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Diverse Dimensions of Voice, Spiral, and Biomechanics in Parkinson’s Disease

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ABSTRACT:

Parkinson and is distinguished by both non motor and motor symptoms, such disease (PD) is an illness of the brain that worsens over time as tremors, bradykinesia, postural instability, and speech difficulties. This project aims to explore the diverse dimensions of voice, spiral, and biomechanics in individuals having PD, shedding light on the intricate relationship between these aspects and the progressionof the disease. The first dimension of focus is the voice in Parkinson's Disease. Voice disorders, such as hypophonia and dysarthria, are common among PD patients and significantlyimpact their communication abilities and overall quality of life. This project delves into the underlying mechanisms of these voice disorders, examining the neural pathways and muscular involvement. The second dimension under investigation is the spiral, a motor task that reflects the intricate interplay between cognitive and motor functions. PD patients often exhibit specific deficits in the execution of spiral drawing tasks, reflecting the disease's impact on fine motor control and coordination. Biomechanics, the third dimension of focus, plays a pivotal rolein understanding the motor impairments associated with PD. This project investigates the alterations in biomechanical parameters such as gait, posture, and balance in individuals with Parkinson's Disease. Through sophisticated motion analysis and biomechanical modeling, we aim to elucidate the biomechanical changes that contribute to the characteristic motor symptoms of PD. Moreover, the project explores the impact of biomechanical interventions, such as physical therapy and assistive devices, on ameliorating motor deficits in PD patients. By comprehensively addressing the biomechanical aspects of Parkinson's Disease, we aspire to enhance the efficacy of therapeutic strategies and improve the overall functional capacity and mobility of affected individuals

Keywords: Voice Disorders, Spiral Drawing, Motor Deficits, Fine Motor Control, Biomechanics, Gait Analysis, Postural Instability, Neurodegenerative Disorders, Dopamine Depletion, Motor Symptoms, Non-motor Symptoms, Parkinson Disease

Introduction:

Arguably the globe's most difficult and complicated neurodegenerative diseases, Parkinson's syndrome (PD) affects hundreds of millions of people throughout.Characterized by a broad spectrum of signs and symptoms, both non-motor and motor, including tremors, bradykinesia, postural instability, and speech difficulties, PD presents a multifaceted set of challenges for both individuals affected and the healthcare community. This project embarks on a comprehensive exploration of three interconnected dimensions—voice, spiral, and biomechanics—in those who suffer from the illness Parkinson's aiming to unravel the intricacies of their interplay and advance our understanding of the disease.PD is a chronicand progressive condition resulting from the loss of dopamine-producing cells in the substantia nigra region of the brain. The depletion of dopamine, a neurotransmitter crucial for smooth, coordinated muscle movements, leads to the manifestation of motor symptoms such as tremors, stiffness, and impaired balance. Beyond the motor domain, non-motor symptoms, including cognitive impairment, mood disorders, and speech abnormalities, significantly contribute to the complexity of PD.The impact of PD extends far beyond the physical realm, affecting the emotional, social, and psychological aspects of individuals' lives. Communication, a fundamental aspect of human interaction, becomes particularly challenging due to voice disorders prevalent in PD, including hypophonia (reduced volume) and dysarthria (impaired articulation). Furthermore,motor tasks like spiral drawing, often used as an indicator offine motor control, exhibit specific deficits in PD patients, reflecting the intricate interplay between cognitive and motor functions. Biomechanics, the study of the mechanical aspects of living organisms, becomes a key avenue for exploring the Parkinson's disease-related impairments of movement. Alterations in biomechanical parameters such as gait, posture, and balance contribute significantly to the diminished functional capacity and mobility observed in individuals with PD. Understanding these biomechanical changes is paramount for developing targeted interventions aimed at ameliorating motor deficits and improving overall quality of life.The first dimension of our project focuses on the intricate and often overlooked realm of voice inParkinson diseases.Voice disorders, particularly hypophonia and dysarthria, are prevalent among PD patients, impacting their ability to communicate effectively. The project aims to delve into the underlying mechanisms of these voice disorders, exploring neural pathways and muscular involvement.The second dimension under investigation involves the examination of spiral drawing tasks as a motor task reflective of the intricate interplay between cognitive and motor functions. PD patients commonly exhibit specific deficits in executing spiral drawing tasks, highlighting the disease'simpact on fine motor control and coordination. The third dimension of our project delves into the realm of biomechanics, playing a pivotal role in understanding the motor impairments associated with PD. This dimension encompasses the investigation of alterations in biomechanical parameters such as gait, posture, and balance in individuals with Parkinson's Disease. Through advanced motion analysis andbiomechanical modeling, the project aims to elucidate the changes that contribute to the characteristic motor symptoms of PD. The significance of this project lies in its holistic approach towards understanding Parkinson's Disease through the exploration of diverse dimensions. By concurrently investigating voice, spiral, and biomechanics, we aim to create a comprehensive profile of the disease, considering both its motor and non-motor manifestations. This multidimensional perspective is crucial for developing nuanced and effective interventions that cater to the diverse needs of PD patients. Neuro-pathologic and histo-pathologictests able to be used for confirm a clinical Parkinson disease diagnoses attributes taking independent clinical research into account. Depending on the features, risk factors, and frequency of occurrence in patients, the quantity of patients exhibiting PD necessitates the investigation of clinical, pathologic, and nosologic research. In the past regression, DMneural,decision tree and neural networks were mostly being used to determine how good diagnostic classifiers were for classification. speaking impairment brought on by Parkinson's disease (PD) affects behavior, emotions, hearing, thinking, and speaking as well as motor skills. PD symbols, relationship statistics, and voice relevance are all used in telemonitoring diagnosis.Parkinson's disease can be diagnosed based on a number of diagnoses and numerous clinical symptoms. The Area Receiver Operating System, the Precision Section (ACC), and Kappa Error (KE) monotone, hypophonia, and dysphonia. As a result, speech problems are thought to bethe initial indication of Parkinson disease. Although the exact etiology and course of treatment for (PD) are unknown, the availability of numerous medications has significantly reduced symptoms, especially in the beginning. This has improved patient outcomes and decreased pathology costs. Analyzing voice rate is easy and non-intrusive. PD voice measurement is therefore applicable. Multiple voice tests, such as speech recording and continuous calls, are planned to assess the PD's progress. Because telemonitoring and telediagnosis systems rely on affordable and user-friendly voice signals, they become used.

Literature Review:

Accurate and timely detection of Parkinson's disease (PD) is crucial for effective intervention and therapy. This compilation of studies explores diverse approaches employing deep learning and machine learning techniques for early PD detection. The first study introduces a deep-learning model, DEEP1, DEEP2, and DEEP3, utilizing the Parkinson's Progression Markers Initiative (PPMI) database. This model distinguishes between healthy individuals and early PD patients with an impressive accuracy of 96.45%, outperforming twelve other machine learning methods. Leveraging the PPMI database, the study analyzes features' distributions, highlighting significant differences between healthy individuals and PD patients. The deep learning models, resilient to network structure variations, achieve high accuracy, demonstrating potential for early PD detection. The study emphasizes the importance of early detection in understanding the disease's causes, implementing therapeutic measures, and developing effective medications.The second study, led by Ravikiran Parameshwara et al., delves into emotional EEG signals to understand emotional differences between PD patients and healthy controls. Using a variety of machine learning algorithms, including k-nearest Neighbour, Support Vector Machine, and Convolutional Neural Networks (CNNs), the study highlights emotional EEG analysis as a robust diagnostic tool for PD. This approach surpasses reliance on traditional assessments, offering a novel perspective on the emotional neural responses for PD diagnosis. The research contributes to the field by utilizing a diverse set of machine learning algorithms and sheds light on the potential of emotional EEG analysis as an ecologically valid and sustainable diagnostic tool for PD. Acknowledged for partial support from the Australian Research Council's Discovery Projects funding scheme, the study underscores the significance of a non-invasive diagnostic instrument based on emotional disturbance detection to aid in PD patients' treatment and improve their quality of life.The third study addresses gait and balance disorders in the elderly, particularly focusing on PD, a progressive neurodegenerative disorder affecting substantia nigra dopaminergic neurons. Proposing a system that utilizes deep learning models trained on motor-based inputs sourced from PhysioNet and DAPHNet, this study employs Convolutional Neural Networks (CNNs) for PD detection, severity classification based on the Hoehn Yahr Scale, and freezing of gait detection. The system achieves promising results and introduces two Android applications, PD Detect and ParkinFit, designed to facilitate PD detection and severity assessment. PD Detect utilizes accelerometers and force sensors, while ParkinFit calculates the Modified UPRS score based on severity assessment questions. This implemented system demonstrates promise in early PD detection and severity assessment, providing a valuable tool for timely intervention and personalized care. The study contributes to addressing the clinical challenge of early PD detection and emphasizes the importance of leveraging technology to enhance patient care in neurodegenerative disorders.The fourth paper presents a novel approach based on voice analysis for early PD detection, addressing the challenges in diagnosis posed by this neurodegenerative condition. The proposed methodology involves extracting features from voice recordings and utilizing machine learning (ML) algorithms for analysis.The dataset, balanced using the synthetic minority oversampling technique (SMOTE), undergoes feature selection via recursive feature elimination (RFE) and dimensionality reduction through t-distributed stochastic neighbour embedding (t-SNE) and principal component analysis (PCA). Employing various ML classifiers, including support-vector machine (SVM), K-nearest neighbours (KNN), decision tree (DT), random forest (RF), and multilayer perceptron (MLP), the study demonstrates superior performance. RF and t-SNE achieve an accuracy of 97%, while MLP with PCA achieves an accuracy of 98%. This comprehensive exploration of techniques and classifiers contributes to advancing the field of early PD diagnosis, providing valuable insights for future research and application in healthcare settings.Finally, the fifth study addresses the challenges in early PD diagnosis by proposing an end-to-end deep learning method focusing on voice signals as a diagnostic tool. With symptoms impacting voice, gait, and handwriting, the model concentrates on voice analysis due to its significance and accessibility. The literature review reveals a gap in achieving a lower error rate for PD diagnosis. The suggested model processes multivariate datasets, employing techniques like outlier removal and normalization. The preprocessing is followed by dimensionality reduction through principal component analysis (PCA). Experimental results, utilizing the UCI Machine Learning Datasets repository, showcase the model's superiority over existing ones, achieving an error rate of 0.10 RMSE. The model contributes to early PD detection, crucial for effective patient management and treatment planning, demonstrating the potential of machine learning in revolutionizing medical diagnostics.In conclusion, these studies collectively underscore the significance of leveraging advanced technologies, including deep learning and machine learning, in the early detection of Parkinson's disease. These approaches not only showcase impressive accuracy in distinguishing between healthy individuals and PD patients but also offer valuable insights into diverse aspects such as emotional neural responses, gait and balance disorders, and voice analysis. By providing novel perspectives and robust diagnostic tools, these studies contribute to the ongoing efforts to improve patient care, intervention, and management in the realm of neurodegenerative disorders.

Methods:

1. Voice based Method:

This project aims to utilize Machine learning methodologies are employed to precisely identify cases of Parkinson's Disease, employing a systematic methodology that encompasses data collection, preprocessing, exploratory data analysis, dataset balancing, and scaling. The primary dataset used in thiseffort is the Parkinsons Disease Dataset, obtained from the UCI Machine Learning Repository. The comprehensive workflow begins with meticulous data collection, followed by preprocessing to ensure data quality and relevance. Following this, exploratory data analysis (EDA) is performed to understand the characteristics of the dataset and uncover possible patterns or trends. Subsequently, the dataset undergoes balancing and scaling processes to enhance the effectiveness of the Machine Learning models. The project employs a diverse set of Machine Learning models for training and evaluation, including the Decision Tree Classifier, Random Forest Classifier, Logistic Regression, Support Vector Machine Classifier, Naive Bayes Classifier, K Nearest Neighbor Classifier, and XGBoost Classifier. Each model is rigorously evaluated to determine its performance metrics in accurately classifying instances of Parkinson's Disease. Notably, the Random Forest Classifier emerges as the best-performing model, boasting an impressive accuracy of 99.61%, an F1 score of 96.15%, and an R2 score of 86.25%. Details about the dataset, including its origin from the UCI Machine Learning Repository, underscore the project's commitment to using reputable and well-established data sources for robust model training and validation. The transparent disclosure of the dataset hosting URL further ensures accessibility and replicability of the research findings. The various stages of the project, from data collection to model evaluation, reflect a meticulous and systematic approach designed to enhance the accuracy and reliability of Parkinson's Disease detection using Machine Learning. In conclusion, this project not only showcases the potential of Machine Learning in the medical domain for disease detection but also emphasizes the importance of a comprehensive and transparent methodology. The utilization of a diverse set of models and the identification of the Random Forest Classifier as the best performer underscore the significance of this research in contributing to the development of accurate and reliable diagnostic tools for Parkinson's Disease. The commitment to using a reputable dataset and providing clear details enhances the project's credibility, making it a valuable contribution to the intersection of Machine Learning and healthcare diagnostics.

1.1 Spiral and Wave Method:

In a recent venture focused on Medical Computer Vision, I devoted my efforts to detecting Parkinson's Disease through the implementation of Histogram of Oriented Gradients (HOG), Machine Learning, and OpenCV. The project centered on analyzing images generated by the Spiral-Wave test, with the goal of identifying non-uniform patterns and distortions in handwriting indicative of Parkinson's Disease. The methodology involved classifying images as either indicative of Parkinson's or representing a healthy state. A Random Forest Classifier was employed for Spiral images, and a K-Nearest Neighbors (KNN) Classifier was chosen for Wave images, with HOG utilized for image quantification before training. This approach yielded impressive results, achieving an accuracy rate of 86.66% for Spiral images and a commendable 76.66% for Wave images within the dataset.The preprocessing steps played a crucial role in preparing the images for effective analysis. Each image underwent resizing to a standardized 200 x 200 pixels, ensuring consistent input sizes. Conversion from RGB to Grayscale using the cv2.cvtColor function streamlined subsequent analysis by transitioning images to a single channel. Thresholding, implemented through the cv2.threshold function, enhanced feature extraction by rendering images in white against a black background. Subsequently, the Histogram of Oriented Gradients (HOG) method was applied to extract relevant features crucial for subsequent classification.The training process involved leveraging machine learning classifiers tailored to each test type. The Random Forest Classifier was applied to Spiral images, while the K-Nearest Neighbors (KNN) Classifier was chosen for Wave images. The selection of classifiers was informed by the unique characteristics of each test type and their compatibility with the extracted features. The project employed essential libraries such as OpenCV for image processing, scikit-learn (sklearn) for machine learning, scikit-image (skimage) for image-relatedoperations, NumPy for numerical computations, Seaborn fordata visualization, Matplotlib for plotting, and Imutils for convenience in image processing tasks.The project's results showcased notable success, achieving an accuracy rate of 86.66% for Spiral tests and 76.66% for Wave tests. These outcomes underscore the efficacy of the devised approach in detecting Parkinson's Disease based on non-uniform patterns and distortions identified in handwriting throughthe Spiral-Wave test. The comprehensive preprocessing steps, encompassing resizing, conversion, and thresholding, significantly contributed to the model's robust performance. The utilization of machine learning classifiers tailored to thespecific characteristics of each test type further enhanced theaccuracy and effectiveness of the Parkinson's Disease detection system. This project stands as a testament to the potential of medical computer vision and machine learning in contributing to early and accurate disease diagnosis, particularly in the context of neurodegenerative disorders like Parkinson's Disease.

