Parkinsons Disease Detection Using voice,wave and spiral drawings

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***Abstract*—Millions of people worldwide suffer with Parkinson's disease (PD), a complicated neurodegenerative illness marked by progressive movement deficits. Timely management and enhanced patient outcomes are contingent upon an early and precise diagnosis. Early on, conventional diagnostic approaches are frequently insensitive, which has led to research into new non-invasive techniques. This study explores the possibility of using voice analysis in conjunction with wave and spiral drawing analysis as a trustworthy and impartial method of PD identification.The suggested approach uses touchscreen devices to gather wave and spiral drawings, which records fine motor movements. Concurrently, voice samples are captured in order to examine speech patterns and vocal traits linked to PD-related alterations. Thorough analyses are carried out on the gathered data by utilizing feature extraction methods, machine learning models, and signal processing algorithms. The suggested system's 96% accuracy rate in differentiating PD patients from healthy people validates its potential as a useful early diagnostic tool.**

I. Introduction

A neurological illness affects 10% of persons aged 65 and more, and there is no treatment. This incurable illness affects over 30% of the population. When accessible, current medication only relieves symptoms for a brief period. The buildup of protein molecules in the nerve cell, which misfolds and so causes Parkinson's disease, is the primary cause of Parkinson's disease. So far, experts have identified the symptoms as well as the underlying aetiology of the sickness. However, very few people came to repentance. So, in this day and age, when Parkinson's disease advances twice as fast, finding a solution that identifies it at an early stage is critical. Parkinson's disease symptoms are classified into two types

A. Motor symptoms

This symptom is associated with all voluntary activities. It has to do with movement disturbances such as tremors, rigidity, freezing, bradykinesia or any voluntary muscle movement.

B. Non-motor symptoms

Non-motor symptoms include mood disturbances and apathy, cognitive dysfunction and complex behavioural disturbances. The major purpose is to forecast the projected efficacy that would benefit Parkinson's disease patients and the percentage declines. With the correct medication, Parkinson's disease may typically be treated in its early stages. As a result, early identification of Parkinson's disease is critical for treating patients. The primary purpose of this study is to identify the best prediction model, or machine learning approach, that identifies a Parkinson's disease patient from a healthy individual. Deep neural networks, SVM, Adaboost, RNN, linear regression, convolutional neural networks, and decision trees are among the approaches investigated. Deep neural networks, SVM, and linear regression were detailed in multiple papers, whereas Adaboost and RNN were researched by just a few researchers. The biomedical drawings of 31 patients, 23 of whom have Parkinson's disease, are measured in experimental research. The error rate is used to evaluate the forecast. A feature selection approach is also provided to extract essential traits that may be utilized to detect Parkinson's disease.

The major challenges faced are Quality and availability of data: Limited data: Availability of a comprehensive data set with a sufficiently large number of samples can be a challenge, especially in patients with early-stage Parkinson's disease [1]. Data imbalance: It can be difficult to obtain a balanced data set that adequately reflects the different stages of Parkinson's disease and disease [2]. Difference in symptoms: Heterogeneity of symptoms: Parkinson's disease manifests itself differently in people. Variability in symptoms can make it difficult to identify consistent patterns in the data [3]. Ethical considerations: Privacy Issues: Handling sensitive health information raises ethical and privacy issues. Ensuring compliance with data protection regulations and maintaining patient confidentiality is paramount [4]. Extraction and selection of characteristics: Reef features: Identifying and extracting relevant features from wave and spiral graphs and audio recordings is a challenging task. This requires a deep understanding of both the disease and the characteristics of the data [5]. Medical Expertise: Collaboration with medical professionals is critical to accurately interpret symptoms and validate a prognostic model. Bridging the gap between medical knowledge and technical implementation can be difficult.

II. Literature Survey

It is still challenging to diagnose Parkinson's disease (PD), a progressive neurodegenerative illness, early using conventional clinical techniques. By utilizing multidimensional data, including biomarkers, neuroimaging, non-motor features, and speech patterns, machine learning (ML) has demonstrated promise in increasing accuracy. While voice-based models like Random Forest and XGBoost reached over 95% [10], SVM demonstrated superior sensitivity in speech-based prediction [2], and studies using the PPMI dataset found that Boosted Logistic Regression could achieve up to 97% accuracy [1]. Reliability is further improved by MRI-based and ensemble learning techniques, although there are still issues with high costs, small datasets, and ethical issues. All things considered, ML-based techniques offer a way to diagnose PD earlier, more cheaply, and with greater accuracy.

