

Vocal Biomarkers and Deep Learning Approaches for Early Parkinson's Disease Detection

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Abstract— Early discovery of Parkinson's disease (PD) remains vital because it enables effective management alongside treatment opportunities. Vocal biomarkers, derived from speech recordings, offer a noninvasive method for early PD diagnosis. In this research the use of various machine learning and deep learning techniques are used to analyze vocal biomarkers for early disease detection. Two datasets are utilized: one consisting of CSV files with extracted features, and the other comprising raw audio files. For the CSV dataset, three detection algorithms known as XGBoost Classifier and Support Vector Machine (SVM) were used and Random Forest—are employed. The raw audio files are processed using Convolutional Neural Networks (CNNs), and VGG 19, to automatically extract and learn relevant features for PD detection. These algorithms are trained and evaluated on features extracted using Mel Frequency Cepstral Coefficients (MFCC), Chroma, and Mel-spectrograms. The result output shows how CNN-MFCC with an accuracy of 90% CNN-Mel with an accuracy of 82.6%, CNN-Chroma with an accuracy of 56.3% and a pretrained algorithm VGG-19 gave an accuracy of 61%. The performance of each classifier is measured to determine their effectiveness in detecting early-stage PD from the vocal features. The CNN-based approach leverages the powerful feature extraction capabilities of deep learning to analyze the complex patterns within the speech recordings.

Keywords—Parkinson's disease, CNN, VGG-19, Audio files, CSV files.

I. INTRODUCTION

Parkinson's disease shows two main symptoms categories which include motor symptoms together with non-motor symptoms. Among the fundamental motor signs of PD one can identify tremor alongside the symptoms of bradykinesia and rigidity and postural instability. The non-motor symptoms of PD include mood disorders with cognitive dysfunction while pain symptoms and sensory dysfunction and dysautonomia also occur.

The majority of PD patients experience both quiet speech and hurry associated speech disturbances. PD identification benefits from the analysis of speech signals which stands as a useful non-invasive testing method. The prediction and identification of PD should be noninvasive according to clinicians and neuroscientist. Early PD detection becomes feasible along with preventive measures through the ability to notice voice changes in PD patients. This disease is a neurodegenerative disorder that affects nerves so it's critical for improving patient outcomes and providing timely interventions. This disease relied on clinical assessments and neuroimaging, which are often expensive and may not be readily accessible to everyone.

However, recent advances in the field of medical research have demonstrated a potential of vocal biomarkers as a non-invasive and cost-effective means of early PD detection.

Vocal biomarkers refer to specific acoustic and linguistic features present in a speech that can serve as indicators of their health and neurological status. In the context of PD, vocal biomarkers encompass a range of speech-related changes, including alterations in pitch, loudness, speech rate, articulation, and prosody. These vocal characteristics [3] can be subtle but are often detectable through automated analysis of both diagnosing and monitoring PD as an early disease stage. A bidirectional long short term memory (LSTM) model functions to identify time-series dynamic speech signal characteristics. The speech features are determined by analyzing the energy levels when speech shifts from an unvoiced to voiced state as well as from voiced to unvoiced state. There exists no research applying joint application of Bidirectional LSTM network and dynamic articulation transition features from speech vehicles. The researchers split the data without sample overlap during cross validation procedures while their proposed method proved effective at accuracy improvement.

Early detection of the disease is a critical challenge in the healthcare. Existing methods rely up on clinical assessments, which may not effectively detect the disease's onset in its early stages. To address this issue, an investigation of the feasibility and efficacy of utilizing vocal features for diagnosis of this disease.

Based on the vocal features with analytics enhancing the life for patients in a non-invasive and cost-effective way will help reduce the healthcare burden due to this neurodegenerative condition. It is hoped that this research, which concerns the use of vocal biomarkers for early PD diagnosis can contribute to these goals: better patient centered care; co designing more accessible healthcare systems- and learning how speech may be used in diagnostic processes involving neurological disease. Parkinson's early detection will in time help others with the disease and also help shape the future of healthcare through technology. The major contribution in this system was to apply a preprocessing steps reducing noise, silence removal and standardization technique followed by extraction of feature using MFCC, Chroma and mel-spectrogram. Fine – tuning of the hyper parameter was done using grid search and bayesian optimization to enhance model performance