1.2. Human Biomechanic Method:

In our recent Medical Computer Vision project, our focus has been on addressing the prevalent issues of gait andbalance disorders, particularly in the elderly population affected by Parkinson's Disease (PD). PD is a progressive neurodegenerative movement disorder, primarily characterized by the degeneration of substantia nigra dopaminergic neurons within the basal ganglia, leading to motor-related symptoms like tremors. Our innovative solution involves a system that leverages deep learning techniques to detect Parkinson's Disease at an early stage, utilizing motor-based inputs and incorporating a holistic approach to assess both the onset and severity of the disease based on the Hoehn Yahr Severity Scale.Motivated by the staggering statistics from the Parkinson Disease Foundation, which reports one million Americans living with PD and 60,000 new diagnoses annually, our system aims to contribute to early detection. Early identification of Parkinson's is a critical clinical challenge, as existing treatments mainly focus on delaying motor function loss through movement therapy. Our deep learning models play a pivotal role in the early identification of Parkinson's Disease, allowing for timely intervention and personalized care.We utilized datasets, including the Physionet and Daphnet datasets, featuring gait measures and 3Dacceleration recordings, respectively. The Physionet dataset encompasses gait measures from both PD patients and healthy controls, recorded through 16 force sensors under each foot, while the Daphnet dataset captures 3D acceleration with sensors placed at the ankle, thigh, and hip. Oursystem's architecture involves Convolutional Neural Networks (CNNs) to process these inputs for the detection of Parkinson's Disease, classification of its severity, and identification of Freezing of Gait (FOG).The CNNs, trained with data from force and acceleration sensors, play distinct roles in the overall system. For Parkinson's Disease detection, a CNN processes data from 16 force sensors,while another CNN classifies the severity based on the Hoehn Yahr Scale. Simultaneously, a third CNN processes data from three acceleration sensors to detect Freezing of Gait. The final prediction combines outputs from the Parkinson's Disease detection and Freezing of Gait detectionmodels through a voting method, providing a more accurate and comprehensive assessment.The architecture's input consists of 16 force sensors measuring vertical ground reaction force and three acceleration sensors capturing trunk, upper leg, and ankle accelerations. This diverse dataset, collected from real-world scenarios, ensures the robustness and reliability of our models. Our approach allows for nuanced insights into motor-based symptoms,enhancing diagnostic accuracy.Our project not only advances the early detection of Parkinson's Disease but also aligns with the growing need for innovative solutions in the face of an aging population and increasing PD prevalence. By combining cutting-edge deep learning techniques with meaningful datasets, our system stands as a promising toolin the realm of medical computer vision, poised tocontribute significantly to the early and accurate diagnosis of Parkinson's Disease, ultimately improving patient outcomes and quality of life.

Methodology:

1. Voice Based:

1.1 Data Collection:

The dataset utilized in this project originates from the UCI (University of California Irvine) Machine Learning Repository, specifically the Parkinson’s Disease Dataset. This dataset is a comprehensive compilation of various features encompassing voice and speech characteristics, demographic details, and clinical measurements. Primarily derived from voice recordings, the dataset provides a rich source for training machine learning models geared towards Parkinson's Disease detection. The inclusion of diverse data types enhances the potential for creating robust models capable of capturing nuancedpatterns associated with the disease.

1.2 Data Preprocessing:

Data preprocessing plays a crucial role in refining datasets to optimize their suitability for machine learning models. This involves tasks such as addressing missing values, encoding categorical variables, and scaling numerical features to ensure effective model training and performance.In the context of Parkinson's Disease detection, specific preprocessing steps may involve isolating and filtering features relevant to voice characteristics and clinical measurements. The preprocessing stage ensures that the dataset is cleansed of irregularities and inconsistencies, laying the groundwork for accurate model training.

