A Project Report
on

Gait process analysis for neuro diseases using Ensemble techniques

submitted in partial fulfillment of the requirements for the award of the degree

of

BACHELOR OF TECHNOLOGY

in

COMPUTER SCIENCE AND ENGINEERING

by

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Bachupally, Hyderabad – 500090

June, 2023

DECLARATION

We hereby declare that the work presented in this project entitled **“Gait process analysis for neuro diseases using ensemble techniques”** submitted towards completion of Project Work in IV year of B.Tech., CSE at ‘BVRIT HYDERABAD College of Engineering for Women, Hyderabad is an authentic record of our original work carried out under the guidance of Ms. Shanmuga Sundari, Assistant Professor, Department of CSE.

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Certificate

This is to certify that the Project Work report on "**Gait process analysis for neuro diseases using ensemble techniques**" is a bonafide work carried out by Sunku Shriya (19WH1A0576); Bhanupriya Maddali (19WH1A0593); V. Sarayu Sowgandhika (19WH1A05A4) in the partial fulfillment for the award of B.Tech. degree in **Computer Science and Engineering, BVRIT HYDERABAD College of Engineering for Women, Bachupally, Hyderabad**, affiliated to Jawaharlal Nehru Technological University Hyderabad, Hyderabad under my guidance and supervision.

The results embodied in the project work have not been submitted to any other University or Institute for the award of any degree or diploma.

Head of the Department	**Guide**
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ACKNOWLEDGEMENTS

We would like to express our sincere thanks to **Dr. K V N Sunitha, Principal**, **BVRIT HYDERABAD College of Engineering for Women**, for providing the working facilities in the college.

Our sincere thanks and gratitude to our **Dr. E. Venkateswara Reddy, Professor & HOD**, Department of CSE, **BVRIT HYDERABAD College of Engineering for Women** for all the timely support and valuable suggestions during the period of our project.

We are extremely thankful and indebted to our internal guide, **Ms. Shanmuga Sundari, Assistant Professor**, Department of CSE**, BVRIT HYDERABAD College of Engineering for Women** for her constant guidance, encouragement, and moral support throughout the project.

Finally, we would also like to thank our Project Coordinator, all the faculty and staff of **CSE** Department who helped us directly or indirectly, parents and friends for their cooperation in completing the project work.

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CONTENTS

ABSTRACT

Neurological diseases often lead to gait abnormalities, impacting mobility and quality of life. Gait analysis is crucial for understanding and managing these conditions. This study proposes a comprehensive approach using ensemble techniques to enhance the accuracy and robustness of gait process analysis in neuro diseases.

The research involves three main stages: data acquisition, feature extraction, and ensemble modeling. Gait data is collected using wearable sensors and motion capture systems. Informative features are extracted, capturing both spatial and temporal aspects of the gait cycle.

The neurological disabilities include a wide range of disorders such as epilepsy, learning disabilities, neuromuscular disorders, ADD, autism, brain tumors and cerebral palsy.

Automatic gait measurement and analysis is an enabling tool for intelligent healthcare and robotics-assisted rehabilitation. A support vector machine-based classifier is developed to classify four types of gait patterns with different neuro diseases. The results demonstrate the effectiveness of ensemble techniques in improving the analysis of gait patterns and provide valuable insights for the diagnosis and management of neuro diseases.

The proposed technique would be ensemble techniques. The gait analysis is coupled with ensemble techniques to improve its performance and accuracy. Ensemble methods combine all the base models to produce an optimal predictive model.

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1. INTRODUCTION

1.1. Objectives:

To assess if a person has any neuro diseases, our goal is to build a support vector machine-based predictor. This offers sufficient depth for a more thorough analysis of the disorders. It offers a clearer knowledge of the patients' conditions. This facilitates the work of medical professionals by offering a more accurate understanding of the disease.

1.2. Methodology:

1.2.1. Dataset:

All data is stored in comma separated files for each subject and speed separately. Due to the different sampling rates, marker and force data are separated as well. The preprocessing consisted of force drift correction and low pass filtering of force and reflective markers. Red circles indicate the dynamic markers used for tracking marker data with a cutoff frequency of 6 Hz. The events of the manually marked oversteps are contained in a separate comma separated file.

File size: 6.25MB

Number of rows: 25,000

Number of columns: 25

The laboratory coordinate system coincided with the following anatomical directions:

x: posterior-anterior direction

y: right-left direction

z: inferior superior (vertical) direction

Marker positions:

The markers are named according to the foot side, anatomical position and the direction: [L/R] [Position] [x/y/z] and occur as columns in the following order:

L FCC x, L FM1 x, L FM2 x, L FM5 x, R FCC x, R FM1 x, R FM2 x, R FM5 x,

L FCC y, L FM1 y, L FM2 y, L FM5 y, R FCC y, R FM1 y, R FM2 y, R FM5 y,

L FCC z, L FM1 z, L FM2 z, L FM5 z, R FCC z, R FM1 z, R FM2 z, R FM5 z

Ground reaction forces:

Force plate 1 (FP1) corresponds to the left foot, force plate 2 (FP2) to the right foot.

The ordering of the columns is as follows:
FP1 x, FP2 x, FP1 y, FP2 y, FP1 z, FP2 z

Overstep events:
Each entry in the file marks the time point (in seconds) where a manual oversteps events were set.

The proposed work has used a multiple-task gait analysis approach. The performed exercise was walking on a split-belt treadmill at 12 different walking speeds in the interval [0.6, 1.7] m/s at 0.1 m/s increments for one minute at each speed. The speed order was unknown to the subjects and randomized, with a tendency to higher speeds at the session's end to minimize fatigue effects. 21 healthy heel-striking subjects (10 male, 11 females, age: 23.8 yrs _ 3.3 yrs, height: 172.8 cm _ 9.4 cm, weight: 66.6 kg _ 10.9 kg; all values are mean _ standard deviation) without injuries or diseases affecting the musculoskeletal system participated in this study.

All subjects gave written informed consent. Subject 4 was excluded from the analysis, as not the whole protocol was completed. The 3D marker positions were sampled at a rate of 200 Hz. The 3D ground reaction forces of each foot were sampled at 1000 Hz. The data set includes the ground reaction forces as well as the marker positions of the markers that were placed on the shoes above the first (FM1), second (FM2) and fifth metatarsal (FM5) heads and on the aspect of the Achilles tendon insertion on the calcaneus (FCC) for dynamic tracking.

Fig. 1: Task set-up

The fig. 1 showcases a task setup designed to facilitate gait analysis, an important process in understanding and evaluating human walking patterns. In the image, a subject is positioned on a specialized walking platform or treadmill, surrounded by motion capture markers and wearable sensors. The image also depicts a motion capture system consisting of multiple cameras positioned around the task area. These cameras work in synchronization to capture the three-dimensional positions of the markers in real-time. This motion capture technology enables the reconstruction of the subject's movements in a digital space, allowing for detailed analysis of joint angles, stride length, and other relevant gait parameters.

Fig. 2: Marker positions

The fig. 2 showcases the marker positions on the feet, representing a crucial aspect of gait analysis. In the image, markers are visibly attached to specific anatomical landmarks on the subject's feet, providing accurate tracking and measurement of foot movements during walking. By tracking the movement of the markers, researchers and clinicians can analyze various gait parameters related to the feet, such as stride length, foot strike pattern, toe-off timing, and foot angles. Overall, the image highlights the importance of marker placement on the feet in gait analysis. By accurately tracking foot movements, researchers and clinicians can gain valuable insights into the dynamics of walking and make informed decisions regarding diagnosis, rehabilitation, and monitoring of individuals with gait-related conditions.

1.2.2. The Proposed Model

The proposed model for gait process analysis in neurological diseases incorporates bagging algorithms, specifically the decision tree classifier, naive Bayes classifier, and logistic regression. This ensemble technique aims to enhance the accuracy and reliability of gait analysis in the context of neuro diseases. Bagging, or bootstrap aggregating, involves training multiple models on different subsets of the dataset and combining their predictions to make a final decision. Each individual model within the ensemble specializes in capturing specific aspects of gait abnormalities related to neurological diseases. This ensemble technique leverages the strengths of each algorithm to improve the accuracy and reliability of gait analysis, ultimately contributing to better diagnosis, treatment, and monitoring of individuals with neurological conditions.

1.3. Organization of Project

Gait process analysis for neuro diseases using ensemble techniques has gained significant importance in response to the need for accurate assessment and management of gait abnormalities in individuals with neurological conditions. Neurological diseases can impact an individual's gait pattern, leading to difficulties in walking and balance.

This field of research focuses on the application of advanced technologies, such as motion capture systems and wearable sensors, to acquire gait data from individuals with neuro diseases. The collected data serves as a valuable resource for studying and understanding the underlying gait impairments associated with specific neurological conditions.

To analyze the gait data effectively, ensemble techniques are employed. Ensemble techniques involve combining the predictions of multiple algorithms to enhance the accuracy and reliability of gait analysis. Algorithms such as Support Vector Machines (SVM), decision tree classifiers, naive Bayes classifiers, logistic regression, and k-Nearest Neighbors (kNN) are utilized within the ensemble to capture different aspects and patterns of gait abnormalities.