The objectives of the framed were to gather data on vocal changes in early-stage Parkinson's patients to contribute for research. Research needs to define the vocal features - including pitch and intensity alongside articulation and prosody - which serve as the most effective indicators between subjects with early disease and healthy participants. To determine early signs of the disease through vocal biomarkers to allow for timely intervention and treatment. To use the best method to classify or diagnose Parkinson's disease with the available methods. Reduce healthcare costs associated with Parkinson's disease by detecting it in its early stages, which can potentially lead to more effective and less expensive treatment options

II. LITERATURE REVIEW

A study proposed a 9-layer CNN model with parallel 1-D convolution layers, achieving 83.3% and 84.5% accuracy on training and testing data. The parallel layers enabled multimodal data integration, improving classification. However, dataset size and diversity remain challenges for model generalizability. [1] A study using the PPMI database and a feed-forward neural network (FNN) achieved 96.6% accuracy, surpassing KNN, logistic regression, and random forest. [2] The classification was performed using various algorithms including logistic regression, support vector machines, random forest, naive Bayes, gradient boosting model, and linear discriminant analysis. Achieving a commendable accuracy of 82% on training data and 84% on testing data. [3] A cubic-SVM model combined with artificial neural network (ANN), achieved competitive accuracy rates of 89.9% and 93.1% on training and testing data, respectively.[4] Subsequently employing Boruta's algorithm for feature selection and various classifiers the model achieved promising accuracy rates of 87% on training data and 93% on testing data.[5] A Scopus dataset comprising MRI scan data of PD patients the study employed deep learning-based classification methods, including 2D CNNs. Achieving accuracy rates of 85.7% and 95.3% on training and testing data respectively.[6] Maximum Relevance Minimum Redundancy algorithm model achieved competitive accuracy rates of 93.7% and 94.6% on training and testing data, respectively.[7] A study focused on spiral and wave drawing samples obtained from Kaggle. Utilizing image preprocessing techniques and explainable artificial intelligence (EXAI) models based on spiral and wave drawings, the study achieved impressive accuracy rates of 93.4% and 98.45%. [8] Researchers employed kinematic data measured using inertial measurement units (IMUs) for detecting and classifying PD stages. The model attained notable accuracy rates of 92.72% and 99.67%. [9] The employment of an OF-k-NN classifier model achieved accuracy rates of 91.48% and 97.95%. However, challenges such as dataset size, feature selection, interpretability, and real-world validation remain focal points for future research endeavors [10] In a researchers focused on feature extraction from accelerometer (ACC) and EMG signals, analyzing various characteristics in different frequency ranges.

Employing differential diagnosis based on the analysis of wave train electrical activity of muscles, achieving an accuracy of 85%. [11]

A subsequent study utilized data collected at the University of San Diego, California, pre-processed using MATLAB EEGLAB. Employing the PDCNNet model and utilizing the S-Transform to obtain time-frequency representation (TFR), the study achieved accuracy rates of 88.25% and 99.97% [12]. Analysis of 150 speech recordings (100 PC-GITA participants with 50 PD and 50 HC) and 50 Italian Parkinson's voice and speech subjects (28 PD, 22 HC) utilized the AST model which received comparisons with network models VGG16, VGG19, ResNet18, ResNet34, vision transformer, and swin transformer [13]. This research investigates voice feature changes in PD patients which might serve as indicators to detect disease onset early [14]. The research will develop methods for predicting Parkinson's disease development. Researchers use multiple sophisticated machines learning approaches [15].

The research displays voice's potential for PD early detection while suggesting voice can serve as a deep phenotype for PD that supports precise medical approaches to improve both accuracy and accessibility and cost-effectiveness of PD management [16]. The Synthetic Minority Over-sampling Technique (SMOTE) established data balance which produced excellent results that surpassed other methods. The combination of dataset balancing using SMOTE with Random Forest algorithm proved exceptional performance [17]. The research builds an automatic PD binary classification system through the assessment of vocal biomarkers to achieve diagnosis. Our analysis using explainability techniques will discover key characteristics of Parkinson's inside voice patterns to improve our definition of Parkinson's diagnosis [18]. The research builds an automatic PD binary classification system through the assessment of vocal biomarkers to achieve diagnosis. Our analysis using explainability techniques will discover key characteristics of Parkinson's inside voice patterns to improve our definition of Parkinson's diagnosis. [19]. By applying an unsupervised dimensional reduction method, the generated model eliminates redundant data and speeds up training and testing. Model performance is estimated with three parameters, including accuracy, F1 score, and area under the curve (AUC) values [20].