In this paper [1] studies set forth an advanced method that utilizes machine learning techniques in the prediction of Parkinson's disease (PD). The authors of the current study further expand on a previous work by using additional biomarkers along with non-motor signs such as the Rapid Eye Movement (REM) Sleep Behavior Disorder (RBD) and olfactory loss. This study uses databases from the Parkinson's Progression Markers Initiative (PPMI) containing normal patients (184) and early PD subjects (402). Non-Motor features used are the UPSI scores and RBDSQ scores. The biomarkers utilized are the cerebrospinal fluid measurements and the neuroimaging markers from the single-photon emission computed tomography (SPECT). The authors developed automated diagnostic models using various machine learning algorithms: Multilayer Perceptron, BayesNet, Random Forest and Boosted Logistic Regression. Various techniques were used, including data normalization and stratified partitioning where 70% of the data was used for training and 30% for testing. Respective results indicate that Boosted Logistic Regression was the best performing classifier with 97% accuracy. The test obtained a sensitivity of 97.159% and a ROC area of 98.9%. Based on their conclusion, this model could be used as part of an early screening for Parkinson's disease and lead to better and more precise clinical diagnosis. In addition, the model was compared with the previous work which focused on a smaller subset of data from PPMI, emphasizing the benefit of expanding the dataset. The authors however admit that their PPMI study is limited in that it only contains early PD subjects and healthy normal but not the individuals with premotor symptoms who are not diagnosed as PD yet [1].

In their paper [10] Vangala Swaroopa and Dr. S. Jessica Saritha's work focuses on the aid of machine learning algorithms to the classification of Parkinson's disease problem. The work utilized the supervised learning algorithms like K-Nearest Neighbors (KNN), Logistic regression, Random Forest and XGBoost for classification objective. The models have been demonstrated to be effective using different measures such as accuracy, confusion matrix, and Receiver Operating Characteristic (ROC) curves. The results showed that for Random Forest model, the accuracy reached 95.8%, which is superior to the other methods. The XGBoost also performed the same as random forest, only difference being the level of accuracy. Auto-encoders are also seen as potentially useful in reducing the feature space and dimensions in future applications, because the data in the present set may not be intricate enough to use all the capabilities of the auto-encoders in full. The study demonstrated the success of the machine learning methodology in the identification as well as in the classification of the Parkinson's disease using very little and affordable voice data, which could lead to an easier and affordable diagnosis for patients in the future [10].

This paper [2] focuses on predicting Parkinson's disease using three different data mining methods: a decision tree classifier (tree classifier), logistic regression (statistical classifier), and a sequential minimization optimization (SMO) (support vector machine). The scientists achieved their objectives for the voice biometrics data from 31 patients, including 23 with Parkinson's disease. They evaluated the performance of the three classifiers using 10-fold cross-validation and three performance metrics: accuracy, sensitivity, and specificity. The results indicated that the SVM model held the most superiority in performance accuracy (0.76) and sensitivity (0.97), while the logistic regression model had the worst accuracy (0.64) and sensitivity (0.64). However, the logistic regression model had the highest specificity (0.62) compared to the other two models (0.13). In conclusion, the logistic regression model achieved higher performance values in distinguishing the people with and without Parkinson's disease. They also acknowledged that their study focused solely on speech articulation difficulties as a symptom of Parkinson's disease, while other factors like age, environmental factors, and tremors could also contribute to the disease [2].