The advantage of using ensemble techniques in gait process analysis is the ability to leverage the strengths of individual algorithms and compensate for their limitations. Each algorithm contributes its unique perspective to the ensemble, improving the overall prediction accuracy and robustness. By combining multiple algorithms, the ensemble model can effectively detect and classify gait abnormalities in individuals with neuro diseases.

The evaluation of the ensemble model's performance is crucial in ensuring its reliability and effectiveness. Various evaluation metrics are utilized, such as accuracy, precision, recall, and F1-score, to assess the model's ability to correctly identify and classify gait impairments. Cross-validation techniques are employed to validate the model's generalizability and to avoid overfitting or underfitting.

The gait process analysis using ensemble techniques for neuro diseases offers significant benefits. It enables a more comprehensive understanding of gait abnormalities and their relation to specific neurological conditions. By accurately analyzing gait patterns, clinicians can make informed decisions regarding diagnosis, treatment planning, and monitoring of disease progression. Additionally, the ensemble model's ability to incorporate diverse algorithms and adapt to different gait profiles enhances its practical applicability and effectiveness in real-world scenarios.

Overall, gait process analysis for neuro diseases using ensemble techniques provides a robust framework for studying and analyzing gait abnormalities associated with neurological conditions. By combining multiple algorithms within an ensemble, this approach improves the accuracy and reliability of gait analysis, leading to better diagnosis, treatment, and management strategies for individuals with neuro diseases.

2. LITERATURE REVIEW

Title: Development of Neuro-Degenerative Diseases Gait Classification Algorithm Using Convolutional Neural Network and Wavelet Coherence Spectrogram of Gait Synchronization

Authors: An-bang liu, Che- wei lin

Summary:

A detection approach combining a convolutional neural network (CNN) and wavelet coherence spectrogram of gait synchronization has been developed to classify NDD based on huge force signals. The main goal of this research was to assist doctors in early NDD diagnosis screening, effective treatment planning, and disease progression monitoring. Using a time-frequency spectrogram of gait force signals, the proposed NDD algorithm was able to distinguish between the gait patterns of HC and NDD patients with an overall sensitivity of 94.34%, specificity of 96.98%, accuracy of 96.37%, and AUC value of 0.97 using 5-fold cross-validation. The measurement of gait involved the use of force plates, accelerometers, and camera-based systems, as well as measuring abnormality in the gait of patients

Since the existing online database that was used only had a small number of patients with NDD, clinical data should also be obtained for verification. The NDD detection algorithm achieved the high performance of greater than 96% of the parameters being evaluated. It also achieved a good condescending performance compared to state-of-the-art NDD detection methods found in the literature. And there is just one area where the study has to be improved. A deep-learning gait classification system using fuzzy recurrence plot images is a potential future advancement for NDD.

Title: Predicting State Transition in Freezing of Gait via Acceleration Measurements for Controlled Cueing in Parkinson's Disease

Authors: Abhishek Halder, Ashish Suri

Summary:

In order to potentially give automatic regulated cueing in Parkinson's independent, we are working to build a machine learning approach for predicting the beginning and end of freezing. We were able to hypothesise a few characteristics that fit the change from walking to freezing thresholds. In order to predict freezing termination, the suggested have a special labelling of classes. The outcomes demonstrate the potential of the current strategy in the prompt deactivation of cues in real time to prevent any cueing-related negative consequences. The main contribution of this trial was obtaining an enhanced clinical benefit for Parkinson's patients. The dataset comprises 3-D accelerations captured by accelerometers positioned at the ankle, thigh, and hip regions of the body.

The investigation was able to draw the conclusion that there is a strong correlation between the f1 scores for all classes and the preceding data point and the PCs. By reducing the prior data point, the likelihood of inaccurate class labeling was also addressed. The extension of the gender-based build on the Parkinson diagnosis work may also be included in this study's future work in order to determine whether gender information may further enhance the FoG stated prediction.

Title: Parkinson's Disease Management via Wearable Sensors: A Systematic Review

Authors: Abdul Rehman Javed, Natalia Kryvinska

Summary:

This paper presents a Systematic Literature Review that provides an in-depth analysis of the Parkinson's disease (PD) symptoms, Motor and Non-Motor Symptoms (NMS), the current diagnosis and management techniques used and their effectiveness. It also highlights the work of different researchers in use of wearable sensors and their proposals to improve the quality of life in a patient with PD by diagnosing, monitoring, and managing PD symptoms remotely using wearable sensors. This paper will be more useful for identifying existing research gaps, giving specialists greater understanding of the illness course, and preventing problems.

In the course of their investigation, researchers combed through numerous databases and condensed their findings into 60 articles that addressed the management of motor and NMS.

Included were also the most recent analyses and studies on cutting-edge wearable technology for Parkinson's disease management. However, a lot of research has been completed with encouraging outcomes to add biopotential devices, audio recording, smartphones, and video recording to complement wearable readings to acquire an accurate insight into PD patients' wellbeing.

Title: Age-Related Modifications of Muscle Synergies and Their Temporal Activations for Overground Walking

Authors: Xiaoyu Guo, Borong He , Kelvin Y. S. Lau, Peter P. K. Chan, Richard Liu, Jodie J. Xie ,Sophia C. W. Ha, Chao-Ying Chen, Gladys L. Y. Cheing , Roy T. H. Cheung ,Rosa H. M. Chan

Summary:

Gait kinematics and electromyographic signals were recorded during superterranean walking at three different speeds in 11 healthy young individuals, 9 healthy adults, and 11 healthy seniors. After that Muscle synergies from EMGs were used to define neuromuscular control, and both groups' synergies were k-means clustered. In later, deeper investigation, it was discovered that the inter-subject variation of temporal activations adversely linked with the sparseness of the synergies in elderly people, but not in young ones, during slow walking. The findings suggest that as people age, their temporal activation patterns also become more variable between individuals, presumably indicating individual differences in muscle synergy for walking.

Title: Diabetic Sensorimotor Polyneuropathy Severity Classification Using Adaptive Neuro Fuzzy Inference System

Authors: Norhana Arsad, Sawal H. M. Ali

Summary:

One of the most prevalent consequences of diabetes is diabetic sensorimotor polyneuropathy (DSPN), which is utilized as an early indicator for non-healing diabetic wounds and diabetic foot ulcers. In this paper, an intelligent DSPN severity classifier employing the Adaptive Neuro Fuzzy Inference System is demonstrated with clear results (ANFIS). Patients have been divided into the following four categories: absent, mild, moderate, and severe. Additionally, accuracy was supported by the outcomes of various machine learning methods. Health care practitioners were able to detect and categorise DSPN severity based on both signs and symptoms and electrophysiological changes caused by DSPN thanks to the proposed ANFIS based severity classifier, which uses both MNSI variables and EMG features.

We effectively identified patients who need emergency medical attention by classifying the severity level of the patients from the EDIC clinical trials using the developed model and observing that, with time, DSPN's severity increases among patients. Both MNSI data and EMG variables improved the performance of the proposed DSPN severity classifier. As a result, this system has the ability to function independently while also assisting health professionals in their decision-making regarding the identification and categorization of DSPN.

Title: Analysis of Brain Functional Network Based on EEG Signals for Early-Stage Parkinson's Disease Detection.

Authors: Wei Zhang, Xiaoxuan Han, Shujuan Qiu,Teng Li

Summary:

The challenging issue of Parkinson's disease early diagnosis has been resolved using a technique known as the scalp EEG Detection method. The Phase synchronization index was used to assess the synchrony of EEG channels in various frequency bands, and the results showed that early PD had significantly lower delta band synchronization than healthy levels. Brain synchronization and functional connection both significantly decline in the delta band. The parietal lobe, occipital lobe, and bilateral posterior temporal lobes were the most important brain areas. These findings demonstrate the presence of PD anomalies in early PD patients and show that these pathological alterations affect the functional network of the brain. The functional brain network graph can be employed by a collection of features generated from graph theory to help with early PD diagnosis.

Title: Looking Disease in the Eye

Authors: Jim Banks

Summary:

The jewel of the body are the eyes. Permanent vision loss has three main causes: age-related, diabetic retinopathy, and glaucoma, with Parkinson's disease being one of the most severe. The morphological data regarding the eye's anatomy, which measures things like layer integrity and shape or the diameters of the blood vessels Clinicians are implementing and creating diagnostic tools based on this knowledge. Fundus imaging and optical coherence tomography are a couple of them (OCT). The PARS system was also created by Haji Reza. The photoacoustic limits are overcome via PARS effect.

They have the same benefits but PARS has no physical contact. By gathering this kind of information, clinicians could observe decreases in tissue health before they show up in the morphological characteristics of the eye. Then comes the OCT, the data provided by this provides deeper information on eye tissue layers and a snapshot of the retina, and it also adds ups 2D, and 3D OCT images. It promises the early diagnosis of the main threats. And, since EyeQue has been developed, there is a convenient way for patients to test on their own. but some professors claim that it is a disruptive technology because of its low cost. It has been said that it makes accurate measurements, but it does not examine eye health.