III. METHODOLOGY

Our approach for early detection of disease using vocal biomarkers involves a comprehensive methodology encompassing data collection, feature extraction, model training, and evaluation. A brief overview of the methodology is shown in the Figure 1.

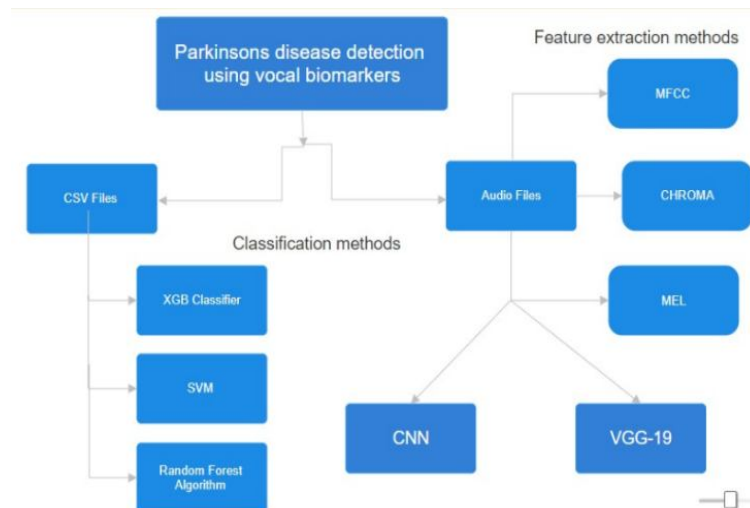


Figure 1. Block diagram

A. Software requirements

- Python Distribution Anaconda includes a Python distribution, which is preconfigured with numerous data science libraries and tools. This Python distribution is designed for ease of use in data-related tasks.
- Conda Package Manager is used to simplify the installation and management of libraries and dependencies. This allows creating isolated environments for different research, which helps in avoiding version conflicts.
- Data Science Libraries: The system offers a broad selection of data science libraries that positions it as an outstanding solution for both data quality assessment and machine learning operations.

- Jupyter Notebook is an interactive environment for data analysis and visualization. Users widely employ this software for the purpose of document generation and distribution which incorporates active computer code alongside mathematical expressions and visualizations along with descriptive textual content.
- Integrated Development Environments (IDEs): Anaconda supports various IDEs like JupyterLab, Spyder, and RStudio, providing flexibility for different coding preferences and research needs. The software requirements specification, which includes all the specifications required for the research development, will be discussed in this chapter. The research is briefly described, module by module, and the software and design requirements are listed

B. Data Collection and Preprocessing

Two types of data were used: CSV files with pre-extracted vocal features and raw audio files. The CSV files include features such as MFCC, Chroma, and Mel-spectrogram values. The audio files are preprocessed to remove noise and standardize their format. Silence removal and normalization ensure consistency in the audio data.

Feature Extraction: For the CSV files, MFCC captures the short-term power spectrum, Chroma represents a 12 pitch classes and Mel-spectrogram provides an visual representation of sound spectrum. For audio files, python libraries like librosa were used to extract MFCC, Chroma, and Mel-spectrogram features directly from the recordings.

Machine Learning Models: For the CSV data, three machine learning algorithms were employed: XGBoost Classifier, Support Vector Machine (SVM), and Random Forest. Each model is trained on the preprocessed features, with hyperparameter tuning to optimize performance. Their effectiveness is evaluated using metrics like accuracy, gdata, Convolutional Neural Networks (CNNs) and fine-tune a pretrained VGG19 model. This is designed with layers to process MFCC, Chroma, and Mel-spectrogram inputs, while VGG19 processes spectrogram images derived from the audio files. Both models are evaluated using the same performance metrics which is depicted in Figure 2.

Model Integration and Comparison: Comparison of performance of model to identify best approach for early PD detection.

Validation and Testing: Cross-validation ensures the robustness and generalizability of the models. The model performance is assessed using confusion matrices and detailed classification reports that show true positive and negative and false positive and negative evaluations.

Implementation and Deployment: The best-performing model(s) are prepared for deployment, possibly integrated into a clinical decision support system. Post-deployment, continuous monitoring would ensure the reliability and effectiveness.