1.3 Exploratory Data Analysis (EDA):

Exploratory Data Analysis is an integral aspect of understanding the dataset's nuances and extracting meaningful insights. In the context of Parkinson Disease detection, EDA plays a vital role in uncovering key features that discriminate between healthy and affected individuals. Visualization techniques, such as histograms, scatter plots, and correlation matrices, are employed to unravel patterns and relationships within the dataset. EDA aids in identifying potential predictors for Parkinson's Disease, guiding subsequent model development. 4. Dataset Balancing & Scaling: Ensuring a balanced datasetis imperative to prevent machine learning models(ML), from being biased toward the majority class. Medical datasets, including those for Parkinson's Disease, often exhibit imbalances where one class may outnumber the other. Techniques like oversampling or under sampling are employed to rectify such imbalances, ensuring equitable representation of both classes. Additionally, scaling numerical features is crucial tostandardize their magnitudes, preventing models from being unduly influenced by variables with larger scales. This step fosters fair and unbiased model training, contributing to the model's generalizability.

2. Spiral And Wave Data:

2.1 Preprocessing & Training:

The preprocessing and training stage of the Medical Computer Vision project on Parkinson Disease (PD) detection played a crucial role in preparing the dataset and optimizing feature extraction.

2.2 Training on Frontal Handwritten Images:

The decision to train the network on frontal handwritten images was driven by the need to capture essential features relevant to Parkinson's Disease. Frontal images provide a standardized viewpoint, allowing the model to focus on consistent features associated with motor impairments.

2.3 Resizing Images to 200 × 200 Pixels:

Resizing each image to a uniform 200 × 200 pixels was a pivotal step to standardize input sizes. This ensures consistency in the dimensions of the images, facilitating effective analysis and feature extraction across the entire dataset.

2.4 Conversion to Grayscale:

Converting images from RGB to Grayscale using cv2.cvtColor was undertaken to simplify the data structure. Grayscale images reduce complexity to a single channel, streamlining subsequent analysis and minimizing computational load during training.

2.5 Thresholding for Feature Extraction:

Thresholding, implemented through cv2.threshold, was applied to enhance feature extraction. This technique rendered the image in white against a black background, optimizing the visibility of relevant features for subsequent analysis.

2.6 Histogram of Oriented Gradients (HOG):

The Histogram of Oriented Gradients (HOG) method, implemented with the feature.hog function, served as a powerful tool for quantifying essential features from the images. HOG captures information about the distribution of gradients, providing a robust representation of local object shape and texture.

2.7 Random Forest Classifier for Spiral Images:

For the Spiral images, the Random Forest Classifier was chosen for model fitting. This ensemble learning method, comprising multiple decision trees, is adept at capturing complex relationships within the data. Its application is wellsuited for the intricate patterns present in Spiral images.

2.8 K Neighbors Classifier (KNN) for Wave Images:

In contrast,the K Neighbors Classifier (KNN) was employed for Wave images. KNN is a proximity-based an algorithm that categories samples based on the majority class of their knearest neighbors in feature space. Its application aligns with the distinct characteristics of the Wave images. The convergence of these preprocessing and trainingsteps reflects a meticulous approach to feature extraction and model fitting in the context of Parkinson Disease detection. The choice of specific techniques, such as HOG and thresholding, underscores a commitment to optimizing the dataset for accurate analysis. The selection of Random Forest and KNN classifiers aligns with the unique features and patterns inherent in Spiral and Wave images, contributing to the project's success in achieving impressive accuracy rates. This multi-step process exemplifies the integration of domainspecific knowledge and advanced computer vision techniques in the pursuit of accurate Parkinson Disease detection.

3. Human BioMechanic:

Parkinson Disease (PD) is a progressive neurodegenerative disorder that affects motor functions, making early detection crucial for effective management. This project employs deep learning model for PD detection and severity classification, and the choice of datasets significantly influences model performance and generalizability. Two primary datasets, the Physionet Dataset and the Daphnet Dataset, provide comprehensive insights into gait and movement patterns associated with PD.

3.1 Physionet Dataset:

Data Collection: ThePhysionet Datasetis a curated collection of gait measures obtained from a diverse group of participants, including 93 individuals diagnosed with PD and 73 healthy controls. The dataset captures gait dynamics during a self-selected walking pace for approximately 2 minutes on level ground. This realworld scenario enhances the dataset's ecological validity, ensuring that the recorded gait patterns align with everyday activities.