Title: Longitudinal Pooling & Consistency Regularization to Model Disease Progression from MRIs

Authors: Jiahong Ouyang , Qingyu Zhao, Edith V. Sullivan , Adolf Pfefferbaum

Summary:

Convolutional Neural Networks (CNN) are used to extract informative features from each visit of the longitudinal MRI and use them to classify each visit via Recurrent Neural Networks (RNNs) in order to predict diagnosis for neurological diseases. However, this model ignores the progressive nature of the disease, which may lead to plausible classifications across visits. They suggested combining features across visits by coupling feature extraction with a brand-new longitudinal pooling layer and enforcing classification consistency in order to get around this problem. A dataset made up of 255 adolescents from the National Consortium on Alcohol and Neurodevelopment in Adolescence, 329 patients with alcohol use disorder (AUD), and 274 healthy controls was used to assess this (NCANDA).

The findings show that the proposed method outperformed cross-sectional and longitudinal baseline methods in terms of accuracy ratings. Information fusion and other tactics are possible additional ways to increase categorization accuracy. The suggested method has no demands regarding the type of input data or the overall amount of time points, as we previously addressed in relation to MRI and neuroimaging applications. Consequently, we consider this to be generalizable to other imaging techniques or to therapeutic uses in a longitudinal situation.

Title: Lacsogram**:** A New EEG Tool to Diagnose Alzheimer's Disease

Authors: Pedro M. Rodrigues , Bruno C. Bispo , Carolina Garrett, Dílio Alves

Summary:

At the various stages of Alzheimer's disease (AD), such as Mild Cognitive Impairment (MCI), Mild and Moderate AD (ADM), and Advanced AD, a new electroencephalogram (EEG) signal processing technique called the lacsogram is utilized to characterize the condition (ADA). Cepstral distances are employed for comparison along with statistical studies to determine the measures of Alzheimer's disease. The findings demonstrated that a greater number of 15 meaningful distances were provided by the lacsogram. The topographic map demonstrates that as AD advances, there are variations in the parietal, temporal, and frontal regions.

The classification accuracy rates for All vs. All, C vs. MCI, C vs. ADM, and MCI vs. ADM-ADA using artificial neural networks (ANN) are 95.55%, 98.06%, 95.99%, and 93.85%, respectively. The suggested method beats the state-of-the-art methodologies in the comparisons of C vs. MCI, C vs. ADM, and MCI vs. ADM-ADA by 5%, 1%, and 2%, respectively. The outperforms the cutting-edge EEG and non-EEG approaches in All vs. All by 6% and 2%, respectively. The findings show that the proposed technique performs better in

AD diagnosis. The database we previously used is a little on the tiny side. The results to come should be updated to a wider population to provide a consistent generalization.

Title: Volumetric Feature-Based Alzheimer's Disease Diagnosis From sMRI Data Using a Convolutional Neural Network and a Deep Neural Network

Authors: ABOL BASHER, BYEONG C. KIM, KUN HO LEE, AND HO YUB JUNG

Summary:

Hippocampal volume atrophy is a diagnostic indicator for Alzheimer's disease. For a number of reasons, including the investigation of memory function, the development of stress, and others, the hippocampal region of interest (ROI) is heavily researched. Slice-wise volumetric features, a technique for diagnosing AD, extracts features from the left and right hippocampi of structural magnetic resonance imaging (sMRI) data. This is a convolutional neural network (CNN) and deep neural network (DNN) model combo. There are 2D and 3D patches; the DVE-CNN model extracts volume information from the 2D patches in order to categorize AD. The data has been trained and tested using the features. The left and right hippocampal data's AUC values were 92.54% and 90.62%, respectively.

Title: A New Dataset for Facial Motion Analysis in Individuals with Neurological Disorders

Authors: Andrea Bandini, Diego L. Guarin, Madhura Kulkarni, Babak Taati

Summary:

This is the first publicly available collection of videos of oro-facial movements used to identify people's neurological conditions. Individuals with oro-facial disability brought on by neurological conditions including amyotrophic lateral sclerosis (ALS) and stroke execute these movements. The data includes manual annotation of facial landmarks as well as significant scores from qualified clinicians. Convolutional neural network (CNN) models will be used to identify the disoriented landmark locations. These data are used to create facial detection algorithms that can evaluate and recognise oro-facial motions automatically. Additionally, it improves the automatic recognition of neurological conditions.

The primary techniques for identifying these oro-facial movements include generative techniques like AAM, discriminative techniques like CLM, ERT, and SDM, and deep learning techniques like FAN. Using these, we were able to create a model that uses facial characteristics including frontal-face, homogeneous illumination, proximity to the camera, and mild to moderate impairment to identify neurological illnesses in people. The predefined model is biased in its ability to identify the impairment. Therefore, optimizing the method can reduce bias and increase the accuracy of landmark localization.

Title: Robust Bayesian Analysis of Early-Stage Parkinson's Disease Progression Using DaTscan Images

Authors: Yuan Zhou , Sule Tinaz, Hemant D. Tagare

Summary:

By defining different progression subtypes, a mathematical model and Bayesian analysis technique are used to assess the heterogeneity of Parkinson's disease. Additionally, it seeks to pinpoint the patterns of spatial advancement and their time constants in people with Parkinson's disease. This makes use of DaTscan, or more specifically, the longitudinal analysis of DaTscan pictures. In order to define the many subtypes of image-based progression, we employ Bayesian inference as a technique. Both the rates and trajectories of these subtypes' evolution vary greatly. All of the disease trajectories are modeled using the multivariate linear dynamical system (MLDS).

Gibbs sampling is the method of choice for Bayesian inference. It uses Bayesian inference and is a new longitudinal model. Finding the Parkinson's disease time constants will be greatly aided by this. Additionally, it offers several fresh concepts for modeling Parkinson's disease. Al PD modeling includes coupled progression of several regions, t-distributed model residues, and mixtures of dynamical systems for heterogeneity. Different TMS advancement rates exist for the DaTscan-based variants as well.

Title: An Algorithmic Approach for Quantitative Evaluation of Parkinson's Disease Symptoms and Medical Treatment Utilizing Wearables and Multi-Criteria Symptoms Assessment

Authors: Tomasz Gutowski, Mariusz Chmielewski

Summary:

This Parkinson's disease symptom evaluation is sensor-based. The assessment is a quantitative assessment. The model can be applied to the analysis of the effectiveness of treatments for neurological diseases. It evaluates the effectiveness used to prescribe the medication.

The model takes a quantitative approach to the identification and severity of symptoms. The currently under development system makes use of a sensor-based data fusion technique to analyse time-correlated wearable sensor data, biological data, and symptoms survey. All Parkinson's disease patients participated in clinical studies so that we could thoroughly analyse the symptoms. The development of the model involves a significant amount of machine learning, biomedical signal processing, and computer-aided diagnosis.

This approach truly is a novel one. It can help arrange complex time-constrained therapy and optimise the course of action. The caliber of the sensor data collected determines how accurately the health state is classified. The movement of the limb and the information gathered about its use are used to evaluate the sensing.

Title: Inertial Sensor Algorithms to Characterize Turning in Neurological Patients with Turn Hesitations

Authors: Vrutangkumar V. Shah , Carolin Curtze , Martina Mancini

Summary:

Due to two factors, turning algorithms using inertial sensors are highly challenging. One is the challenge of recognizing two distinct turns made simultaneously in the same direction, and the other is the neurological disease-related underestimation of turn angle due to brief hesitations. Both the discrete turn method and the merging turn algorithm will be evaluated for generalizability. To obtain a legitimate result from the discrete turn algorithm, we must compute the absolute smoothed rational rate, identify valid minima, confirm that the maxima are suitably large, and identify the turn start and end points. In contrast, the merged turn algorithm includes a few extra phases like merging the close turns and expanding or shrinking the turn start and end.

A crucial stage in both methods is turn characterization. We can draw the conclusion that the discrete turn algorithm performs better than the El-Gohary method in terms of accuracy and efficiency when figuring out turn angles and directions that happen simultaneously at the same location. In order to determine the angle and direction, the merged turn algorithm first determines the discrete turns before combining them together into a single turn.

Title: Closed-Loop Neuromodulation for Parkinson’s Disease: Current State and Future Directions

Authors: Samhwan Kim, Seongtak Kang , Jinmo Kim, Doyoung Lee

Summary:

Deep brain stimulation (DBS) is a neurosurgical procedure in which electrodes are inserted into specific deep brain areas to administer electrical stimulation. Despite having a wide range of uses, DBS has emerged as the most beneficial therapeutic therapy for individuals with movement problems. It can be applied to treat psychological and neurological conditions. DBS has demonstrated to be quite helpful at managing Parkinson's disease symptoms. We can now identify abnormal brain activity and stimulate diseased circuitry as a result thanks to technological advancements. Parkinson's disease treatments, both electrical and neurochemical, work to correct aberrant brain activity. It makes use of biomarkers. Electrical, behavioral, and neurochemical biomarkers are some of the several kinds of biomarkers. All of this is based on Parkinson's disease neuromodulation procedures. Both open loop and closed loop systems will be employed. We research biomarkers because of their strong associations with Parkinson's disease.