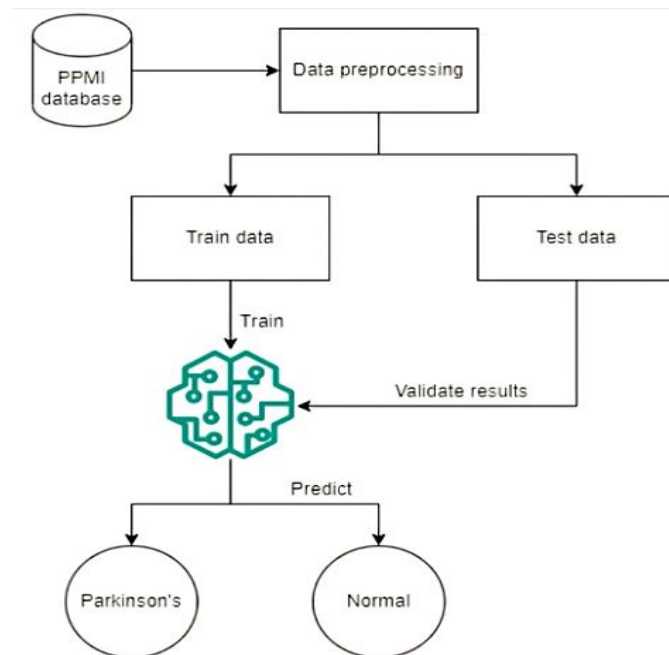


Figure 2. Proposed architecture

Method For CSV Files

The methodology for detecting Parkinson's disease using a SVM classifier begins with the import of necessary libraries, including those for data handling, visualization, and machine learning. The dataset, which is loaded from a CSV file, undergoes an initial exploration to understand its structure and characteristics. The first few rows would check for missing values, and examining basic statistical details. A heatmap of the correlation matrix is created to visualize the relationships between different features.

Method For Audio Files

CNN

Detecting Parkinson's disease using a CNN involves several technical steps, starting with data preprocessing and feature extraction from audio files. Using the librosa library, MFCC are extracted and averaged to represent the audio signals numerically. The dataset, consisting of three categories (mild Parkinson's, normal, and Parkinson's), the data is split into 0.80 and 0.20 ratio for training and testing respectively. Features are reshaped to fit the CNN input requirements. The CNN architecture includes layers for convolution, max-pooling, flattening, and dense connections, with ReLU activations and a final softmax layer for classification which is given below in Figure 3. The model is compiled using Adam optimizer and trained for 25 epochs, with validation of the test set.

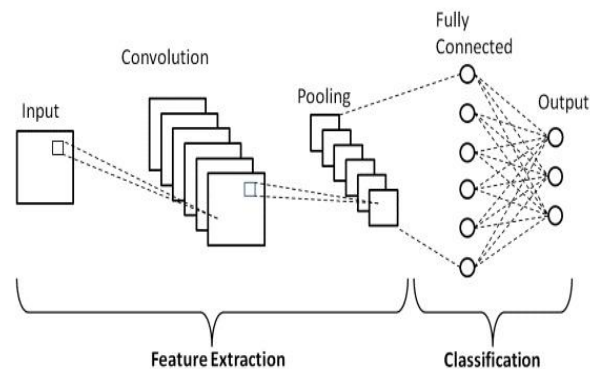


Figure 3. Flowchart of CNN

A performance evaluation of the model uses accuracy along with precision and recall measures and F1-score and creates a confusion matrix for assessment. The performance assessment depends on calculating these metrics using predictions obtained from the test set. Both training and validation sets receive accuracy and loss results from the deployed save model.

Mel-Frequency Cepstral Coefficients

This methodology begins with loading audio file and resampling it to a consistent sample rate of 22,050 Hz. The process includes several steps: pre-emphasis to boost high frequencies, framing the audio into small overlapping windows, next apply a Hamming filter to each frame, followed by applying Fourier Transform to get the frequency spectrum, and to get power spectrum Mel filter bank is used mimicking human auditory perception. The logarithm of the Mel filter bank energies is taken, followed by a Cosine Transform to decorrelate the resulting coefficients, yielding the MFCCs. These coefficients are then averaged over all frames to form a robust feature vector that captures the timbral characteristics of the audio signal.

