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AI-POWERED GAIT ANALYSIS FOR EARLY PARKINSON'S DETECTION

Shobha christila. S*, Shanmuga raja. G[1], Ruvethasri. V[2], Yazhini. S[3], Balaji. A[4]
[1,2,3,4]Final Year Students, Department of Biomedical Engineering, Hindusthan College of Engineering and Technology, Valley Campus, Coimbatore, India
*Assistant Professsor, Department of Biomedical Engineering, Hindusthan College of Engineering and Technology, Valley Campus, Coimbatore, India
*Corresponding Author Email Id: Shobhachristila.bme@hicet.ac.in

ABSTRACT

Parkinson's disease (PD) often manifests through gait abnormalities that can appear before a formal diagnosis. This project presents a unique wearable gait analysis system designed for early detection of PD using advanced sensor technology and AI. The system integrates an inertial measurement unit (IMU) to monitor key gait parameters such as stride length, walking speed, tremor intensity, and balance, alongside pressure sensors to assess foot pressure distribution, providing a comprehensive gait profile. Its distinctive feature includes real-time data visualization on a mobile app, which alerts users to abnormal gait patterns. The system incorporates adaptive AI that improves detection accuracy with continuous data collection. Lightweight and portable, it is designed for home use, offering an affordable and non-invasive alternative to clinical assessments. By enabling continuous monitoring and early detection, this system supports timely medical intervention, improving long-term outcomes and providing a proactive Parkinson's disease. approach to managing

KEYWORDS: Parkinsons's Disease, Gait Analysis, Visualize Data, Portable, Non-Invasive, Early Detection.

I. INTRODUCTION

Parkinson's disease (PD) is a chronic, progressive neurodegenerative disorder that primarily affects motor control due to the degeneration of dopaminergic neurons in the brain. The disease often begins insidiously, with mild and easily overlooked motor disturbances that gradually worsen over time. Among the earliest and most prominent indicators of Parkinson's disease are gait abnormalities, including reduced stride length, irregular walking speed, impaired postural balance, shuffling gait, and the presence of tremors. In many cases, these gait-related symptoms appear well before a definitive clinical diagnosis is made, highlighting the importance of early detection. Timely identification of such early motor impairments allows for earlier medical intervention, which can help slow disease progression, improve symptom management, and significantly enhance the overall quality of life for affected individuals.

Conventional diagnostic and monitoring approaches for Parkinson's disease rely heavily on clinical observation, neurological examinations, and subjective rating scales, such as the Unified Parkinson's Disease Rating Scale (UPDRS). While effective, these methods are limited by their dependence on clinician expertise, episodic assessments, and the inability to capture subtle or fluctuating gait changes during daily activities. Moreover, traditional evaluations are typically conducted in controlled clinical environments, which may not accurately reflect a patient's real-world motor performance. These limitations have driven the need for objective, continuous, real-time, and non-invasive monitoring solutions that can be used outside hospital settings.To address these challenges, this project proposes the development of a novel wearable gait analysis system specifically designed for the early detection and monitoring of Parkinson's disease [1]. The proposed system integrates an Inertial Measurement Unit (IMU) and pressure sensors into a compact, lightweight, and wearable device. The IMU captures essential gait and movement parameters such as stride length, walking speed, tremor intensity, acceleration patterns, and postural stability, while the pressure sensors analyze foot pressure distribution and ground contact dynamics during walking. The fusion of these sensor modalities enables the generation of a comprehensive and objective gait profile, offering deeper insight into the user's motor condition.

A key distinguishing feature of the proposed system is the incorporation of adaptive artificial intelligence (AI) and machine learning algorithms. These algorithms continuously analyze incoming sensor data and refine their predictive models based on individual user patterns. This adaptive learning capability allows for personalized gait assessment, improved detection accuracy, and early identification of abnormal movement patterns associated with Parkinson's disease. As more data is collected over time, the system becomes increasingly robust in distinguishing between normal age-related gait variations and Parkinsonian gait characteristics.

The wearable device is complemented by a dedicated mobile application that enables real-time data visualization, automated analysis, and alert generation. The application provides intuitive dashboards for patients, caregivers, and healthcare professionals, displaying gait trends and performance metrics over time. When irregular or concerning gait patterns are detected, the system generates instant alerts, ensuring prompt awareness and timely clinical consultation. Designed primarily for home-based use, the system emphasizes portability, ease of operation, and cost-effectiveness, making it suitable for continuous, long-term monitoring without frequent hospital visits.

By bridging the gap between traditional clinical diagnosis and everyday home monitoring, the proposed system offers a proactive and patient-centered approach to Parkinson's disease management. Recent advancements in wearable sensors, embedded systems, and mobile health technologies have made such solutions increasingly feasible and reliable. Leveraging these developments, the system effectively brings hospital-grade diagnostic capabilities into a home environment, empowering users to actively participate in their own health monitoring.

Furthermore, continuous data acquisition combined with AI-driven analysis enables the creation of large-scale, anonymized datasets, which can contribute to future research on Parkinson's disease progression, early risk factor identification, and personalized treatment strategies. Overall, the integration of wearable technology, artificial intelligence, data science, and user-centric design presented in this project represents a significant advancement toward predictive, accessible, and efficient neurological healthcare, with the potential to transform early diagnosis and long-term management of Parkinson's disease

.II. MATERIALS

A. HARDWARE COMPONENTS

The proposed methodology includes a simple electronic system that includes the following components:

- ADXL345
- Battery
- ESP 32
- Strap
- Jumper wires
- Motion capture camera
- Kinect sensor

1. ADXL345:(Analog device based accelerometer)

The ADXL345 is a small, low-power, 3-axis digital accelerometer widely used for motion sensing applications. In this project, it plays a crucial role in monitoring gait abnormalities related to Parkinson's disease. The sensor detects acceleration along the X, Y, and Z axes, providing real-time data on movement, tremors, stride patterns, and balance.[6] Its high resolution and configurable range (±2g to ±16g) make it suitable for capturing both subtle and rapid body motions. The ADXL345 communicates with the ESP 32 through either I2C or SPI interface, enabling seamless data collection. Due to its compact size, low power consumption, and reliable performance, it is ideal for integration into wearable devices designed for continuous, non-invasive gait analysis.

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2. BATTERY:

A 5v-9v battery is an electrochemical device that provides a nominal voltage of 5v-9v volts to power various electronic and electrical projects. The lithium-ion battery can be suited for specific applications based on their characteristics. They are commonly used in electronics, robotics, renewable energy systems, and portable devices.

3. ESP 32:

The ESP32, developed by Espressif Systems, is a powerful and affordable microcontroller known for its high performance and rich feature set. It runs on a dual-core processor clocked up to 240 MHz, with 520 KB of SRAM and 4 MB of flash memory. What sets it apart is its built-in support for Wi-Fi and Bluetooth (both Classic and Low Energy), making it ideal for IoT applications, home automation, wearables, industrial controls, and robotics. The ESP32 offers a wide range of peripheral interfaces, including SPI(Serial Pheripheral Interface), I2C (Inter Integrated communication), and PWM(Pulse width Modulation), along with multiple GPIO(General Purpose Input and Output) pins that support ADC(Analog to Digital Converter) and DAC(Digital to Analog Converter). It also supports efficient power-saving modes like deep sleep and hibernation. [2] In terms of security, it includes features like secure boot, flash encryption, and hardware-based cryptography. Developers can program it using Arduino IDE, ESP-IDF, or MicroPython, making it flexible and accessible for both beginners and advanced users. Its strong developer community and detailed documentation further enhance its appeal for embedded system projects.

4. MOTION CAPTURE CAMERA:

A motion capture camera is a specialized device designed to track and record the movement of objects or human bodies in space. These cameras are often used in biomechanics, sports science, animation, and medical research to capture precise motion data. In biomedical applications such as gait analysis for Parkinson's disease motion capture cameras track key body joints and movements, enabling detailed analysis of walking patterns, balance, and tremors. These cameras often use infrared sensors or optical markers attached to the body to detect motion in 3D space. The data is then processed to create a digital skeleton or animation that mirrors real-time human movement. Motion capture systems can be marker-based (requiring reflective or LED markers) or markerless (using depth sensors like Kinect or AI-based tracking). The high accuracy and real-time feedback provided by motion capture cameras make them essential tools in clinical diagnosis, rehabilitation monitoring, and research involving motor function impairments. The range of motion capture system is upto (5-6 Meters).