3. THEORETICAL ANALYSIS OF THE PROPOSED PROJECT

3.1. Requirements Gathering

3.1.1. Software Requirements

- Operating System: Windows 10
- Programming Language: Python 3.8
- Tools: Google Colab, Jupyter
- Packages: Numpy, Pandas, Matplotlib, Scikit-learn, Tkinter

3.1.2. Hardware Requirements

- Processor: Intel core i5
- Memory: RAM 8GB

3.2. Technological Description

1. Programming Language:

- Python: Python is a widely used programming language with excellent libraries and frameworks for data analysis, machine learning, and deep learning. It provides the necessary tools to implement LSTM models, ensemble techniques, and data preprocessing tasks.

2. Data Processing and Analysis:

- Pandas: Pandas is a powerful library for data manipulation and analysis. It provides data structures such as DataFrames, which can efficiently handle and process large datasets.
- NumPy: NumPy is a fundamental library for numerical operations in Python. It offers multidimensional arrays and mathematical functions for efficient computation.

3. Ensemble Techniques:

- Scikit-learn: Scikit-learn is a widely used machine learning library that offers various ensemble techniques, such as bagging, boosting, and stacking. It provides classes and functions for implementing these ensemble methods.

4. Data Visualization:

- Matplotlib: Matplotlib is a popular plotting library in Python. It enables the creation of visualizations to analyze and present the data in a visually appealing manner.
- Seaborn: Seaborn is a statistical data visualization library built on top of Matplotlib. It provides higher-level abstractions and aesthetically pleasing visualizations.

5. Other Supporting Libraries:

- Scikit-learn: In addition to ensemble techniques, Scikit-learn provides various tools for data preprocessing, feature selection, and evaluation metrics.
- Stats: It imports statistical techniques and algorithms for data analysis, modeling, and inference within ML workflows.

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6. Development Environment:

- Jupyter Notebook: Jupyter Notebook provides an interactive environment for prototyping and experimenting with code.

4. DESIGN

4.1. Introduction

The aim of this project is to develop an ensemble-based approach for gait process analysis in individuals with neurodegenerative diseases. Gait abnormalities are common symptoms in various neurodegenerative conditions such as Parkinson's disease, Alzheimer's disease, multiple sclerosis, and Huntington's disease. Analyzing gait patterns can provide valuable insights into disease progression, assist in early diagnosis, and monitor treatment effectiveness.

Traditional gait analysis methods often focus on individual machine learning models, which may have limitations in capturing the complexity and variability of gait patterns in neurodegenerative diseases. Ensemble techniques, on the other hand, have shown promise in improving accuracy and robustness by combining multiple models' predictions.

This project aims to leverage ensemble techniques to enhance gait analysis by integrating diverse sources of gait data, such as motion capture systems, wearable sensors, or video recordings. By combining the strengths of multiple models, we expect to achieve more accurate and reliable assessments of gait abnormalities in neurodegenerative diseases.

4.2. Architecture

Gait analysis in neuro diseases using ensemble techniques involves several key steps as shown in Fig. 3. First, the input consists of gait data acquired from individuals with neurological conditions. This data then undergoes a comprehensive data preprocessing stage to ensure its quality, including noise removal and synchronization.

Next, the dataset is split into a training set and a test set, facilitating the evaluation of the model's performance. The gait analysis process is then conducted, which involves extracting informative features from the preprocessed data and applying ensemble techniques.

In the ensemble step, multiple algorithms, including Support Vector Machines (SVM), Naive Bayes, Decision Tree, Logistic Regression are employed to build an ensemble model. This model combines the predictions of individual algorithms to enhance accuracy and robustness.

The trained ensemble model is then utilized for prediction, where it is applied to unseen gait data to predict and classify gait abnormalities associated with neurological diseases. The output of this step provides valuable insights and information regarding the presence and severity of neurological conditions.

Overall, this enables the analysis of gait data in individuals with neurological diseases, leveraging ensemble techniques and various algorithms to improve prediction accuracy. The output of the workflow contributes to better understanding, diagnosis, and treatment planning for gait-related abnormalities in neurological conditions.

The dataset comprises two data sets: one for the deciding force and the other for the position of the foot marker. The foot marker position dataset includes 24 attributes, but the dataset made up of force points has 6 attributes.

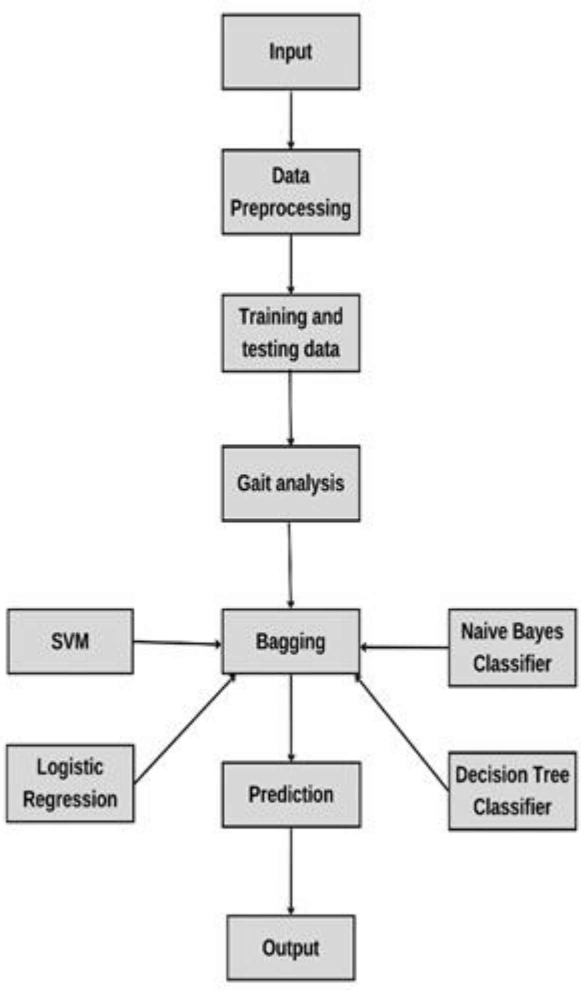

Fig. 3. Architecture of Gait analysis

4.3. Support Vector Machine

Support Vector Machine (SVM) is a simple machine learning technique that may be applied to both classification and regression tasks as shown in Fig. 4. It is typically used for categorization tasks. SVM's task is to classify the data points and find the optimal hyperplane in an n-dimensional plane. When categorizing data points, the maximum number of hyperplanes is used. The primary criteria are the maximum number of datapoints between the two classes and the selection distance of the ideal hyperplane. The acquired ideal separation hyper plane is once more employed to more precisely and accurately identify upcoming datapoints. SVM is a good choice when it comes to memory efficiency and high dimensional spaces. As performance declines, the computational time of this program grows, which is due to large datasets and noisy data.

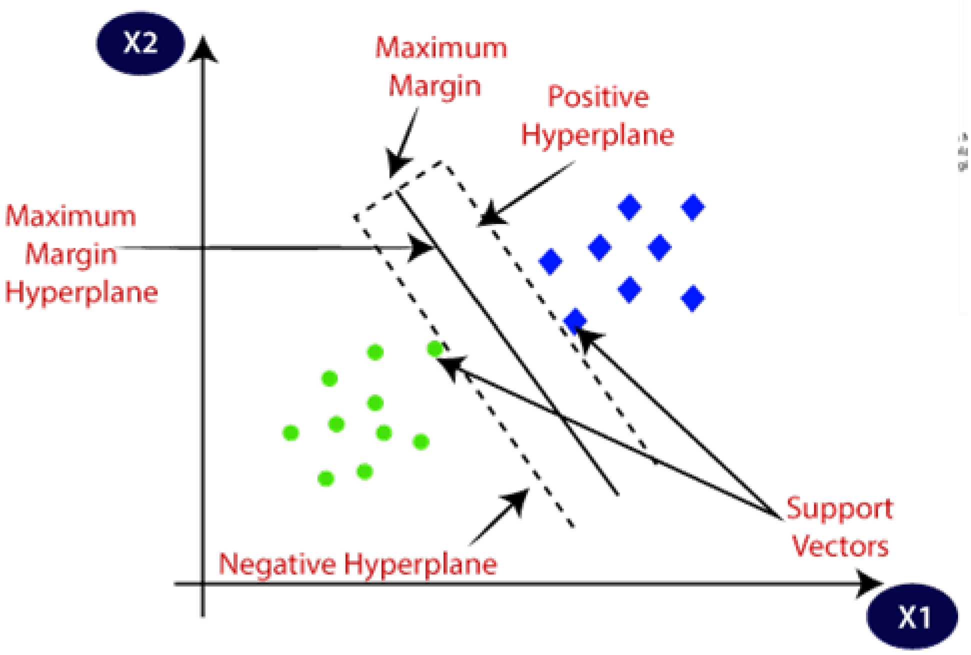

Fig. 4. Support Vector Machine

4.4. Naïve Bayes Classifier

Naïve Bayes algorithm is a superior learning method. It originated from the Bayes theorem; a tool used to solve classification [21] difficulties. High dimensional training dataset is one of the applications for text classification. Due to its effectiveness and simplicity, the naive bayes classifier is the best option for developing simple machine learning models utilized in quick predictions. Since the predictions are dependent on the object's likelihood, the classifier is also referred to as probabilistic. Spam filtration, sentiment analysis, and article classification are among examples.