Chroma Feature

Chroma feature extraction involves computing the audio signal to obtain its time-frequency representation. The magnitude spectrum from the STFT is mapped into 12 pitch classes (chromas) corresponding to the 12 semitones of the musical octave. This process effectively reduces the dimensionality of the frequency spectrum, emphasizing the harmonic and melodic content of the audio. Each chroma vector, representing the energy distribution among the 12 pitch classes, is averaged over time frames to create the final feature vector, which encapsulates the harmonic structure of the audio.

Mel Spectrogram

The Mel Spectrogram is derived by first computing the STFT of the audio signal to obtain its time-frequency representation. The magnitude spectrum obtained from the STFT is then passed through a set of Mel-spaced filters, which are designed to approximate the human ear's perception of sound. This results in a Mel-scaled spectrogram representing energy distribution with respect to time and also frequency. The spectrogram values

are logarithmically compressed to reduce dynamic range and highlight perceptually relevant features. The Mel spectrogram frames are then averaged over time to form the final feature vector, providing a detailed representation of the audio's spectral content.

VGG-19

Pre-trained VGG19 model initially, audio features such as MFCC are extracted from audio files using the librosa library. The dataset consists of three classes (mild Parkinson's, normal, and Parkinson's), and these extracted features are converted into numpy arrays as shown in Figure 4. The data processing structure divides information into training test pairs while adjusting their shape to suit VGG19 input parameters. The grayscale images need to have their data expanded through channel repetition to become RGB images which match VGG19 input specifications.

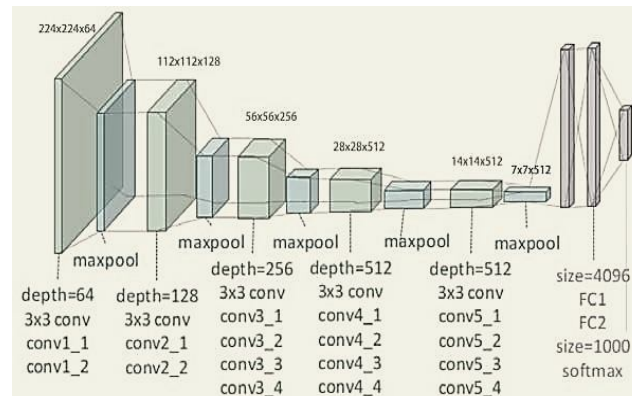


Figure 4. Overview of the proposed system

The VGG19 model serves as the starting base model after training it on ImageNet because its highest layers are separated from the rest which receive frozen weights to maintain learning. The model receives four additional custom layers which consist of a flatten layer followed by dense layers with ReLU and dropout then finishes with a dense layer that uses softmax activation. The trained model implements Adam optimizer in combination with sparse categorical cross-entropy loss to compile training of the processed dataset. The program shows the training history that includes both loss and accuracy data pertaining to training and validation sets. Evaluation of the model happens through confusion matrix analysis and detailed classification report generation which reveals accuracy measures together with precision and recall statistics as well as F1 score rates per class type.

IV. RESULTS AND DISCUSSION

This division deals with the results obtained from the classification algorithms applied for the research.

A. Result

There are many different graphs which would explain about various outputs achieved during training phase.

CNN

A deep learning technique designed to take care of structured data in images.

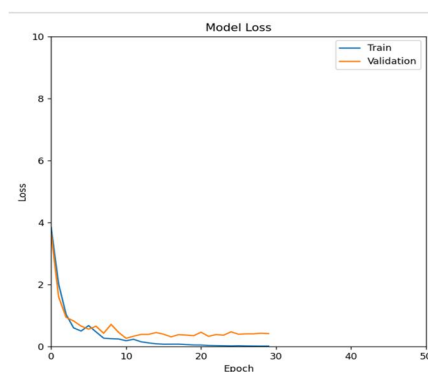


Figure 5a. Model Loss graph

The graph in figure 5a shows the number of epochs versus loss which is know as loss curve

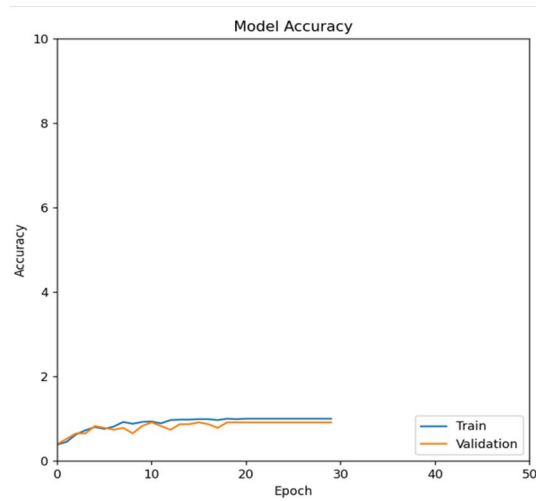


Figure 5b. Model accuracy graph

Graph in figure 5b shows the number of epochs versus accuracy which is know as accuracy curve. The figure 6 shows the confusion matrix here the columns shows predicted class and rows depict the actual class.