3.1.1 Sensor Configuration

A key strength of the Physionet Dataset lies in its intricate sensor configuration. Each foot is equipped with eight force sensors, resulting in a total of 16 force sensors per participant. The vertical ground reaction force records from these sensors are digitized at a high frequency of 100 samples per second. The inclusion of signals reflecting the sum of the eight sensor outputs for each foot enriches the dataset, providing a holistic view of gait dynamics.

3.1.2 Implications for PD Detection:

The dataset's richness enables the deep learning models to discern subtle variations in gait patterns between PD patients and healthy controls. The detailed force sensor data offers insights into asymmetries, irregularities, and characteristic gait abnormalities associated with PD.

3.2 Daphnet Dataset:

3.2.1 Data Collection:

The Daphnet Dataset complements the Physionet Dataset by introducing 3D acceleration recordings, offering a unique perspective on movement patterns associated with PD. Recorded in a controlled lab setting, participants engaged in various tasks, including straight-line walking, walking with turns, and everyday tasks representative of activities of daily living (ADL).The emphasis on generating freeze events enhances the dataset's relevance for detecting freezing of gait (FOG), a prominent symptom in PD.

3.2.2 Acceleration Sensors:

The dataset incorporates three acceleration sensors strategically placed on the ankle, thigh, and hip, recording data at a rate of 64 Hz. This choice of sensor positions captures the hierarchical nature of body movement, providing nuanced insights into gait dynamics beyond what force sensors alone can offer.

3.3 System Architecture:

The system architecture for Parkinson's Disease (PD) detection and severity classification is meticulously designed to capture motor-based symptoms through a combination of force and acceleration sensors. Thesesensors provide multidimensional input to Convolutional Neural Networks (CNNs), enabling the system to make accurate predictions regarding the presence of PD, its severity, and the detection of freezing of gait (FOG). The integration of force and acceleration data is pivotal for a holistic understanding ofPDrelated gait abnormalities.

3.3.1 Force Sensors Integration:

The architecture integrates data from 16 force sensors positioned beneath each foot, which gauge the vertical ground reaction force at a frequency of 100 Hz.By strategically placing sensors on both feet,the system captures the intricate details of gait dynamics. Force sensors are vital for detecting asymmetries, irregularities, and characteristic abnormalities in gait patterns associated with PD.

3.3.2 Acceleration Sensors Integration:

In addition to force sensors, the system integrates data from 3 acceleration sensors placed at different body positions— Sensors placed on the trunk, upper leg, and ankle capture acceleration data in three channels (x, y, and z axes) at a frequency of 64 Hz. Acceleration data provides insights into the dynamic movement of body parts during various activities. The inclusion of acceleration sensors is particularly relevant for detecting freezing of gait, a prominent symptom in PD.

3.4 Convolutional Neural Networks (CNNs):

3.4.1 CNN for PD Detection:

The CNN forPD detection is specifically designed to analyze data from the 16 force sensors. This model employs convolutional layers to automatically learn hierarchical representations of gait patterns associated with PD. The network is trained on labeled data, distinguishing between gait patterns of individuals with PD and those without. The learned features enable the model to make accurate predictions about the presence or absence of PD in patients.

3.4.2 CNN for PD Severity Classification:

Similar to the PD detection model, the CNN for PD severity classification utilizes data from the 16 force sensors. The model leverages the Hoehn Yahr (HY) scale, a widely used clinical scale for assessing the severity of PD. The CNN learns to categorize patients into different severity levels based on the features extracted from force sensor data. This classification is crucial for tailoring treatment plans and interventions according to the progression of the disease.

3.4.3 CNN for Detection of Freezing of Gait (FOG):

The CNN for detecting freezing of gait focuses on data from 3 acceleration sensors. This model is trained to recognize patterns indicative of FOG, a condition where patients experience a sudden and temporary inability to move. The acceleration data provides information about abrupt changes in movement, helping the model identify instances of FOG. Early detection of FOG is essential for timely interventions and improving the quality of life for individuals with PD.