4.5. Decision Tree Classifier

The decision tree gets its information from a tree, which is also defined as an asset of discrete rules that are designed for simple comprehension. The decision tree classifier's main benefit is its ability to use various feature subsets and decision rules at various stages of categorization. Regular decision trees have a root node, various internal and leaf nodes, and branches that connect those nodes as displayed in Fig. 5. The class that should be allocated to a sample is indicated by the leaf nodes. In a tree, each internal node corresponds to a feature, and each branch shows how those features come together to form the classifications.

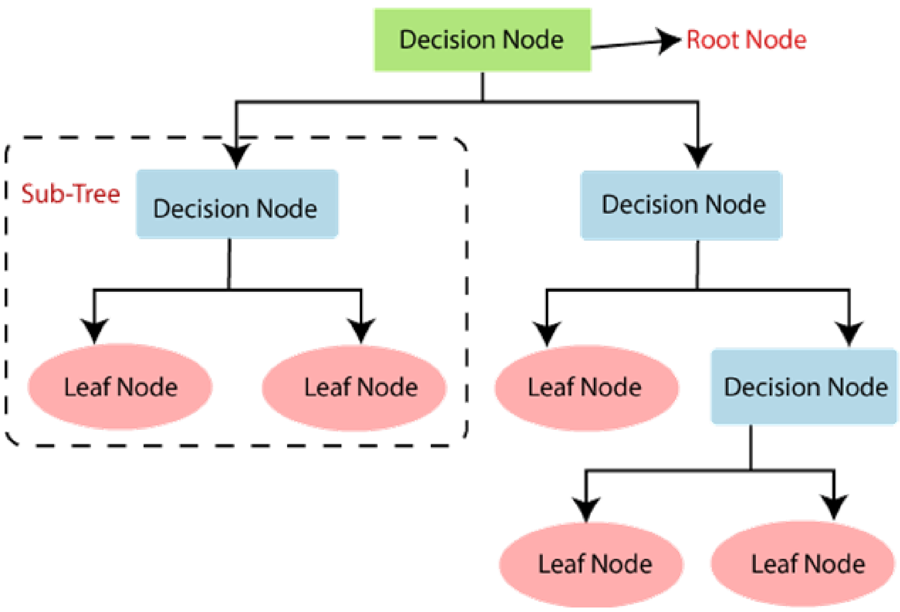

Fig. 5. Decision Tree Classifier

4.6. Logistic Regression

Logistic regression is frequently used as an approximation of whether an event will occur, such as whether it will come or not, and is based on the independent variable datasets that are provided. Due to the fact that the result is a probability, the dependent variable is restricted to the range of 0 and 1 as shown in Fig. 6.

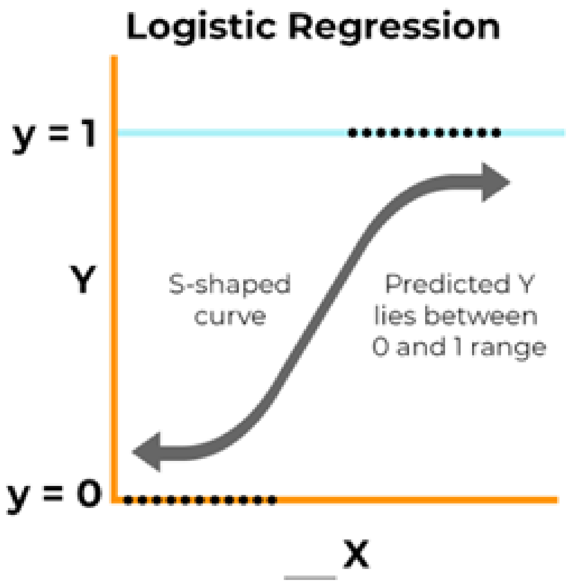

Fig. 6. Logistic Regression

4.7. Ensemble Method

The basic objective of these ensemble techniques is to increase model accuracy by mixing numerous models rather than just one. The accuracy dramatically improves as the combined model's findings get better. The popularity of ensemble techniques in the field of machine learning has grown as a result as shown in Fig.7.

4.7.1. Algorithm:

BaggingClassifier(Classifier C, TrainingSample T, Iterations I)

Output: result R

for i=1 to I

T(i) = bootstrap sample from T

R(i) = training a classifier on T(i) via C

end for

C(i) = argmax (1) for i: L(i) = y

The output consists of result R and we start by iterating over the entire sample data. Then create a bootstrap sample from the training sample data T. The iterations start from I to total number of iterations (I). Now, train the classifier for each training sample via the classifier (C). To get the best output, choose the maximum among the set of classifiers.

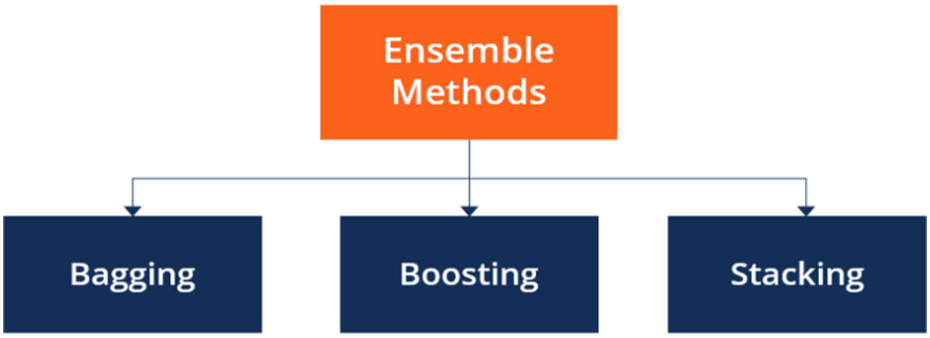

Fig. 7. Ensemble techniques

5. IMPLEMENTATION

5.1. Coding

GitHub link: Project Code

5.2. Evaluation metrics

5.2.1. Confusion Matrix

In the context of gait process analysis for neuro diseases using ensemble techniques, a confusion matrix is a tool used to evaluate the performance and accuracy of a classification model. It provides a tabular representation of the model's predicted classifications compared to the actual ground truth labels.

A confusion matrix is typically a square matrix that consists of four cells, representing the four possible outcomes of a binary classification problem:

- True Positive (TP): The model correctly predicts a positive class (e.g., presence of a neurodegenerative disease) when the actual label is also positive.
- True Negative (TN): The model correctly predicts a negative class (e.g., absence of a neurodegenerative disease) when the actual label is also negative.
- False Positive (FP): The model incorrectly predicts a positive class when the actual label is negative (also known as a Type I error).
- False Negative (FN): The model incorrectly predicts a negative class when the actual label is positive (also known as a Type II error).

The confusion matrix is organized as follows

Table 1. Confusion Matrix

	Predicted Positive	Predicted Negative
Actual Positive	TP (True Positive)	FN (False Negative)
Actual Negative	FP (False Positive)	TN (True Negative)

Using the confusion matrix, several evaluation metrics can be derived to assess the model's performance:

1. **Accuracy:** It measures the overall correctness of the model's predictions and is calculated as **(TP + TN) / (TP + TN + FP + FN).**

2. **Precision:** It indicates the proportion of correctly predicted positive instances among all instances predicted as positive and is calculated as **TP / (TP + FP).**

3. **F1 Score:** It is the harmonic mean of precision and recall, providing a balance between the two metrics.

By analyzing the values in the confusion matrix and calculating these evaluation metrics, it becomes possible to assess the performance of the ensemble model for gait process analysis in neurodegenerative diseases. This information helps to understand the model's predictive capabilities, identify potential areas for improvement, and make informed decisions about the accuracy and reliability of the ensemble model.

5.3. Results

The graph displayed below in Fig. 8 shows the force cloud generated by each foot of various people. This examines the force that a person uses to go forward when walking.