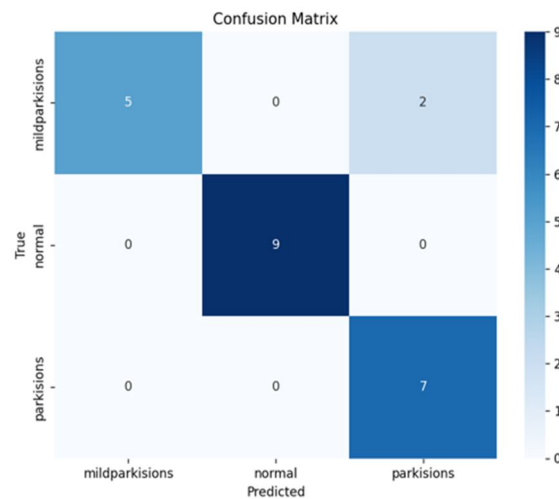


Figure 6. Confusion matrix

Table I shows the classification report of CNN model proposed in this research showing the classification of the different classes of 0,1 & 2 for the parkison's disease.

TABLE I. CLASSIFICATION REPORT OF CNN

	Precision	Recall	F1-score	Support
0	1.00	0.71	0.83	7
1	1.00	1.00	1.00	9
2	0.78	1.00	0.88	7
Accuracy			0.91	23
Macro avg	0.91	0.90	0.90	23
Weighted avg	0.91	0.91	0.91	23

VGG 19

Visual geometry group is a pretrained CNN with multiple layers depth trained with different set of images which would easier to adapt to the currently used dataset. Figure 7a shows the model loss which gives the value of total loss that's occurred during the training phase

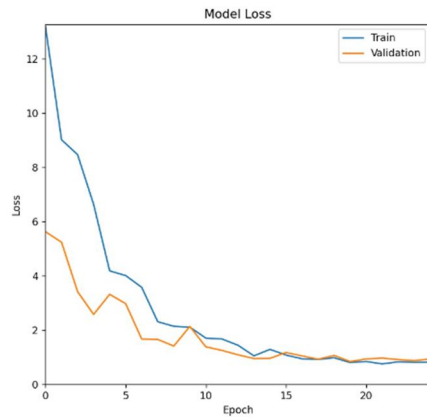


Figure 7a. Model loss graph

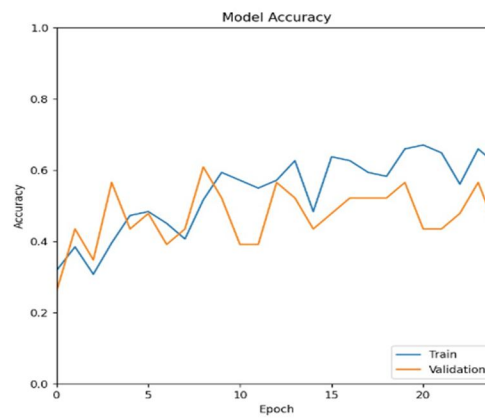


Figure 7b. Model accuracy graph

The model accuracy shown in the Figure 7b shows the epochs versus accuracy which depicts a increase in the training accuracy.

TABLE II. CLASSIFICATION REPORT

	Precision	Recall	F1-score	Support
Mild Parkinson	0.33	0.14	0.20	7
Normal	0.54	0.78	0.64	9
Parkinson	0.86	0.86	0.86	7
Accuracy			0.61	23
Macro avg	0.58	0.59	0.56	03
Weighted avg	0.57	0.61	0.57	03

The table 2 shows the classification report with respect to VGG 19 where precision, recall, F1-score and support values have been tabulated.