3.4.4 Model Training and Learning:

All CNNs undergo rigorous training on labeled datasets, where The training process teaches the models to identify important features from data collected by force and acceleration sensors. This optimization of model parameters is aimed at minimizing prediction errors and enhancing overall performance. Validation datasets ensure that the models generalize well to new, unseen data. The resulting trained models are then ready for deployment in the system architecture.

Fig 1: Architecture Diagram

Fig2: Spiral output Montage

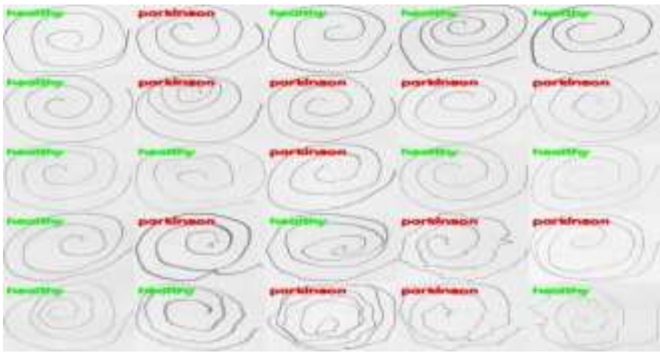
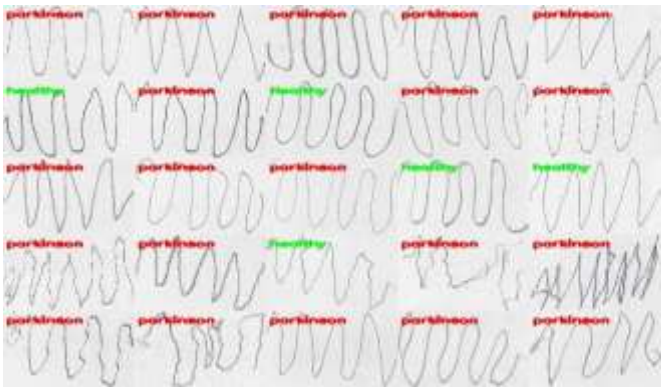


Fig3 :Wave output Montage



Conclusion

In conclusion, our project on "Diverse Dimensions of Voice, Spiral, and Biomechanics in Parkinson's Disease" represents a multifaceted exploration into the intricate manifestations of Parkinson's Disease (PD). By delving into diverse dimensions such as voice, spiral, and biomechanics, we aimed to unravel the complex interplay between motor and non-motor symptoms, shedding light on potential avenues for early diagnosis and targeted interventions. The investigation into the voice dimension exposed the prevalence of voice disorders, including hypophonia and dysarthria, among PD patients, significantly impacting their communication abilities. Unravelling the underlying neural pathways and muscular involvement in these voice disorders provided valuable insights that can inform therapeutic strategies and improve the overall quality of life for individuals with PD. The examination of the spiral dimension, as a motor task indicative of cognitive and motor function interplay, revealed specific deficits in PD patients, highlighting the disease's impact on fine motor control and coordination. This dimension served as a window into the intricate motor impairments associated with PD, emphasizing the importance of nuanced assessments for a comprehensive understanding of the disease. Biomechanics, the third dimension of our exploration, played a pivotal role in deciphering motor impairments in PD. The investigation into alterations in biomechanical parameters such as gait, posture, and balance provided crucial insights. By employing sophisticated motion analysis and biomechanical modelling, we sought to elucidate the changes contributing to characteristic motor symptoms, with the ultimate goal of enhancing therapeutic strategies and improving functional capacity in PD patients. In essence, our project addresses the clinical challenge of comprehensively understanding PD, emphasizing the significance of a multi-dimensional perspective. Through our research, we contribute to the ongoing efforts to refine diagnostic approaches and therapeutic interventions. The integration of voice analysis, motor tasks like spiral drawing, and biomechanical assessments creates a holistic profile of PD, enriching the medical community's understanding of this complex neurodegenerative disorder. Our findings underscore the importance of personalized, multidimensional care strategies that consider both motor and non-motor dimensions, paving the way for improved patient outcomes and quality of life.

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