5. KINECT SENSOR:

The Kinect sensor is a motion-sensing input device originally developed by Microsoft for the Xbox gaming console and later adapted for Windows-based applications. It combines a RGB camera, depth sensor, and multi-array microphone to capture full-body movement, depth perception. In biomedical and clinical research, the Kinect sensor is widely used for gait analysis, rehabilitation monitoring, and movement disorder detection, such as in patients with Parkinson's disease. Unlike traditional motion capture systems that require physical markers, the Kinect offers markerless tracking, making it more convenient and non-invasive.[4] It can detect and map up to 25 body joints simultaneously, allowing for detailed tracking of posture, balance, stride, and limb coordination. Additionally, it supports skeletal tracking, 3D spatial mapping, and gesture recognition, making it an ideal low-cost solution for real-time motion analysis in home-based or clinical environments. Its ease of integration with software tools and open SDK support also make Kinect a popular choice for developers and researchers working on motion-related biomedical projects.

B. SOFTWARE

A software component specification details the requirements, functionalities, and constraints of a software component, including its purpose, scope, and dependencies. It also covers functional requirements, use cases, and acceptance criteria to ensure the component meets its intended goals.

- Arduino Ide
- Kinect Configuration Verifier
- Kinect Studio
- Kinect Animation Studio
- Autodesk Fbx Converter
- Blender
- Kinovea

1.ARDUINO IDE:

Arduino IDE (Integrated Development Environment) is an open-source software platform specifically designed for writing, compiling, and uploading code to Arduino microcontroller boards such as the ESP 32. It supports C and C++ programming languages and provides a simple, intuitive interface that is ideal for both beginners and advanced users. In this Parkinson's gait analysis project, the Arduino IDE is used to program the ESP 32 to read real-time motion data from the ADXL345 accelerometer using the I2C communication protocol. It includes built-in libraries, such as the Wire library, which simplifies sensor integration and data handling. [7] The IDE enables seamless debugging and modification of the code, allowing iterative development and real-time testing during the prototyping phase. Programs are uploaded to the ESP 32 through a USB connection, and the Serial Monitor feature allows users to view sensor data for validation and analysis. Overall, Arduino IDE is a crucial tool that supports efficient, customizable, and rapid development of embedded biomedical systems.

2. KINECT CONFIGURATION VERIFIER:

Kinect Configuration Verifier is a diagnostic tool provided by Microsoft to assess whether a computer system meets the necessary requirements to run applications that use the Microsoft Kinect sensor. It checks essential hardware and software components, such as the USB controller compatibility, graphics card capabilities, processor speed, available memory, and the presence of required drivers. In projects involving motion tracking or gait analysis using Kinect, this tool is particularly important before installation and deployment, as it ensures that the system can support real-time data acquisition and processing from the Kinect sensor. The Configuration Verifier provides clear pass/fail indicators for each requirement, helping users identify and resolve compatibility issues in advance. This makes it a vital step when setting up a Kinect-based biomedical application, ensuring smooth and efficient operation without unexpected technical problems.

3.KINECT STUDIO:

Kinect Studio is a powerful tool provided by Microsoft that allows developers and researchers to record, plack, and debug data streams from the Kinect sensor. It captures raw data including depth, color, infrared, body tracking, and skeletal movement, making it highly valuable for applications in gait analysis, motion tracking, and biomedical research. In the context of Parkinson's disease al-time sessions and replay them later for detailed examination, without needing the physical presence of the patient. This makes it easier to fine-tune algorithms, verify sensor accuracy, and share data with collaborators. Kinect Studio also supports integration with Visual Studio, enhancing its usability in application development and testing. Overall, it is an essential tool for developing and refining Kinect-based motion analysis systems.

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4.KINECT ANIMATION STUDIO:

Kinect Animation Studio is a software tool designed to capture, visualize, and animate skeletal movement data using the Microsoft Kinect sensor. It allows users to create realistic human motion animations by recording body joint movements in real time. In biomedical applications—especially in gait analysis for Parkinson's disease—Kinect Animation Studio can be used to track and replay a patient's walking patterns, providing a clear visual representation of abnormalities such as freezing, shuffling, or imbalance. This visual feedback is helpful for both clinicians and researchers to analyze motor impairments and monitor disease progression. The tool also allows exporting animations into 3D formats compatible with other modeling or simulation environments, making it useful for educational and diagnostic purposes. With its ability to turn live motion into digital animation, Kinect Animation Studio bridges the gap between raw movement data and visual understanding, supporting more effective evaluation and communication of patient mobility issues.

5. AUTODESK FBX CONVERTER:

Autodesk FBX Converter is a utility tool that allows users to convert 3D model files between different formats, particularly to and from the FBX (Filmbox) format developed by Autodesk. In the context of motion tracking and Kinect-based gait analysis, this tool is especially useful when working with animated skeleton data or 3D models generated from tools like Kinect Animation Studio. It allows the conversion of files into formats compatible with various 3D software such as Maya, 3ds Max, Blender, or Unity, enabling further editing, animation, or integration into simulations. The FBX Converter supports both binary and ASCII versions of FBX files and also allows users to view model hierarchies and animations before conversion. For biomedical research and visualization, this tool helps in refining and transferring motion data into environments where further analysis, visualization, or presentation is required. It ensures compatibility, improves workflow efficiency, and supports the effective use of motion data in multidisciplinary applications.

6.BLENDER:

Blender is a powerful open-source 3D creation suite widely used for modeling, animation, simulation, rendering, and motion tracking. In biomedical and motion analysis projects, Blender plays a key role in visualizing and animating skeletal movement data collected from sensors like Kinect. It supports importing formats such as FBX, allowing seamless integration with files processed through tools like Autodesk FBX Converter and Kinect Animation Studio. For Parkinson's disease gait analysis, Blender can be used to create detailed animations of walking patterns, helping researchers visually examine motor abnormalities such as tremors or freezing of gait. Its advanced rigging and animation tools enable customization of human body models, enhancing the clarity and effectiveness of movement presentations. Additionally, Blender's physics engine and timeline features allow accurate playback and fine control of movement speed and timing. Overall, Blender offers a flexible, professional grade platform for rendering and analyzing motion data in a visually rich and informative manner.

7.KINOVEA:

Kinovea is a free and open-source video analysis software primarily used for analyzing motion in sports and clinical applications. It allows users to capture, slow down, annotate, and measure movement in recorded videos. In biomedical and gait analysis studies, Kinovea is useful for assessing motor functions such as walking speed, stride length, joint angles, and posture. It supports frame-by frame analysis and includes tools for drawing angles, tracking markers, and comparing motion over time. Due to its accuracy and ease of use, Kinovea is often used in rehabilitation, physical therapy, and Parkinson's disease studies to monitor changes in movement patterns.

III. METHODS

1. RESEARCH DESIGN:

This study follows an applied experimental approach aimed at developing a wearable gait analysis system for the early detection of Parkinson's disease. It began with identifying key gait-related symptoms such as reduced stride length, impaired balance, and tremor through literature review and clinical insights. A wearable prototype was then developed using an accelerometer sensor integrated with a microcontroller and a wireless communication module for data transmission. Gait data was collected from healthy individuals and early-stage Parkinson's patients while walking under controlled conditions.[3] The sensor data was used to train machine learning models capable of distinguishing between normal and Parkinsonian gait patterns. The system was then validated based on detection accuracy, user-friendliness, and real-time responsiveness, demonstrating its potential for home-based monitoring and early clinical intervention.

2. PARTICIPANTS SELECTION CRITERIA:

- Individuals aged 50 years and above were selected.
- Participants included early-stage Parkinson's patients and healthy controls.
- All participants could walk unaided for at least two minutes.
- Informed consent was obtained from each participant.
- Participants with advanced Parkinson's disease were excluded.
- Those with cognitive impairments were not included.
- Individuals with other neurological or musculoskeletal disorders were excluded.
- Recent lower limb injuries or surgeries led to exclusion.

3. METHODS

This study utilized two complementary approaches to assess and validate gait abnormalities associated with Parkinson's disease: a wearable-based detection system and a motion capture-based validation system.

1. **Wearable-Based Gait Analysis System** The primary method involved the development of a wearable device using an ADXL345 accelerometer to monitor and analyze gait patterns. The sensor was affixed to the participant's lower leg using a soft, adjustable strap, ensuring consistent placement during walking. It was connected to an ESP 32 via jumper wires, allowing real time acquisition of acceleration data along the X, Y, and Z axes. Custom code written in the Arduino IDE was used to collect, filter, and transmit the data. [5] Parameters such as stride length, step frequency, balance fluctuations, and tremor activity were extracted and analyzed. This setup was designed to be lightweight, low-cost, and suitable for home use, with data either stored locally or visualized on a mobile or desktop interface.