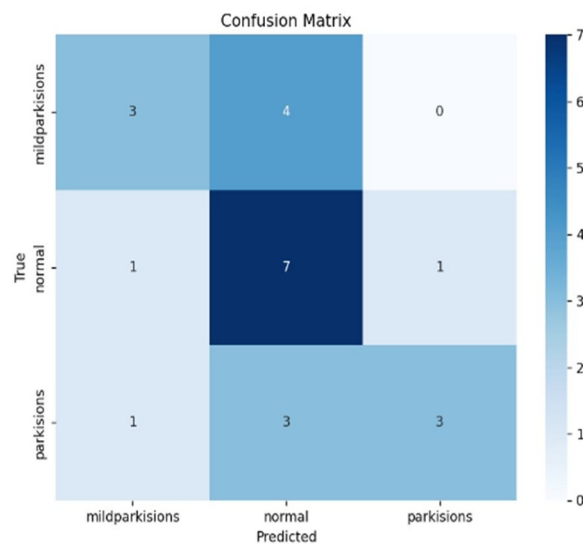


Figure 8 Confusion matrix

The figure 8 shows the prediction of the VGG 19 classifier both true class and false predicted class.

GUI Interface

A graphical user interface would give an interactive display so that the users can easily make use of the research done. This GUI requires uploading an audio file in .wav file and the model will train the sample and then finally using a vocal biomarker would predict the Parkinson's disease as shown in Figure 9.

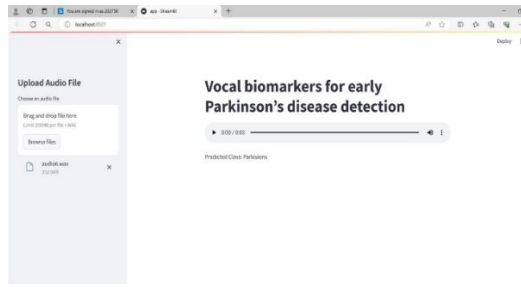


Figure 9. GUI output

B. Discussion

This study investigated the use of vocal biomarkers for PD detection, employing Convolutional Neural Networks (CNNs) with three feature extraction methods: MFCC, Chroma features, and spectrogram features and VGG-19 with MFCC feature extractor. The results showed that MFCC features achieved the highest accuracy due to their ability to capture the nuanced changes in speech patterns associated with PD, while Chroma features, being more suited to musical content, provided the least accuracy. Mel-spectrogram features yielded moderate accuracy. These findings highlight the critical importance of selecting relevant features for effective PD detection. Future work could explore hybrid feature sets, advanced CNN architectures, longitudinal data analysis, and multimodal approaches to further enhance detection accuracy.

C. Comparison Table

The comparison table shows the parameters like accuracy of the obtained result followed by precision, recall and F1-score values for various algorithms used in the research as shown in Table 3

TABLE III: COMPARISON TABLE

PARAMETERS	METHADOLOGIES		
	CNN[3]	CNN- MFCC	VGG-19
ACCURACY	0.89	0.90	0.61
PRECISION	0.87	0.93	0.58
RECALL	0.88	0.90	0.61
F1 SCORE	0.89	0.91	0.57

V. CONCLUSION

Detecting this disease using vocal biomarkers represents a promising, non-invasive approach to early diagnosis and monitoring. Vocal characteristics such as tremor, monotonicity, and changes in speech rate and volume can be indicative of the presence. Recent advancements in ML and signal processing have enabled the development of models that can analyze these vocal features with high accuracy.

Studies demonstrate that vocal biomarkers can effectively differentiate normal and person with PD and healthy controls, providing a cost-effective and accessible screening tool. This method offers several benefits, including ease of administration, the potential for remote monitoring, and the ability to track disease progression over time. However, variability in vocal characteristics due to factors such as age, sex, and other health conditions can affect accuracy, and robust, large-scale studies are needed to refine models and account for these variables.

Integration with other biomarkers and the development of standardized protocols will enhance the reliability and utility of vocal biomarkers in clinical practice. In conclusion, while vocal biomarkers hold significant promise for Parkinson's disease detection, technological advancements are necessary to fully realize their potential and implement them widely in clinical settings.

FUTURE SCOPE

The future scope of using vocal biomarkers for detecting PD is vast also promising. Development of standardized protocols and large-scale, multi-centre studies will be crucial in validating these tools across diverse populations and settings. Remote monitoring and telemedicine applications can significantly improve patient care, especially for those in underserved or remote areas. Implementing wearable devices and mobile applications capable of continuous speech analysis could enable real-time monitoring of disease progression and treatment response.

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