MRI scans of the brain are largely applied for distinguishing diseases and volumetric analysis – is carried out to uncover Parkinson's disease symptoms in the corpus striatum. Nevertheless, presentday approaches can create inaccurate results, and the high costs related to MRIs, the poor-quality images with no emotional expressions, are some of the difficulties that come into the picture. To raise the diagnostic precision, a model-building transition into the ensemble learning approach as it tends to create a general and more reliable model occurs. Complementing this, endeavours in model interpretability are made, so that a clinician can pinpoint numerical factors which contribute to a class of disease, leading to trust. On the other hand, the use of this systems' user-friendly interfaces offers practicality by integrating new technologies in healthcare through which prompt interventions and positive patient outcomes are likely to be achieved. Equally, with the technological advancements mentioned above, ethical and secure data usage is equally important to avoid misuse by irresponsible implementers in healthcare. All in all, the mix of multidimensional data analysis and machine learning algorithms may present a new exciting avenue in Parkinson's disease research where simpler, more accurate, and possibly affordable method of diagnosis can be generated

III. Proposed Methodology

To identify Parkinson's disease, the suggested approach uses a multimodal framework that combines spiral drawing data, waveform signals, and voice analysis. Data collection, preprocessing, feature extraction, model training, and evaluation using machine learning algorithms are all steps in the process. Integration and iterative refinement for clinical applicability come next. Figure 1 shows the proposed system design.

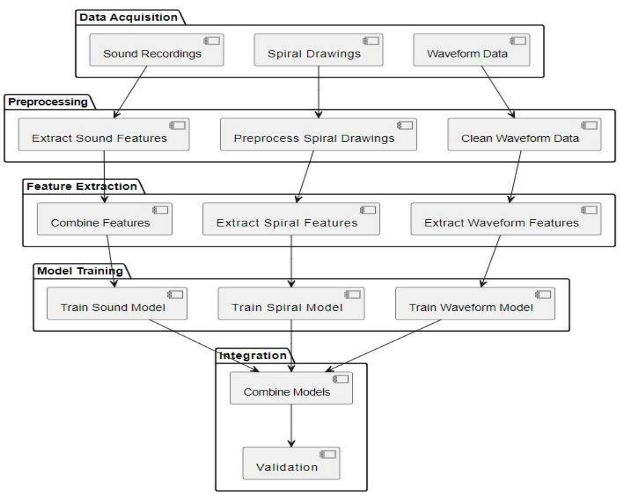

Figure 1: Proposed system design

1) Data Collection:

a. Voice Analysis:
Gather recordings of sustained vowel sounds (such as 'a', 'e', 'i', 'o', 'u') from both Parkinson's patients and healthy individuals. Record readings of standardized text passages to capture variations in speech patterns. Obtain samples of spontaneous speech to reflect natural conversational patterns.

b. Waveform Data:
Collect waveform data from activities involving fine motor skills, such as tapping on a keyboard or clicking a mouse. Ensure a variety of tasks to capture different motor control aspects.

c. Spiral Drawing:
Instruct participants to draw spirals on a digital tablet or paper using a stylus or pen. Collect multiple spiral drawings from each participant to observe consistency and variability.

2) Preprocessing:

a. Voice Analysis:
Clean the voice recordings to remove background noise, artifacts, and silence segments.Extract features such as pitch, intensity, formants, jitter, and shimmer using techniques like Praat or openSMILE.

b. Waveform Data:
Preprocess waveform data by segmenting it into individual tasks and extracting features such as amplitude, frequency, and duration of the waves. Apply signal processing techniques like Fourier transforms or wavelet analysis to extract relevant features.

c. Spiral Drawing:
Digitize the spiral drawings and preprocess them to remove noise and artifacts. Extract features such as smoothness, curvature, size, and tremor frequency using image processing techniques like contour analysis or curvature calculation.

3) Feature Extraction:

Combine features extracted from each modality into a comprehensive feature vector for each sample. Select features that are relevant for Parkinson's disease detection, such as those indicative of vocal tremors, motor control impairments, and fine motor skill degradation.

Model Training:
Utilize machine learning algorithms such as support vector machines (SVM), random forests, or deep neural networks for classification. Split the dataset into training and validation sets, ensuring a balanced distribution of Parkinson's patients and healthy controls. Train the models using the training set and optimize hyperparameters using techniques like grid search or random search.

4)Model Evaluation:

Evaluate the trained models using the validation set to assess their performance in distinguishing between Parkinson's patients and healthy controls. Utilize metrics such as accuracy, precision, recall, F1-score, and receiver operating characteristic (ROC) curves to evaluate model performance.