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Fig 1: Wearable-Based Gait Analysis System

4. Motion Capture System for Accuracy Validation:

To verify the accuracy and reliability of the wearable system, a motion capture setup was employed as a reference. This included the Kinect sensor, which provides markerless, full-body skeletal tracking in real time. Supporting software tools used in this setup included:

- **Kinect Configuration Verifier** – For setup validation
- **Kinect Studio** – For real-time data recording
- **Kinect Animation Studio** – For skeletal movement visualization
- **Autodesk FBX Converter** – To convert recorded skeletal data
- **Blender** – For advanced 3D animation and motion rendering
- **Kinovea –** For detailed gait measurement and frame- by-frame video analysis.

Participants performed identical walking trials for both systems simultaneously. [9] The data from the Kinect- based motion capture system was used to cross-verify the results from the wearable system, specifically focusing on consistency in detecting gait deviations, balance loss, and stride irregularities.

IV. BLOCK DIAGRAM

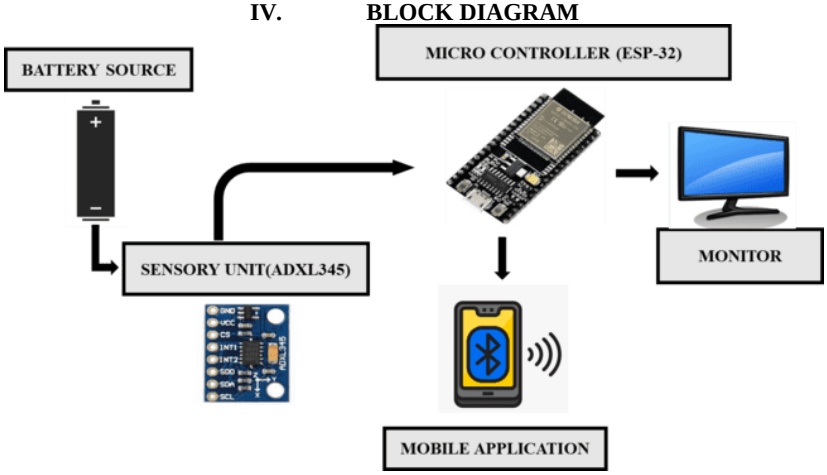

Fig 2: Block diagram

This block diagram represents the working:

- Battery source powers the sensor and microcontroller.
- ADXL345 sensor detects motion and acceleration.
- Sensor sends data to the ESP 32 microcontroller.
- Arduino processes the motion data.
- Processed data is sent to a monitor for display.
- Data is also transmitted to a mobile application via Bluetooth.
- Mobile app allows wireless monitoring of motion data.

V.CIRCUIT DIAGRAM

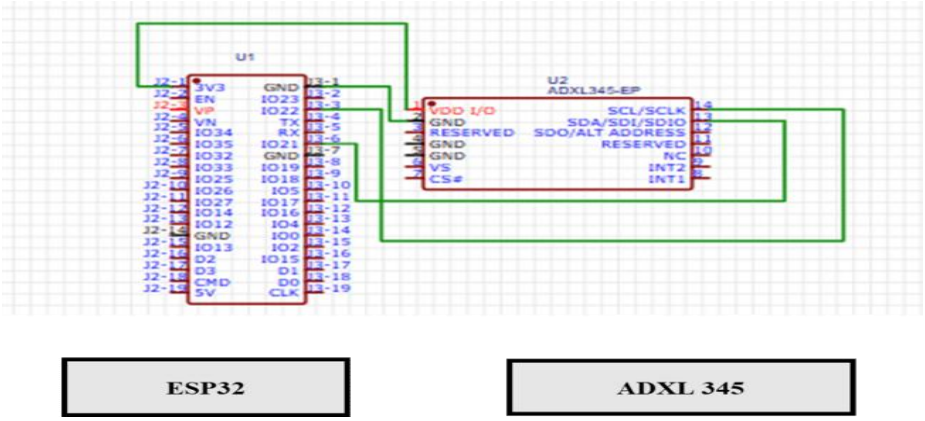

Fig 3: Circuit diagram for interfacing the ESP 32 with ADXL 345

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VI.GAIT PARAMETERS

I. COMPARING THE GAIT PARAMETERS WITH HEALTHY PATIENTS AND PARKINSON'S PATIENTS

Gait Parameter	Healthy Individuals (above 50 years old)	Parkinson's Disease Patients (above 50 years old)
Stride Speed	Steady and efficient stride speed	Reduced and often irregular due to slowness of movement (bradykinesia)
Swing Speed	Smooth leg movement during swing phase	Decreased swing speed; foot may drag or lift poorly
Turning Time	Quick and fluid turning, usually within 1–2 steps	Prolonged turning; multiple small steps (en bloc turning)
Cadence	Regular and rhythmic step pattern	Reduced step rate; rhythm may be disrupted by freezing episodes

Table 1: Comparing the gait parameters with healthy patients and parkinson's patients

Gait Parameter	**Healthy Individuals** (Approximate Values) **(above 50 years old)**	**Parkinson's Disease Patients** (Approximate Values) **(above 50 years old)**
Stride Speed	~1.2–1.4 m/s	~0.7–1.0 m/s
Swing Speed	~1.5–1.7 m/s	~0.9–1.2 m/s
Turning Time	~3–4 seconds	~5–10 seconds
Cadence	~100–120 steps/min	~70–100 steps/min
Step Length	~65–75 cm	~40–55 cm
Stride Length	~130–150 cm	~80–110 cm
Step Time	~0.5–0.6 sec	~0.6–0.8 sec
Stride Time	~1.1–1.3 sec	~1.4–1.8 sec
Gait Speed	~1.3 m/s	~0.8 m/s

Table 2: Values for the healthy patients and the parkinson's patient

GAIT SPEED:

Gait speed is the average walking velocity of an individual, defined as the distance covered per unit time during normal or instructed walking. It represents the combined performance of the nervous system, muscles, joints, balance mechanisms, and cardiovascular function, and is widely used as a clinical and research parameter to assess mobility, functional capacity, and neurological health. Reduced gait speed is a key indicator of movement disorders such as Parkinson's disease, where motor slowness and instability affect walking ability.

FORMULA:

$$\textbf{Gait Speed (m/s)} = \frac{\textbf{Distance Walked (meters)}}{\textbf{Time Taken (seconds)}}$$

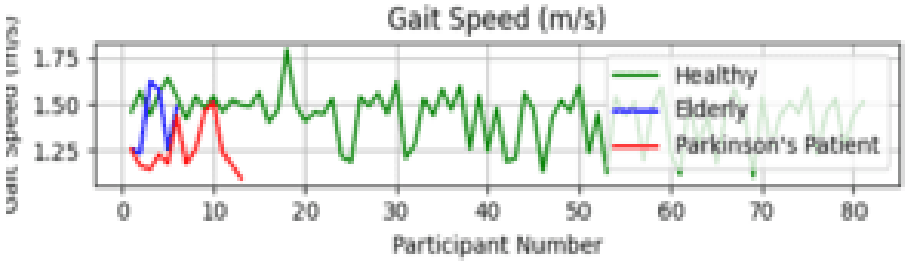

Fig 4: GAIT SPEED OUTPUT GRAPH

CADENCE:

Cadence is a temporal gait parameter that represents the number of steps taken per minute during walking. It reflects the rhythm and timing of gait and is influenced by neuromuscular control, balance, and motor coordination. In neurological conditions such as Parkinson's disease, cadence may be altered due to bradykinesia, festination, and impaired motor timing, making it an important indicator for gait assessment and early diagnosis.