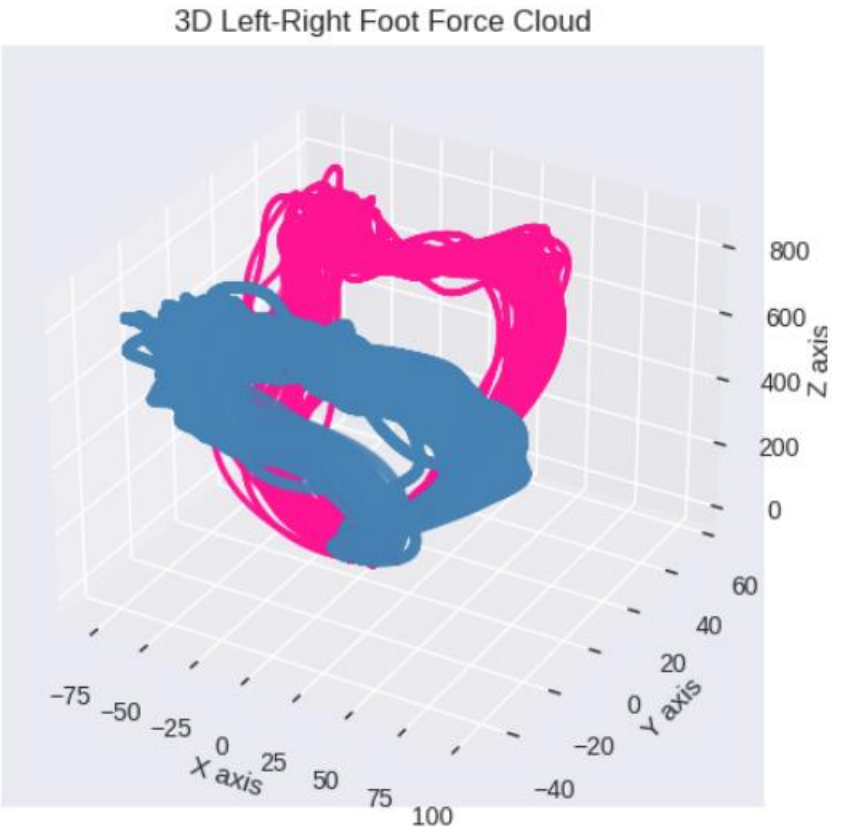

Fig. 8. Foot Force Cloud

The graph below in Fig. 9 shows each person's foot positioning as they move forward. It examines the foot's posture.