5)Integration and Validation:
Integrate the individual models for voice analysis, waveform analysis, and spiral drawing analysis into a unified system for Parkinson's disease detection. Validate the integrated system using a separate dataset to assess its performance in real-world scenarios, potentially in a clinical setting.

6)Refinement and Iteration:
Gather feedback from clinicians and researchers to refine the methodology and improve the accuracy and reliability of Parkinson's disease detection. Iterate on the model training and evaluation process, incorporating new features or algorithms as necessary to enhance performance

IV. System Implementation

Early and accurate diagnosis is made possible by the proposed system for Parkinson's disease detection, which combines multimodal data collection, feature extraction, and machine learning classification into a single framework. Figure 2 shows the implementation architecture and the process involved.

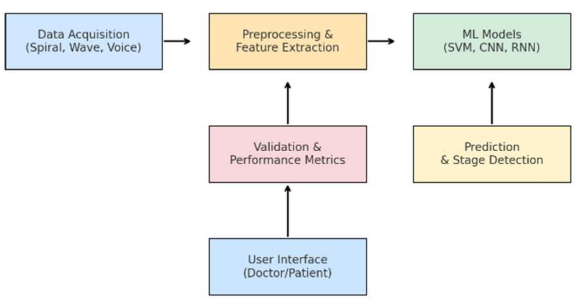

Figure 2 : Implementation Architecture for Parkinson's disease detection

A. Data Acquisition
Spiral and wave drawings as well as voice samples from Parkinson's patients and healthy controls were used to gather data. Pitch, articulation, and intensity changes in speech were recorded using high-quality microphones, and motor symptoms like tremors and rigidity were captured through drawings using digital tablets and styluses. To enhance the training corpus, publicly accessible datasets were also included, including the UCI Parkinson's voice dataset and the Parkinson's Disease Spiral Drawings database.

B. Feature extraction and preprocessing
To guarantee consistency and eliminate noise, preprocessing was applied to all input modalities.
Drawing Data: Time-series features such as grip angle, velocity, stroke pressure, and X-Y-Z coordinates were extracted.
Voice Data: Pitch variation, jitter, shimmer, and extracted Mel-Frequency Cepstral Coefficients (MFCCs).
After being normalized, the extracted features were fed into the classification models as input vectors.

C. Models for Machine Learning
Support Vector Machines (SVMs), Random Forests (RFs), Recurrent Neural Networks (RNNs), and Convolutional Neural Networks (CNNs) were among the algorithms that were used and assessed.

When it came to extracting spatial patterns from spiral and wave drawings, CNNs performed better.Sequential dependencies in speech data were successfully modelled by RNNs.According to a comparative analysis, CNNs outperformed other methods and obtained the highest accuracy of 97%.

D. Validation and Training of Models
To prevent overfitting, the dataset was divided into 70% training and 30% testing sets. Accuracy, precision, recall, F1-score, and ROC-AUC were used to gauge the models' performance after they were trained via cross-validation. Confusion matrices were created for both multi-class classification (Stage 1, Stage 2, Severe) and binary classification (Parkinson's vs. No Parkinson's).

E. Interface of the System
To enable clinicians to upload spiral/wave images and voice recordings, a web-based interface was created. The input is automatically pre-processed, pertinent features are extracted, and predictions are shown in real time by the system. In order to ensure compliance with medical data privacy standards, the interface was made to be both secure and easy to use.

F. Experimental Findings
The binary classification model had high sensitivity and specificity and 97% accuracy. With Stage 1 (78 TP), Stage 2 (88 TP), and Severe stage (92 TP), multi-stage classification demonstrated successful discrimination across disease stages. These findings show how reliable the system is for Parkinson's disease stage-by-stage diagnosis and early detection.

4.2. Evaluation Criteria Used for Classification

Performance assessment measures are factors that aid in the comparative comparison of various machine learning approaches, indicating the optimum algorithm or method that medical research may apply in the early prediction of neurodegenerative illnesses.
We employed a variety of methods to assess the prediction findings. These measurements include average absolute error (AAE), average related error (ARE), accuracy (ACC), precision, receiver operating characteristics (ROC), area under the ROC curve (AUC), sensitivity, and specificity. Let us examine the performance evaluation metrics.