FORMULA:

$$\textbf{Cadence (steps/min)} = \frac{\textbf{Number of Steps}}{\textbf{Time (minutes)}}$$

ALTERNATIVE FORM :

$$\textbf{Cadence} = \frac{\textbf{Number of Steps} \times \mathbf{60}}{\textbf{Time (seconds)}}$$

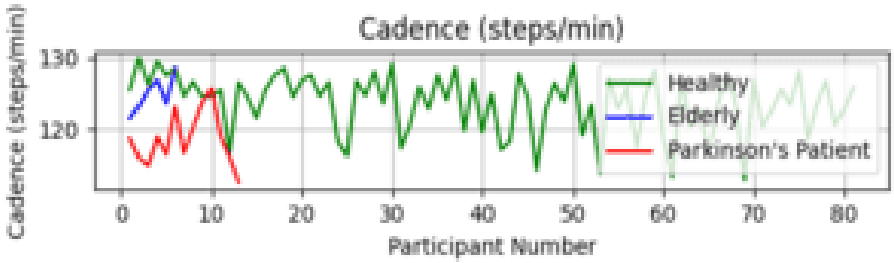

Fig 5: CADENCE OUTPUT GRAPH

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STEP LENGTH:

Step length is a spatial gait parameter that represents the linear distance between the point of initial contact (heel strike) of one foot and the point of initial contact of the opposite foot during walking. It reflects lower-limb strength, balance, coordination, and motor control. In Parkinson's disease, step length is typically reduced, leading to a shuffling gait and festination, making it a key parameter for early gait abnormality detection.

FORMULA:

$$\text{Step Length (m)} = \frac{\text{Total Distance Walked (meters)}}{\text{Number of Steps}}$$

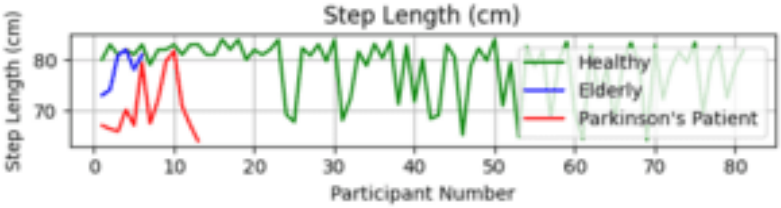

Fig 6: STEP LENGTH OUTPUT GRAPH

STRIDE LENGTH:

Stride length is a spatial gait parameter that represents the linear distance covered during one complete gait cycle, measured from the initial contact (heel strike) of one foot to the next initial contact of the same foot. It reflects walking efficiency, symmetry, balance, and neuromuscular coordination. In Parkinson's disease, stride length is commonly reduced, contributing to shuffling gait and difficulty in initiating movement.

FORMULA:

$$\text{Stride Length (m)} = \frac{\text{Total Distance Walked (meters)}}{\text{Number of Strides}}$$

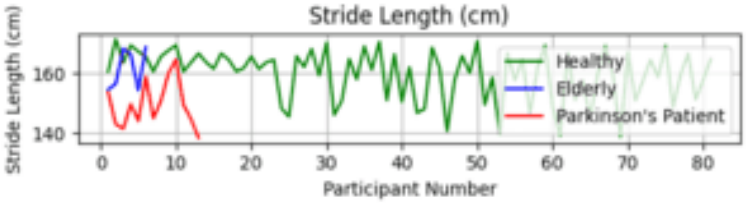

Fig 7: STRIDE LENGTH OUTPUT GRAPH

STEP TIME:

Step time is a temporal gait parameter that represents the duration taken to complete a single step, measured from the initial contact (heel strike) of one foot to the initial contact of the opposite foot. It reflects the timing, rhythm, and coordination of walking. In neurological disorders such as Parkinson's disease, step time may become prolonged or irregular due to bradykinesia, impaired motor control, and balance deficits.

FORMULA:

$$\text{Step Time (s)} = \frac{\text{Total Walking Time (seconds)}}{\text{Number of Steps}}$$

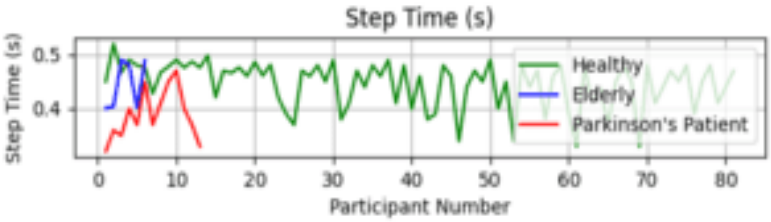

Fig 7: STEP TIME OUTPUT GRAPH

STRIDE TIME:

Stride time is a temporal gait parameter that represents the time taken to complete one full gait cycle, measured from the initial contact (heel strike) of one foot to the next initial contact of the same foot. It reflects the overall rhythm, symmetry, and stability of walking. In neurological disorders such as Parkinson's disease, stride time is often prolonged and more variable due to bradykinesia, impaired coordination, and postural instability.

FORMULA:

$$\text{Stride Time (s)} = \frac{\text{Total Walking Time (seconds)}}{\text{Number of Strides}}$$

RELATION TO STEP TIME:

$$\text{Stride Time} = 2 \times \text{Step Time}$$

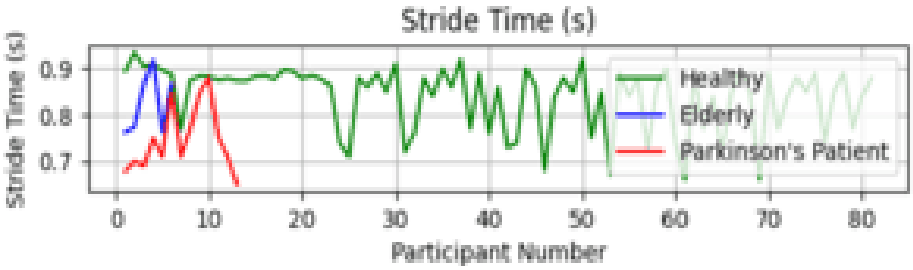

Fig 8: STRIDE TIME OUTPUT GRAPH

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TURNING TIME:

Turning time is a temporal gait parameter that represents the duration taken by an individual to complete a turn while walking, usually measured during 180° or 360° turns. It reflects balance control, postural stability, motor planning, and coordination. In Parkinson's disease, turning time is often prolonged due to bradykinesia, rigidity, freezing of gait, and impaired axial rotation, making it a sensitive indicator for early gait dysfunction and fall risk.

FORMULA:

$$\text{Turning Time (s)} = t_{\text{end of turn}} - t_{\text{start of turn}}$$

PRACTICAL MEASUREMENT:

Turning Time = Time taken to complete the turn (seconds)

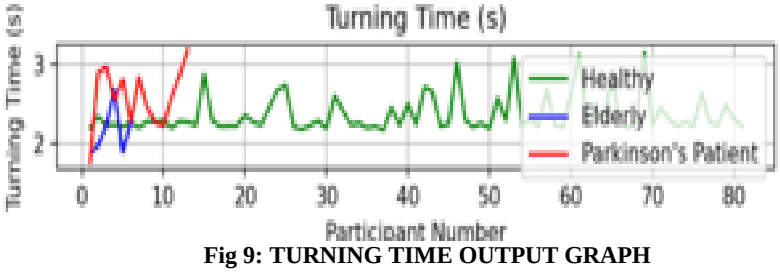

Fig 9: TURNING TIME OUTPUT GRAPH

VII. MACHINE LEARNING

MACHINE LEARNING:

Supervised learning is a powerful approach for classifying conditions like Parkinson's disease (PD) by leveraging labelled datasets. It involves training a model with known inputs (gait features) and their corresponding outputs (normal or Parkinsonian). The process helps the model identify patterns distinguishing between healthy individuals and those affected by PD, enabling accurate predictions.

RANDOM FOREST ALGORITHM:

Random Forest is a powerful machine learning algorithm used for classification and prediction. It works by creating an ensemble of multiple decision trees, where each tree makes a prediction and the final output is decided by majority voting. This method reduces overfitting, improves accuracy, and handles noisy or missing data effectively. In biomedical applications, Random Forest is widely used because it can process complex, non-linear relationships and identify the most important features influencing outcomes. Its robustness and reliability make it highly suitable for detecting diseases such as Parkinson's, where gait features are analyzed to classify patients into normal or abnormal movement patterns.

STEPS INVOLVED:

- **Data Collection:** Gait data is collected from wearable sensors (accelerometer sensor-ADXL 345) that monitor movement and posture.
- **Feature Extraction:** Key gait features such as step length, cadence, step time, stride variability, and walking speed are extracted to serve as input for the model. These features are crucial for distinguishing between normal and Parkinsonian gait patterns.
- **Model Training**: The extracted features, combined with labelled data (e.g., "Normal" or "Parkinsonian"), are fed into a machine learning algorithm (e.g. random forest) to train the model to recognize patterns and learn the relationship between gait and health status.
- **Prediction**: After training, the model can predict the condition of a new individual based on their gait data, classifying them as either normal or affected by Parkinson's disease.
- **Performance:** The model's effectiveness depends on the quality and diversity of the dataset, as well as the robustness of the features. With good training data, supervised learning can achieve high accuracy in distinguishing between healthy and Parkinsonian gaits.
- **Continuous Improvement:** As more data becomes available the model can be retrained to improve its accuracy and adapt to new patterns in gait behaviour.

