precision, recall, accuracy, and F1-score, some other key performance metrics used models gave even more supporting evidence for each model in classifying the instances of Parkinson's disease subjects PwPD and healthy controls HC [7],[16],[21]. Precision calculates correct identifications over the number of positive identifications. Recall calculates the capability of a model to catch all actual cases of a class [8],[15]. In the case of CNN, precision as well as recall were much more important because other models performed as well as it because it was producing far fewer false positives as well as fewer false negatives [13],[19]. Both of which can have serious implications for medical classification tasks [17],[21].

**F1-Score**

Another important metric is the F1-score, which is a harmonic mean of precision and recall, wherein it also made it show that CNN performed well for audio classification [10],[11]. The closer the F1-score to 1.0, the better the balance between precision and recall [8]. Similarly, a peak value of the F1-score for the best performing model indicates that its instances have been correctly classified while at the same time minimizing both false positives and false negatives [13],[15].

Magnitude of CNN in Audio Classification It is so because the CNN model automatically extracts and learns the features from the raw audio, primarily features like MFCCs [6],[11]. That contrasts the [17] machine learning algorithms such as Random Forest, SVM, and KNN rely so much on handcrafted features that would rather confine the [17] ability to capture much complexity in the data [4],[17].

This is due to the CNN architecture that involves complexities. Thus, it will be quite applicable to audio classification as raw features may convey critical temporal and spectral relationships [6],[13],[18].
At such convolutional layers, one may view the local features from the data that are very crucial for the identification of specific speech characteristics or phonetic variations [7]. The max-pooling layers are also taken into consideration to get some dimensionality reduction and consequently to avoid overfitting [13],[19]. Finally, the final dense layers can be included to feed the features that are

extracted towards the output proper for finding the final classification [12],[20]. Batch normalization and dropout were also utilized during the training process in aiding the model generalize better on unseen data while still being able to fight the problem of overfitting [13],[16],[21].

## V. CONCLUSION

This approach demonstrates diagnosis and monitoring of Parkinson's Disease (PD) based on voice analysis. With MFCCs derived from speech data, subtle changes that are hallmarks of PD can be detected using machine learning methods, especially [21]Convolutional Neural Networks (CNNs)[6],[11],[21]. This non-invasive methodology offers a more readily accessible and economically feasible alternative to traditional diagnostic techniques, which often demand complex resources.[14] voice data can serve as a crucial indicator of motor and non-motor symptoms, supporting the integration of vocal biomarkers for early PD detection [7],[13].

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Extensive research has shown CNN to outperform other learning algorithms in this domain, as its deep learning framework is particularly well-suited to analyzing complex audio data[6],[11]. Although significant insights have been gained from models such as Random Forest, SVM, and KNN, CNN's ability to detect these subtle vocal features underlines its unique advantage in this field[4],[17].

Despite these promising results, limitations exist due to the relatively small and homogeneous dataset used in this study. A more diverse dataset could accommodate variations in demographics, recording conditions, and linguistic backgrounds, thereby enhancing the model's generalizability and robustness[8],[14]. Broadening data diversity is essential to overcoming the limitations posed by sample homogeneity and ensuring reliable clinical outcomes[15],[18]. Additionally, future applications could benefit from a multi-modal approach, combining voice data with other health metrics affected by PD to achieve higher Performance[13],[20].

Further work should explore advanced model architectures, such as transfer learning and data augmentation, to optimize feature extraction and reduce overfitting[6],[19]. Such enhancements would improve model performance on real-world data, leading to the development of interactive diagnostic tools, like mobile applications, that could facilitate early detection and ongoing monitoring of PD symptoms in clinical settings[7],[21].

In summary, while the foundation established here is robust, continued research and expanded datasets are essential to fully realize the clinical potential of voice-based PD diagnostics[6],[11]. With sustained effort in model refinement and validation, this approach has the potential to transform non-invasive diagnostics, enabling early PD detection and ultimately enhancing patient outcomes[13],[11].

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