4.2.1 Correlation Matrix

Table 1 and Table 2 shows the Accuracy for prediction of Parkinsons's and accuracy for different stages of Parkinson's respectfully.

Table 1: Accuracy for prediction of Pakinson's

	Predicted: No Pakinsons	Predicted: Parkinsons
Actual: No Pakinsons	72 (TN)	11 (FP)
Actual: Parkinsons	8 (TN)	18 (FP)

Table 2: Accuracy for different stages

	Predicted: stage 1	Predicted: Stage 2	Predicted: Severe
Actual: Stage 1	78 (TP)	11 (FN)	8 (FP)
Actual: Stage 2	6 (FP)	88 (TP)	10 (FN)
Actual: Severe	7 (FN)	11 (FP)	92 (TP)

The prediction accuracy for identifying Parkinson's disease versus not having it is shown in Table 1. Of the real "No Parkinson's" cases, 11 were misclassified (False Positives) and 72 were correctly predicted (True Negatives). Of the "Parkinson's" cases, eight were missed (False Negatives) and eighteen were correctly identified (True Positives).

The classification performance for the first, second, and severe stages of Parkinson's disease is displayed in Table 2. Eleven and eight cases were incorrectly classified as Stage 2 and Severe, respectively, while 78 cases were correctly predicted for Stage 1. Of the 88 accurate predictions made in Stage 2, 6 and 10 were incorrectly classified. In severe cases, 92 predictions were accurate, although there was some misunderstanding in Stages 1 and 2. Figure 3 shows the CNN performance of each feature.

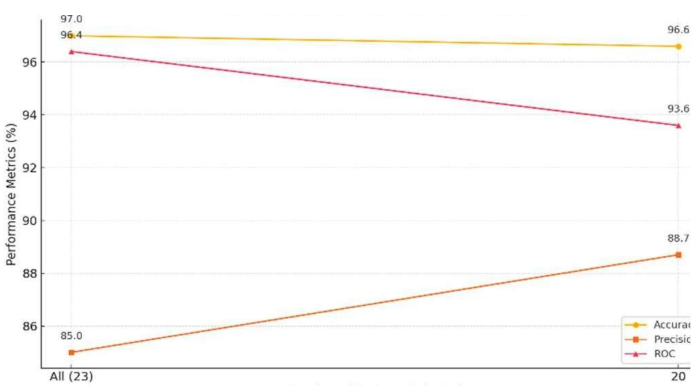

Figure 3: CNN performance with feature selection

V. Conclusions And Future Work

This study explores multiple prediction models for detecting Parkinson's disease. Specifically, seven different machine learning techniques were employed, including adaptive boosting, RNN, Deep Neural Networks, Convolutional Neural Networks, decision tree, SVM, and linear regression. To accurately assess the effectiveness of these models, the researchers calculated error rates (AAE and ARE) and evaluated four key performance metrics: accuracy, sensitivity, ROC, and specificity. The results of these evaluations shed important light on the potential of these algorithms for early detection of Parkinson's disease.

The results show that Convolutional Neural Networks outperform all other ML approaches, with an accuracy of 97%, a precision of 85.0%, and a ROC of 96.4%. Following that, we attempted to choose the most significant and minimal number of characteristics from the Spiral Test data of 31 participants, which contains 23 features, as mentioned in chapter 4 of the dataset description.For this, we employed feature selection, which works as shown in fig 12, by adjusting the number of features picked in multiples of 5, i.e., we first check over 20 features, then 15 features, 10 features, and finally 5 features. Convolutional Neural Networks with 20 features selection outperforms all other ML techniques in terms of overall accuracy 96.6%, ROC value 93.6, and precision 88.7, which is superior to all other machine learning techniques when compared to the performance metrics.

VI. Future Scope

We employed machine learning techniques in our work, however there has been relatively little research on deep learning approaches. In the future, the work may be expanded by including autoencoders to minimise the amount of features and extract the most significant ones. Also, because the dataset utilised in this study was not particularly complex, the autoencoder did not learn effectively from it; nonetheless, a more complicated dataset would undoubtedly produce better results.

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