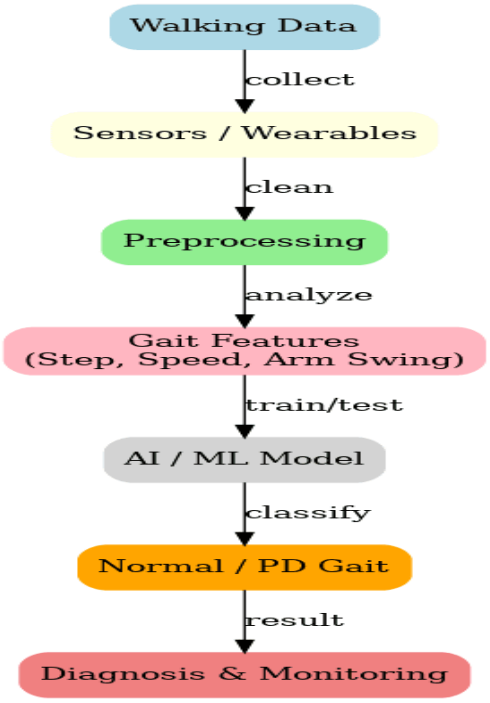

Fig 10: Flow chart

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VIII. DEVELOPED MODEL

The developed wearable gait analysis model is specifically designed for individuals aged 50 years and above, as this age group is more susceptible to age-related motor decline and early signs of Parkinson's disease. The model emphasizes a comprehensive assessment of walking patterns, aiming to understand how aging affects movement, balance, and coordination. Participants are evaluated while walking on various surfaces, including flat, inclined, and uneven paths, to analyze stability under different environmental conditions.To capture a holistic view of gait performance, the testing protocol includes functional tasks such as turning, stepping over obstacles, and walking while performing a secondary cognitive task like talking. These tasks help assess the participant's ability to coordinate movements and maintain balance during multitasking, which is often impaired in early stages of neurodegenerative disorders. Additionally, longer walking trials are conducted to evaluate endurance and fatigue, as reduced stamina and gait deterioration over time can be early indicators of mobility issues or neurological decline.By systematically measuring parameters such as stride length, step time, cadence, turning time, and postural sway, the developed model can identify subtle gait abnormalities that may not be evident in routine clinical observation. The data collected through these tests not only facilitates early detection of gait impairments but also provides valuable insights for designing interventions to reduce the risk of falls in elderly individuals. Overall, the model offers a non-invasive, accurate, and user-friendly solution for monitoring gait performance, enabling timely medical intervention and promoting safer, more independent mobility for the aging population.

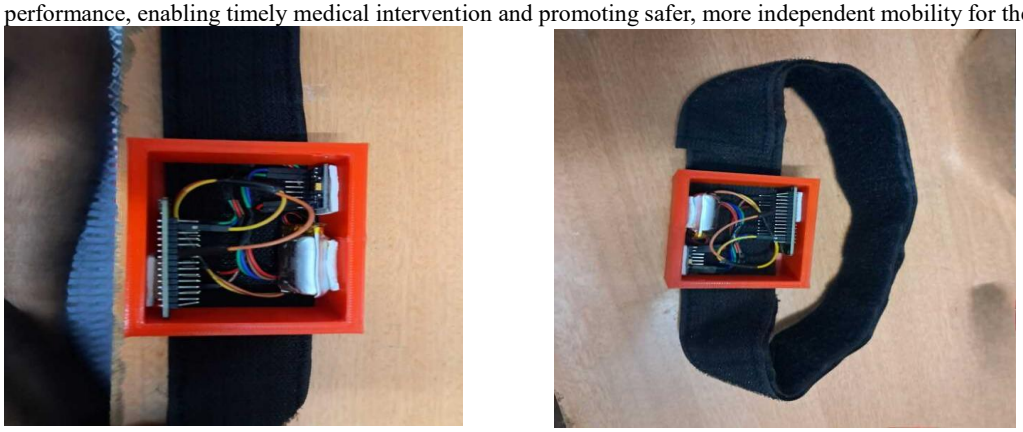

Fig 11: Prototype Image

IX.DISCUSSION

The wearable gait analysis system developed in this study demonstrates a robust and effective approach for differentiating between the gait patterns of healthy individuals and those affected by Parkinson's disease (PD). By leveraging accelerometer-based motion sensing, the system captures fine-grained spatiotemporal gait parameters, including stride length, stride time, step length, cadence, and turning time, which are often altered in the early stages of PD. The analysis revealed characteristic abnormalities in PD patients, such as reduced stride speed, shorter step length, increased stride time, and prolonged turning time, consistent with the bradykinesia and postural instability commonly associated with the disease. These findings highlight the system's sensitivity in detecting subtle gait impairments that may not be evident during routine clinical observation. Validation against gold-standard motion capture systems showed strong agreement, confirming the accuracy and reliability of the wearable device for gait assessment [10]. This establishes that accelerometer-based wearables can serve as a practical alternative to expensive, stationary motion capture systems, providing clinicians and researchers with objective gait data without the need for specialized laboratory setups. The lightweight and non-invasive nature of the device further ensures that it can be worn comfortably for prolonged periods, enabling continuous, real-world monitoring in home environments—a crucial factor for capturing day-to-day gait variability in PD patients.

The system's home-based monitoring capability facilitates early detection and timely intervention, which is essential for slowing disease progression and improving long-term patient outcomes. Continuous gait monitoring allows for the identification of emerging symptoms, tracking of disease progression, and evaluation of therapeutic interventions over time. Moreover, the device offers a cost-effective solution compared to conventional clinical assessments, reducing the burden on healthcare systems and improving accessibility, particularly for patients in remote or underserved areas.Looking forward, integration of machine learning algorithms can further enhance the system by enabling automatic detection, classification, and prediction of gait abnormalities. This would reduce reliance on manual data interpretation and improve diagnostic efficiency. Additionally, advancements in wearable design and battery technology can increase long-term wearability, user comfort, and device adoption. The inclusion of real-time alerts, cloud-based data sharing, and mobile application integration would further support remote monitoring by healthcare professionals, enabling proactive management of Parkinson's disease.

Overall, this wearable gait analysis system represents a promising advancement in both clinical and personal settings, providing an accessible, reliable, and non-invasive platform for early detection, continuous monitoring, and personalized management of Parkinson's disease. Its combination of accuracy, portability, and affordability positions it as a transformative tool in the field of neuromonitoring and digital healthcare.

X.OUTPUT/ RESULTS

Out of the 100 participants analyzed using the wearable gait analysis system, 50 were male and 50 were female. The system predicted 76 participants (76%) as healthy, 16 participants (16%) as Parkinson's patients, and 8 participants (8%) as elderly without Parkinson's. Among males, 43 were healthy, 5 were identified as Parkinson's patients, and 2 as elderly, while among females, 33 were healthy, 11 were Parkinson's patients, and 6 as elderly. This indicates that Parkinson's predictions were slightly higher in females (22%) compared to males (10%), suggesting gender-based variations in the dataset.

The ages of predicted Parkinson's patients ranged from 73 to 85 years, with notable cases including Pankajam (85), Chitra (84), Rajeswari (84), and Padmavathi (82), highlighting that the system predominantly identified older individuals, aligning with epidemiological trends of Parkinson's disease. The healthy participants mostly fell in the 52–79 years age range, whereas the elderly group without PD included participants aged 75–82 years. Overall, the system successfully distinguished between healthy, elderly, and Parkinson's-affected individuals, demonstrating its effectiveness in early detection and monitoring of gait abnormalities, particularly in older adults. These results confirm the system's capability to provide accurate, non-invasive, and real-time screening of Parkinson's disease in a home-based setting.