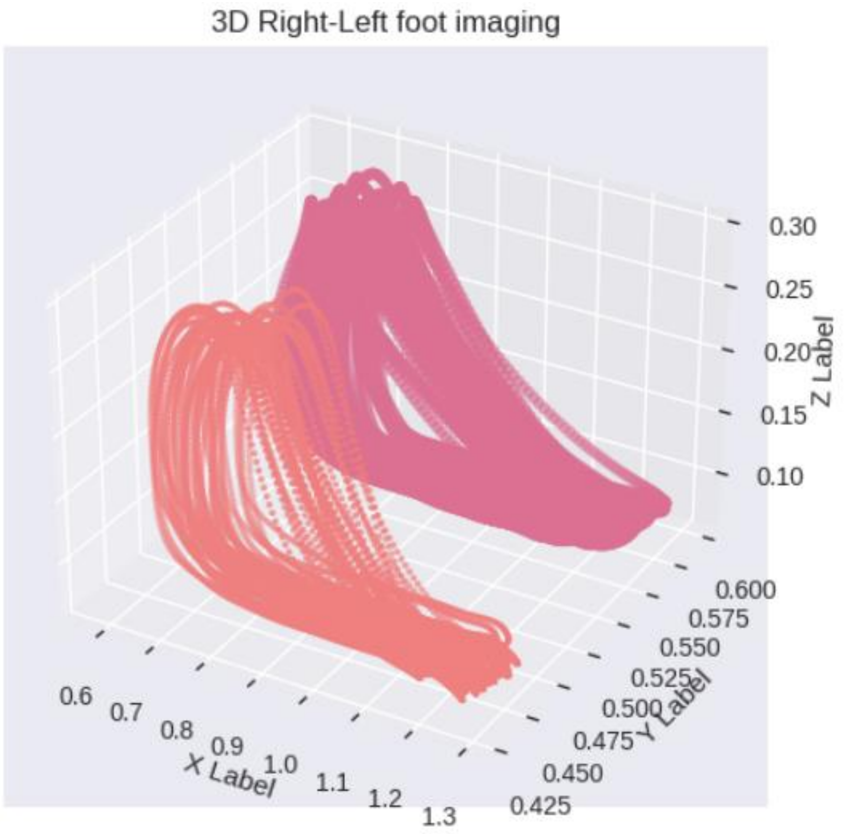

Fig. 9. Foot Imaging

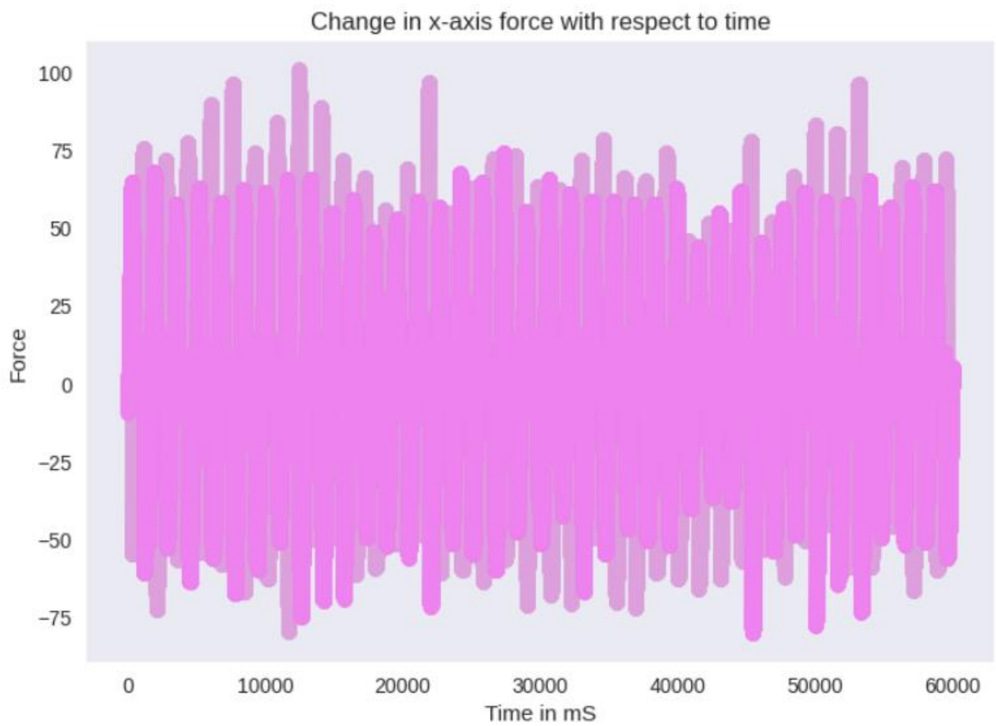

Fig. 10. Change in X-axis force w.r.t Time

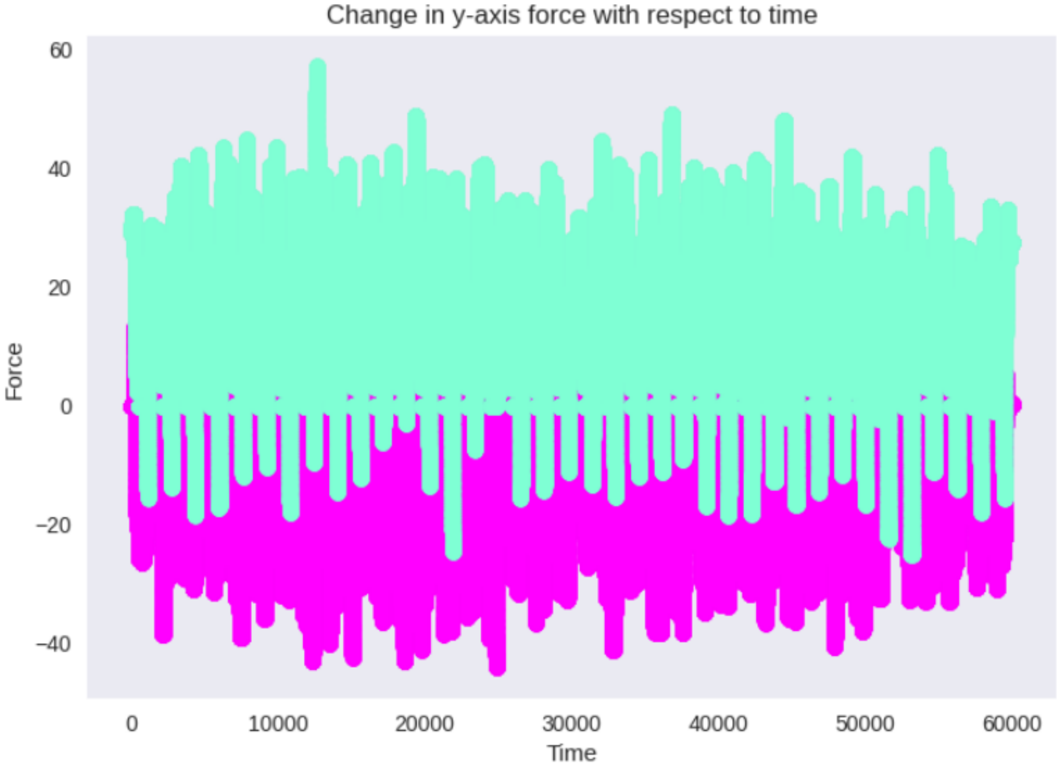

Fig. 11. Change in Y-axis force w.r.t Time

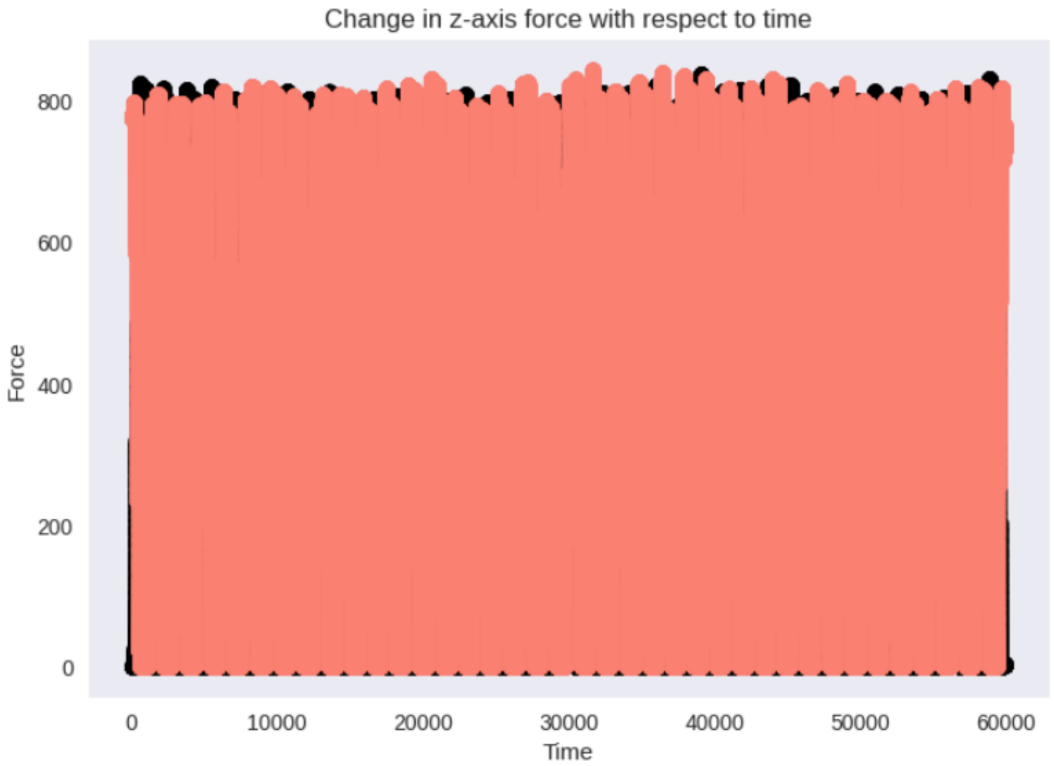

Fig. 12. Change in Z-axis force w.r.t Time

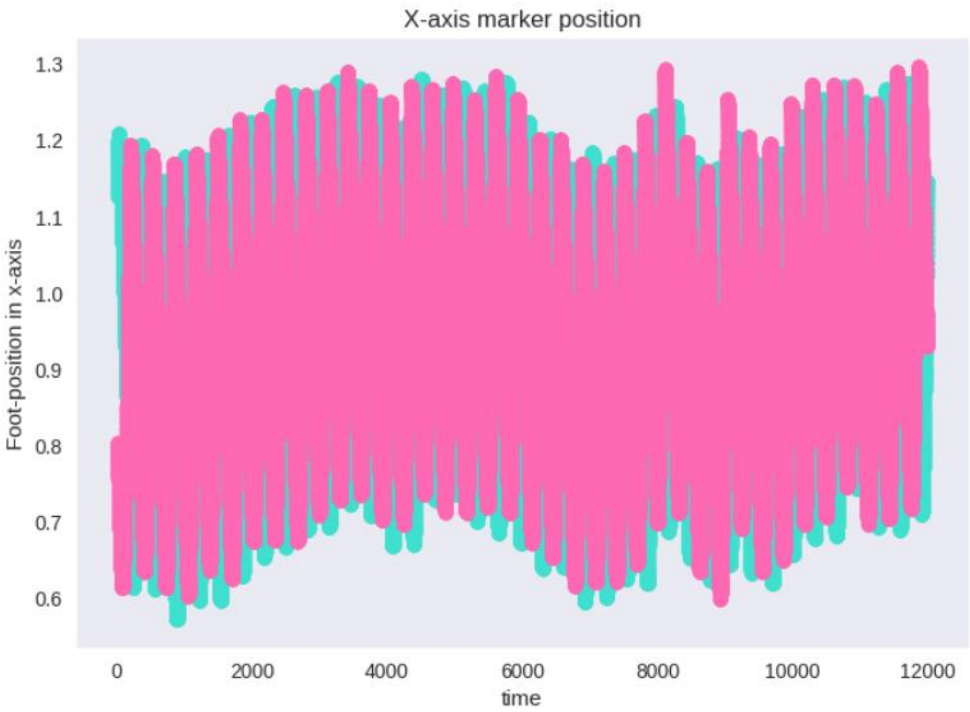

Fig. 13. X-axis Marker Position

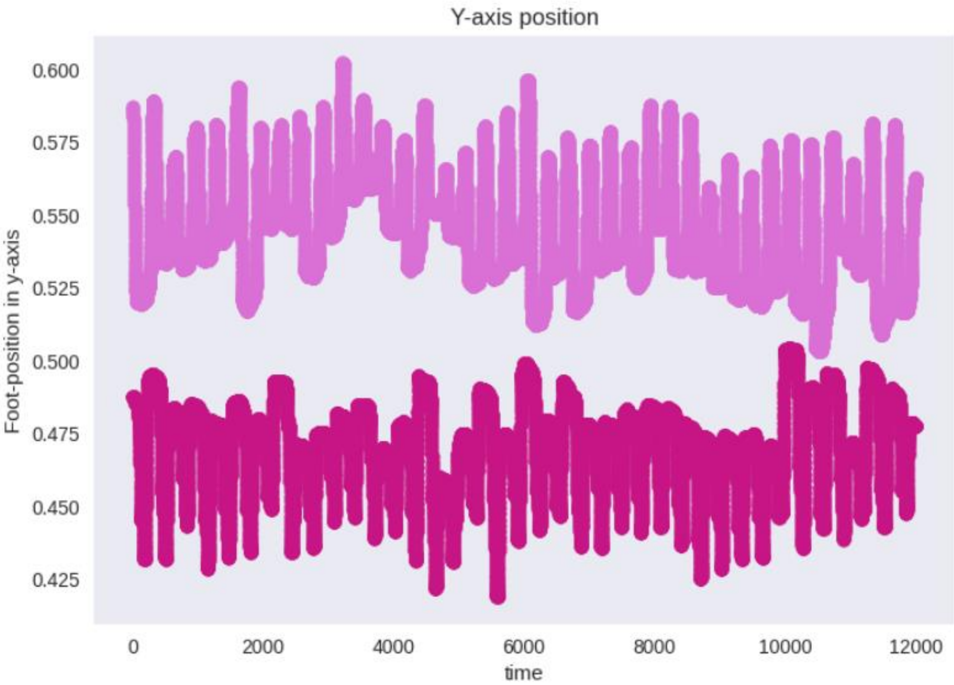

Fig. 14. Y-axis Marker Position

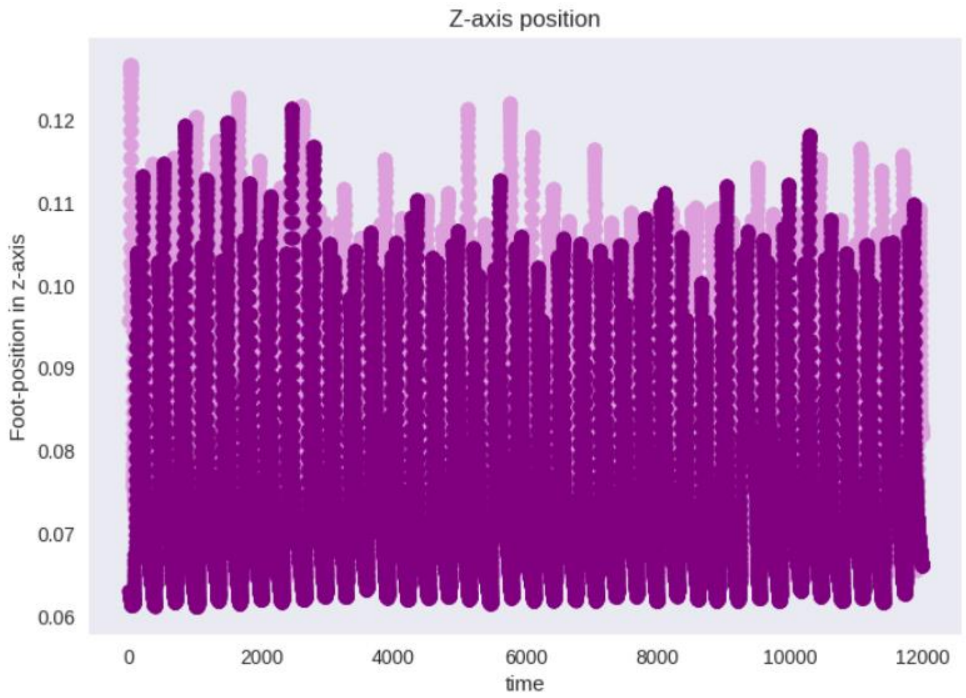

Fig. 15. Z-axis Marker Position

```
force1 = int(input("Enter the force exerted by left foot: "))
force2 = int(input("Enter the force exerted by right foot: "))
result = predict_neuro_disease(force1, force2)
print(result)
```

```
Enter the force exerted by left foot: 687
Enter the force exerted by right foot: 785
The person has a neurological disease.
```

Fig. 16. Presence of neuro disease outcome

```
force1 = int(input("Enter the force exerted by left foot: "))
force2 = int(input("Enter the force exerted by right foot: "))
result = predict_neuro_disease(force1, force2)
print(result)
```

```
Enter the force exerted by left foot: 456
Enter the force exerted by right foot: 258
The person does not have a neurological disease.
```

Fig. 17. Absence of neuro disease outcome

Based on the findings as stated in Table 1, it is recommended to choose bagging since it has the highest accuracy and is suited for employing gait analysis to forecast neuro disorders.