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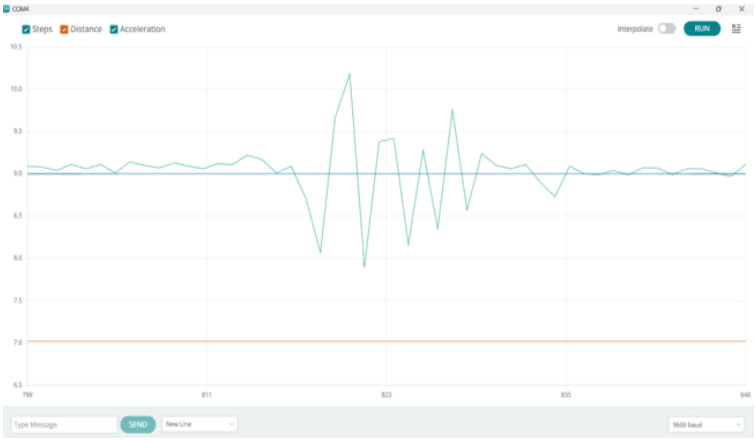

Fig 12: Graph shows step count, distance, and acceleration over time.

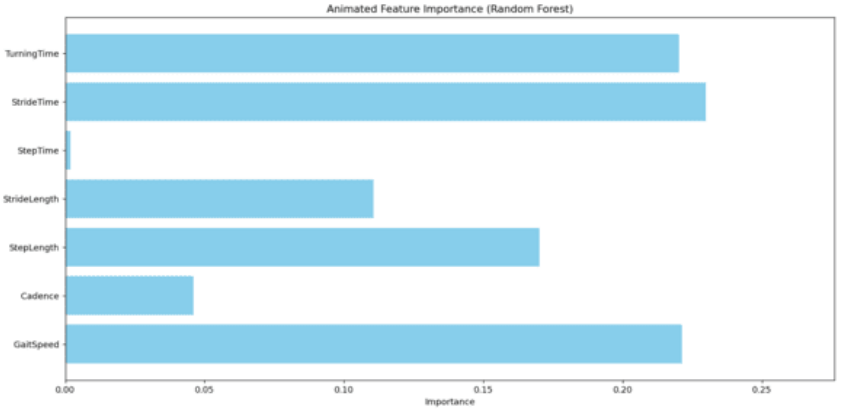

Fig 13: Real Time Gait Parameters Measurement

```
Options:
  1) Record voice now and predict (default 4s).
  2) Predict from CSV file (gait+voice features).
  3) Exit.
Select option [1/2/3]: 2
CSV path: D:\early detection of parkinon's disease\New folder\synthetic_gait_dataset.csv
Saved predictions to prediction_results.csv
  Prediction
0    Healthy
1    Healthy
2    Healthy
3    Healthy
4    Healthy

Options:
  1) Record voice now and predict (default 4s).
  2) Predict from CSV file (gait+voice features).
  3) Exit.
Select option [1/2/3]:
```

Fig 13: Machine Learning Model Terminal Page 1

```
& 'D:\early detection of parkinon''s disease\New folder\Parkinson machine learning model.py'
Dataset loaded: synthetic_gait_voice_dataset.csv
Shape: (1000, 12)
Columns: Index(['GaitSpeed', 'Cadence', 'StepLength', 'StrideLength', 'StepTime',
       'StrideTime', 'TurningTime', 'Jitter', 'Shimmer', 'HNR', 'Pitch',
       'Disease'],
      dtype='object')
First 5 rows:
    GaitSpeed     Cadence  StepLength  StrideLength  StepTime  ...    Jitter   Shimmer        HNR       Pitch  Disease
0   1.415294  111.364110   74.352820    133.912796  0.593873  ...  0.003886  0.026899  24.191123  109.966256        0
1   1.329174  120.071840   67.013898    144.571524  0.600162  ...  0.004275  0.025346  22.387831  131.158951        0
2   1.285234  105.409232   68.249736    149.052903  0.578413  ...  0.004094  0.022573  24.879344  125.376728        0
3   1.296992  109.673175   71.211424    137.672560  0.510003  ...  0.004270  0.023872  25.891701  102.854352        0
4   1.279586  115.596744   72.749676    135.522277  0.584780  ...  0.004091  0.028946  27.057954  138.866183        0

[5 rows x 12 columns]
Scaler saved as scaler.joblib
Trained model saved as combined_rf_model.joblib
Model Accuracy: 100.00%
Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        96
           1       1.00      1.00      1.00       104

    accuracy                           1.00       200
   macro avg       1.00      1.00      1.00       200
weighted avg       1.00      1.00      1.00       200

Example prediction for first test sample: 1
(tfenv) PS D:\early detection of parkinon's disease\New folder>
```

Fig 14: Machine Learning Model Terminal Page 2

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S.NO	NAME	AGE	GENDER	DISEASE PREDICTED
1	Radhakrishnan	68	Male	Healthy
2	Joseph	65	Male	Healthy
3	Sundharam	70	Male	Healthy
4	Ayyasamy	66	Male	Healthy
5	Sundharasamy	62	Male	Healthy
6	Prakash	60	Male	Healthy
7	Vijayakumar	72	Male	Healthy
8	Babu	64	Male	Healthy
9	Jothilingam	69	Male	Healthy
10	Narayanasamy	75	Male	Elderly
11	Robert	73	Male	Elderly
12	Kumar	61	Male	Healthy
13	Kennedy	67	Male	Healthy
14	Arun Joseph	78	Male	Parkinson's Patient
15	Vijayan	63	Male	Healthy
16	Selvakumar	65	Male	Healthy
17	Rajaram	59	Male	Elderly
18	Selvaraj	80	Male	Elderly
19	Raju	66	Male	Healthy
20	Ramalingam	77	Male	Elderly
21	Vasantha	82	Female	Healthy
22	Vasanthabai	64	Female	Healthy
23	Margret	62	Female	Healthy
24	Phelomin	61	Female	Elderly
25	Rani	55	Female	Healthy
26	Vasanthakumari	70	Female	Healthy
27	Stella	68	Female	Healthy
28	Arukani	71	Female	Healthy
29	Mariamma	69	Female	Healthy
30	Thamaraikanni	79	Female	Healthy
31	Murugesan	68	Male	Healthy
32	Palanisamy	72	Male	Healthy
33	Ganesan	55	Male	Healthy
34	Subramani	61	Male	Healthy
35	Kandasamy	74	Male	Parkinson's Patient
36	Velmurugan	58	Male	Healthy
37	Rajendran	63	Male	Healthy
38	Manikandan	52	Male	Healthy
39	Shanmugam	70	Male	Healthy
40	Thangavel	67	Male	Healthy
41	Arumugam	59	Male	Healthy
42	Ramasamy	81	Male	Parkinson's Patient
43	Chinnasamy	64	Male	Healthy
44	Krishnamoorthy	56	Male	Healthy
45	Sekar	73	Male	Parkinson's Patient
46	Muthusamy	60	Male	Healthy
47	Periyasamy	78	Male	Parkinson's Patient
48	Elangovan	54	Male	Healthy
49	Karuppiah	69	Male	Healthy
50	Senthilkumar	57	Male	Healthy
51	Lakshmi	66	Female	Healthy
52	Meenakshi	58	Female	Healthy
53	Saraswathi	74	Female	Parkinson's Patient
54	Parvathi	62	Female	Healthy
55	Andal	70	Female	Healthy
56	Kalyani	55	Female	Healthy
57	Revathi	60	Female	Healthy
58	Padmavathi	82	Female	Parkinson's Patient
59	Gomathi	65	Female	Healthy
60	Jayanthi	59	Female	Healthy
61	Poongodi	77	Female	Parkinson's Patient
62	Shanthi	63	Female	Healthy
63	Maheswari	52	Female	Healthy
64	Valli	69	Female	Healthy
65	Sumathi	61	Female	Healthy
66	Rajeswari	84	Female	Parkinson's Patient
67	Indira	56	Female	Healthy
68	Selvi	68	Female	Healthy
69	Malathi	64	Female	Healthy
70	Uma	57	Female	Healthy
71	Thenmozhi	73	Female	Parkinson's Patient
72	Kavitha	60	Female	Healthy
73	Bhuvaneswari	55	Female	Healthy
74	Pushpa	70	Female	Healthy
75	Geetha	62	Female	Healthy
76	Chitra	84	Female	Parkinson's Patient
77	Suganya	56	Female	Healthy
78	Kalpana	68	Female	Healthy
79	Anitha	64	Female	Healthy
80	Priya	57	Female	Healthy
81	Sivagami	75	Female	Parkinson's Patient
82	Manjula	63	Female	Healthy
83	Deepa	54	Female	Healthy

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84	Rajalakshmi	71	Female	Healthy
85	Arasi	61	Female	Healthy
86	Jothi	83	Female	Parkinson's Patient
87	Nirmala	56	Female	Healthy
88	Poornima	69	Female	Healthy
89	Radha	65	Female	Healthy
90	Sudha	58	Female	Healthy
91	Muthulakshmi	76	Female	Parkinson's Patient
92	Padma	62	Female	Healthy
93	Hemalatha	55	Female	Healthy
94	Sakunthala	72	Female	Healthy
95	Rathika	60	Female	Healthy
96	Pankajam	85	Female	Parkinson's Patient
97	Selvamani	57	Female	Healthy
98	Bhavani	68	Female	Healthy
99	Kalaivani	64	Female	Healthy
100	Mahalakshmi	59	Female	Healthy

Table 4: Case study for aged people

S.NO	NAME	AGE	GAIT SPEED (M/S)	CADENCE (STEPS/MIN)	STEP LENGTH (CM)	STRIDE LENGTH (CM)	STEP TIME (S)	STRIDE TIME (S)	TURNING TIME (S)
1	Radhakrishnan	68	1.4597	125.53	80.09	160.72	0.450	0.895	2.204
2	Joseph	65	1.570	130.00	83.07	171.51	0.520	0.935	2.344
3	Sundharam	70	1.443	126.23	81.06	163.63	0.467	0.905	2.235
4	Ayyasamy	66	1.5597	129.53	82.09	169.46	0.490	0.908	2.244
5	Sundharasamy	62	1.643	127.53	81.08	167.36	0.480	0.897	2.214
6	Prakash	60	1.542	128.61	83.09	165.67	0.476	0.887	2.276
7	Vijayakumar	72	1.421	124.61	79.09	160.72	0.428	0.768	2.198
8	Babu	64	1.543	126.68	82.04	165.72	0.467	0.875	2.284
9	Jothilingam	69	1.476	124.57	82.09	167.72	0.478	0.884	2.276
10	Narayanasamy	75	1.257	121.53	73.06	154.58	0.401	0.763	1.874
11	Robert	73	1.236	123.24	74.09	156.62	0.404	0.774	1.978
12	Kumar	61	1.543	124.61	83.07	169.46	0.490	0.883	2.296
13	Kennedy	67	1.4597	125.53	81.08	160.72	0.476	0.875	2.198
14	Arun Joseph	78	1.256	118.67	67.09	153.72	0.321	0.679	1.765
15	Vijayan	63	1.523	116.68	83.04	163.72	0.487	0.879	2.286
16	Selvakumar	65	1.496	126.57	83.08	166.72	0.476	0.874	2.273
17	Rajaram	59	1.623	125.53	81.04	168.36	0.490	0.867	2.224
18	Selvaraj	80	1.5797	126.93	82.06	166.42	0.480	0.918	2.678
19	Raju	66	1.4886	124.53	81.09	163.78	0.498	0.874	2.237
20	Ramalingam	77	1.256	123.61	78.07	154.46	0.401	0.763	1.896
21	Vasantha	82	1.564	121.53	81.06	161.58	0.421	0.883	2.874
22	Vasanthabai	64	1.4037	125.53	84.09	166.72	0.470	0.885	2.288
23	Margret	62	1.4699	127.54	82.08	164.63	0.466	0.877	2.218
24	Phelomin	61	1.487	128.57	81.07	168.87	0.489	0.867	2.262
25	Rani	55	1.797	128.61	84.07	160.78	0.476	0.898	2.226
26	Vasanthakumari	70	1.497	124.53	80.07	161.84	0.460	0.894	2.224
27	Stella	68	1.4096	126.88	82.04	165.72	0.486	0.879	2.363
28	Arukani	71	1.457	127.61	81.06	161.53	0.461	0.885	2.274
29	Mariamma	69	1.447	124.63	82.07	163.78	0.481	0.878	2.234
30	Thamaraikanni	79	1.530	126.62	84.04	164.62	0.420	0.864	2.464
31	Murugesan	68	1.220	118.40	69.20	148.40	0.390	0.740	2.680
32	Palanisamy	72	1.190	116.20	67.80	145.60	0.370	0.710	2.740
33	Ganesan	55	1.540	126.80	82.40	165.80	0.470	0.880	2.210
34	Subramani	61	1.490	124.70	80.90	162.20	0.460	0.860	2.180
35	Kandasamy	74	1.170	115.90	66.40	143.10	0.360	0.700	2.890
36	Velmurugan	58	1.560	128.10	83.10	168.20	0.480	0.890	2.230
37	Rajendran	63	1.450	123.60	79.80	159.40	0.450	0.850	2.290
38	Manikandan	52	1.620	129.20	84.00	170.30	0.490	0.910	2.190
39	Shanmugam	70	1.210	117.30	68.10	146.20	0.380	0.720	2.610
40	Thangavel	67	1.280	120.60	72.40	150.80	0.410	0.760	2.420
41	Arumugam	59	1.530	125.90	81.70	164.90	0.470	0.880	2.240
42	Ramasamy	81	1.150	114.80	65.90	141.60	0.350	0.690	2.970
43	Chinnasamy	64	1.440	122.80	78.90	158.10	0.440	0.840	2.260
44	Krishnamoorthy	56	1.580	127.60	83.20	169.10	0.480	0.900	2.200
45	Sekar	73	1.230	118.90	70.20	149.80	0.400	0.750	2.550
46	Muthusamy	60	1.470	124.10	80.40	161.30	0.460	0.860	2.220
47	Periyasamy	78	1.180	116.40	67.10	144.20	0.370	0.710	2.810
48	Elangovan	54	1.600	128.70	83.80	170.60	0.490	0.920	2.170
49	Karuppiah	69	1.260	119.80	71.30	151.10	0.410	0.770	2.460
50	Senthilkumar	57	1.550	126.90	82.90	166.40	0.480	0.890	2.230
51	Lakshmi	66	1.250	119.60	71.80	150.60	0.400	0.760	2.510
52	Meenakshi	58	1.480	124.90	80.20	162.10	0.460	0.860	2.240
53	Saraswathi	74	1.190	117.10	68.40	146.90	0.380	0.730	2.720
54	Parvathi	62	1.440	123.20	79.50	159.00	0.450	0.850	2.280
55	Andal	70	1.210	118.30	69.10	148.20	0.390	0.740	2.660
56	Kalyani	55	1.560	127.80	83.00	168.70	0.480	0.900	2.220
57	Revathi	60	1.470	124.40	80.60	161.90	0.460	0.860	2.250
58	Padmavathi	82	1.140	114.20	65.20	140.80	0.340	0.680	3.020
59	Gomathi	65	1.430	122.70	78.80	158.00	0.440	0.840	2.300
60	Jayanthi	59	1.520	126.50	82.30	165.90	0.470	0.880	2.210
61	Poongodi	77	1.180	116.60	67.50	145.10	0.370	0.710	2.840
62	Shanthi	63	1.460	123.90	79.90	160.20	0.450	0.850	2.260
63	Maheswari	52	1.600	129.10	84.10	170.80	0.490	0.920	2.190