Table 2. Comparison Table

S.no	Algorithms	Accuracy
1	SVM	90.5
2	Naive-Bayes Classifier	92.15
3	Logistic Regression	94.37
4	Bagging	98.79

6. CONCLUSION AND FUTURE SCOPE

This model will assist us in determining whether a person has a neuro illness. It will carefully examine how the feet move and how much force is used when walking. The gait analysis can assist us in determining the optimum criteria to identify the disease's symptoms. Support vector machines, naive bayes classifiers, logistic regression, and bagging were all tried in this model; nevertheless, bagging produced the best results, with an accuracy of 98.79%. By combining different algorithms to improve accuracy, bagging has improved performance. This is highly helpful for medical professionals like doctors and nurses to critically analyze the symptoms and accurately diagnose brain disorders. The efficiency of gait analysis in predicting neuro illnesses has only increased when it is supplemented with ensemble methods like bagging. By doing this, patients can recover from illnesses much more quickly and receive timely medical guidance. Since the focus of the current effort is solely on foot movement. In the future, we can increase the scope of diagnosing neuro disorders to include things like eye movements, body posture, and facial expressions. Additionally, feature selection algorithms can be used to improve selection criteria metrics.

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8. APPENDIX

1. **Importing dataset**

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt

d1 = pd.read_csv('/content/drive/MyDrive/data/GP1_0.6_marker.csv')
d2 = pd.read_csv('/content/drive/MyDrive/data/GP1_0.8_marker.csv')
d3 = pd.read_csv('/content/drive/MyDrive/dataset/dataset1.csv')

d1.head()
d2.head()
```

2. **Data preprocessing**

```
d3['target1'] = np.where(d3['forcel'] > 620, 1, 0)
d3['target2'] = np.where(d3['forcer'] > 620, 1, 0)
d3.head()
print(d3.isnull().sum())
d3.dropna()
Q1 = d1.quantile(0.25)
Q3 = d1.quantile(0.75)
IQR = Q3 - Q1
outliers = ((d1 < (Q1 - 1.5 * IQR)) | (d1 > (Q3 + 1.5 * IQR))).sum()
print(outliers)
from scipy import stats
z_scores = np.abs(stats.zscore(d1))
threshold = 3
outliers = np.where(z_scores > threshold)
```

```
# Remove outliers
df_clean = d1[(z_scores < threshold).all(axis=1)]
print("No of outliers removed: ", len(d1) - len(df_clean))
```

3. **Linear Regression**

```
import statsmodels.api as sm
y = d1.iloc[:, 0].values
X = d1.iloc[:, 1:].values
X = sm.add_constant(X)
model = sm.OLS(y, X)
results = model.fit()
print(results.summary())
```

4. **Correlation using Heatmap**

```
import seaborn as sb
plt.style.use("seaborn")
d1.corr()
p1 = sb.heatmap(d1.corr())
p1
```

5. **Gait analysis**

```
from mpl_toolkits.mplot3d import Axes3D
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np

def datanormalizer(data):
    a = 1
    b = 0
    c = 0
    newData =
pd.DataFrame(index=np.arange(0,60),columns=['FP1_x','FP2_x','FP1_y','FP2_y','FP1
_z','FP2_z'])
    for each in data.index:
        a = a+1
        if a%1000 == 0:
            newData.iloc[c] = data.iloc[b:a,:].sum()/1000
```

```
            b = a
            c = c+1
    return newData
data = pd.read_csv('/content/drive/MyDrive/data/GP1_0.6_force.csv')
data.head()
```

6. **Data Visualization**

```
timer = np.arange(0,60000)
plt.scatter(timer,data['FP1_x'],color="plum")
plt.scatter(timer,data['FP2_x'],color="violet")
plt.xlabel('Time in mS')
plt.ylabel('Force')
plt.title('Change in x-axis force with respect to time')
plt.grid()
plt.show()

fig = plt.figure()
ax = fig.add_subplot(111,projection='3d')
ax.scatter(data['FP1_x'],data['FP1_y'], data['FP1_z'], color='steelblue', marker='o')
ax.scatter(data['FP2_x'],data['FP2_y'], data['FP2_z'], color='deeppink', marker='.')
ax.set_xlabel('X axis')
ax.set_ylabel('Y axis')
ax.set_zlabel('Z axis')
plt.title("3D Left-Right Foot Force Cloud")
plt.show()


q = datanormalizer(data=data)

plt.scatter(np.arange(0,60),q['FP1_x'])
plt.scatter(np.arange(0,60),q['FP2_x'])
plt.title('Decreased data')
plt.xlabel('Sample Data')
plt.ylabel('X label data')
plt.show()
```

```
timer = np.arange(0,12000)
plt.scatter(timer,data['L_FCC_x'],color='turquoise')
plt.scatter(timer,data['R_FCC_x'],color='hotpink')
plt.title('X-axis marker position')
plt.xlabel('time')
plt.ylabel('Foot-position in x-axis')
plt.grid()
plt.show()

from mpl_toolkits.mplot3d import Axes3D

fig = plt.figure()
ax = fig.add_subplot(111,projection='3d')
ax.scatter(data['L_FCC_x'],data['L_FCC_y'], data['L_FCC_z'], color='palevioletred', marker='o')
ax.scatter(data['R_FCC_x'],data['R_FCC_y'], data['R_FCC_z'], color='lightcoral', marker='.')
ax.set_xlabel('X Label')
ax.set_ylabel('Y Label')
ax.set_zlabel('Z Label')
plt.title("3D Right-Left foot imaging")
plt.show()
```

7. **Train and Test split**

```
from sklearn.model_selection import train_test_split
x_train, x_test,y_train,y_test = train_test_split(x,y,test_size=0.6,random_state=42)
```

8. **SVM**

```
from sklearn.svm import SVC
svm = SVC(random_state = 6)
svm.fit(x_train,y_train)
print("acc of svm is :",svm.score(x_test,y_test))
```

9. **Logistic Regression**

```
from sklearn.linear_model import LogisticRegression
lr = LogisticRegression()
lr.fit(x_train,y_train)
print("test accuracy for Log Regressin is  {}".format(lr.score(x_test,y_test)))
```

10. **Naïve Bayes Classifier**

```
from sklearn.naive_bayes import GaussianNB
nb = GaussianNB()
nb.fit(x_train,y_train)
print('accuracy of bayes in test data is :', nb.score(x_test,y_test))
```

11. **Decision Tree Classifier**

```
from sklearn.tree import DecisionTreeClassifier
dt = DecisionTreeClassifier()
dt.fit(x_train,y_train)
print('Accuracy of dec tree in test data is:',dt.score(x_test,y_test))
```

12. **Bagging**

```
from sklearn.ensemble import BaggingClassifier
from sklearn.metrics import accuracy_score

bag_model = BaggingClassifier(
    estimator = DecisionTreeClassifier(),
    n_estimators = 150,
    max_samples = 0.1,
    oob_score = True,
    random_state = 42
)

bag_model.fit(x_train,y_train)
print(bag_model.oob_score_)
```

13. **Cross Validation**

```
from sklearn.model_selection import cross_val_score
from sklearn.ensemble import BaggingClassifier
bag_model = BaggingClassifier(
    estimator=DecisionTreeClassifier(),
    n_estimators=180,
    max_samples =0.3,
    oob_score = True,
    random_state = 0
)
scores  = cross_val_score(bag_model,x,y,cv = 12)
scores.mean()
```

14. Prediction

```
def predict_neuro_disease(force1, force2):
    X = d3[['forcel', 'forcer']]
    y = d3[['target1', 'target2']].apply(lambda x: 'Yes' if x[0]==1 and x[1]==1 else 'No',
axis=1)
    base_classifier = DecisionTreeClassifier()
    bagging_classifier = BaggingClassifier(base_classifier, n_estimators=10,
random_state=42)
    bagging_classifier.fit(X, y)
    user_input = [[force1, force2]]
    prediction = bagging_classifier.predict(user_input)[0]
    if prediction == 'Yes':
        return "The person has a neurological disease."
    else:
        return "The person does not have a neurological disease."
```

15. Evaluation Metrics

```
from sklearn.metrics import confusion_matrix
y_pred = bag_model.predict(x_test)

print("Confusion Matrix: ")
print(confusion_matrix(y_test, y_pred))
```