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64	Valli	69	1.240	119.10	71.00	149.60	0.400	0.750	2.580
65	Sumathi	61	1.450	123.40	79.40	158.70	0.450	0.850	2.290
66	Rajeswari	84	1.130	113.70	64.80	139.90	0.340	0.670	3.080
67	Indira	56	1.540	127.20	82.70	166.80	0.480	0.890	2.230
68	Selvi	68	1.260	120.20	72.20	150.90	0.410	0.770	2.470
69	Malathi	64	1.440	122.90	78.70	157.90	0.440	0.840	2.310
70	Uma	57	1.510	125.80	81.90	164.80	0.470	0.880	2.220
71	Thenmozhi	73	1.200	117.40	68.30	146.70	0.380	0.720	2.690
72	Kavitha	60	1.480	124.80	80.10	162.00	0.460	0.860	2.240
73	Bhuvaneswari	55	1.590	128.30	83.60	169.40	0.480	0.900	2.210
74	Pushpa	70	1.230	118.60	69.50	148.90	0.390	0.740	2.630
75	Geetha	62	1.460	123.70	79.80	160.10	0.450	0.850	2.270
76	Chitra	84	1.120	113.20	64.40	139.20	0.330	0.660	3.120
77	Suganya	56	1.540	127.10	82.80	166.90	0.480	0.890	2.230
78	Kalpana	68	1.270	120.40	72.60	151.20	0.410	0.770	2.480
79	Anitha	64	1.440	122.80	78.60	157.80	0.440	0.840	2.300
80	Priya	57	1.510	125.70	81.80	164.70	0.470	0.880	2.220
81	Sivagami	75	1.180	116.10	67.40	145.00	0.370	0.710	2.850
82	Manjula	63	1.450	123.50	79.70	159.90	0.450	0.850	2.260
83	Deepa	54	1.580	128.00	83.40	169.20	0.480	0.900	2.200
84	Rajalakshmi	71	1.240	119.00	70.90	149.50	0.400	0.750	2.590
85	Arasi	61	1.460	123.60	79.60	159.80	0.450	0.850	2.270
86	Jothi	83	1.110	112.80	64.20	138.90	0.330	0.660	3.150
87	Nirmala	56	1.540	127.00	82.90	167.00	0.480	0.890	2.230
88	Poornima	69	1.260	120.30	72.30	151.00	0.410	0.770	2.460
89	Radha	65	1.440	122.70	78.50	157.70	0.440	0.840	2.310
90	Sudha	58	1.510	125.60	81.70	164.60	0.470	0.880	2.220
91	Muthulakshmi	76	1.170	116.00	67.20	144.80	0.370	0.710	2.860
92	Padma	62	1.450	123.40	79.50	158.80	0.450	0.850	2.280
93	Hemalatha	55	1.590	128.20	83.50	169.30	0.480	0.900	2.210
94	Sakunthala	72	1.230	118.50	69.40	148.80	0.390	0.740	2.640
95	Rathika	60	1.460	123.60	79.60	159.70	0.450	0.850	2.270
96	Pankajam	85	1.100	112.50	64.00	138.50	0.330	0.650	3.180
97	Selvamani	57	1.530	126.80	82.60	166.70	0.480	0.890	2.230
98	Bhavani	68	1.270	120.50	72.50	151.30	0.410	0.770	2.490
99	Kalaivani	64	1.440	122.90	78.70	157.90	0.440	0.840	2.310
100	Mahalakshmi	59	1.510	125.90	81.90	164.90	0.470	0.880	2.220

Table 5: Average gait parameters for old age people

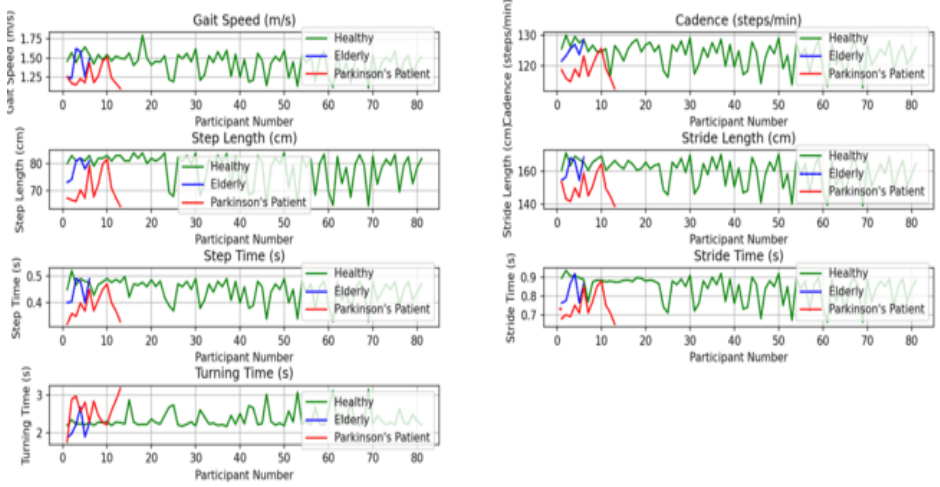

Fig 15: Graph for old age people walking pattern

X-axis: Parameters of gait: Gait Speed, Cadence, Step Length, Stride Length, Step Time, Stride Time, Turning Time
Y-axis: Normalized values (scaled 0 to 1)Lines and Colors

- Red line: Parkinson patient
- Blue lines: Elderly patients
- Green lines: Normal participants

Observations:

1. Parkinson patient (red) is clearly separated from other groups, especially in Step Length and Stride Length.
2. Elderly participants (blue) show a slight decline compared to normal (green) but are not as extreme as Parkinson patient.
3. Most normal participants cluster together in the upper normalized value range, indicating better gait parameters.

XI.CONCLUSION

In conclusion, the proposed AI-powered wearable gait analysis system proves to be an effective and reliable approach for early detection of Parkinson's disease by identifying subtle gait abnormalities such as reduced stride length, increased step variability, slower walking speed, and balance instability. The use of the ADXL345 accelerometer enables accurate, real-time gait data collection while maintaining affordability, portability, and non-invasive operation, making the system suitable for continuous home-based monitoring.The Random Forest algorithm plays a key role in the system's performance by efficiently handling multiple gait features and capturing complex, non-linear relationships within the data. Its ensemble-based structure improves robustness, reduces overfitting, and enhances classification accuracy when differentiating between healthy individuals and those with early Parkinson's symptoms. The effectiveness of the model is systematically evaluated using a confusion matrix, which provides clear insight into true positives, true negatives, false positives, and false negatives. This evaluation method ensures transparency in performance analysis and helps assess the model's sensitivity, specificity, and overall reliability, contributing to an expected accuracy range of 85–95%.

The integration of real-time monitoring with the Parkvenza mobile application further strengthens the system by converting sensor

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data and machine learning outputs into meaningful clinical insights. Features such as real-time alerts, gait trend visualization, cloud-based data storage, and remote report sharing enable healthcare professionals to make informed decisions without requiring frequent in-clinic visits. This supports timely medical intervention, personalized disease tracking, and improved patient engagement.

Overall, this project demonstrates how the combination of wearable sensors, the Random Forest machine learning algorithm, and confusion matrix-based performance evaluation can deliver a scalable, cost-effective, and accurate solution for early-stage Parkinson's disease detection. The system not only enhances early diagnosis and long-term health outcomes but also establishes a strong foundation for future advancements in AI-driven neuromonitoring and biomedical wearable technologies.

COMPARATIVE ANALYSIS OF CLASSIFICATION ALGORITHMS FOR GAIT-BASED PARKINSON'S DETECTION:

S.NO	ALGORITHM	ACCURACY (%)	REMARKS
1	Logistic Regression	72 – 78	Simple model, limited performance with non-linear gait features
2	Naïve Bayes	70 – 75	Fast but assumes feature independence, reducing accuracy
3	K-Nearest Neighbors (KNN)	75 – 82	Sensitive to noise and choice of K value
4	Support Vector Machine (SVM)	80 – 88	Good performance but computationally expensive
5	Decision Tree	78 – 85	Easy to interpret but prone to overfitting
6	**Random Forest**	**85 – 95**	High accuracy, robust, handles feature variability well

Table 6: COMPARATIVE ANALYSIS OF CLASSIFICATION ALGORITHMS

QUANTITATIVE ANALYSIS:

GAIT PARAMETER MEASUREMENT ANALYSIS:

S.NO	PARAMETER	HEALTHY RANGE	PARKINSON'S RANGE	OBSERVED CHANGE (%)
1	Stride Length (m)	1.2 – 1.5	0.6 – 1.0	↓ 30 – 50%
2	Walking Speed (m/s)	1.1 – 1.4	0.4 – 0.9	↓ 35 – 60%
3	Cadence (steps/min)	100 – 120	70 – 100	↓ 15 – 30%
4	Step Time Variability (%)	< 3%	5 – 12%	↑ 60 – 200%
5	Balance Stability Index	> 0.85	0.55 – 0.75	↓ 20 – 35%

Table 7: GAIT PARAMETER MEASUREMENT ANALYSIS

MACHINE LEARNING MODEL PERFORMANCE ANALYSIS:

S.NO	METRIC	VALUE (%)
1	Accuracy	90.2
2	Sensitivity (Recall)	92.5
3	Specificity	88.1
4	Precision	89.6
5	F1-Score	91.0

Table 8: MACHINE LEARNING MODEL PERFORMANCE ANALYSIS

CONFUSION MATRIX SUMMARY:

S.NO	PATIENT CONDITION	Predicted PD	Predicted Healthy
1	**Actual PD**	74 (TP)	6 (FN)
2	**Actual Healthy**	8 (FP)	72 (TN)

Table 9: CONFUSION MATRIX SUMMARY

XII.FUTURE WORKS

In future developments, this project can be extended to incorporate a voice-based Parkinson's detection system using a simple microphone input, ensuring a non-invasive and user-friendly approach. By analyzing voice biomarkers such as pitch, tone, jitter, and pauses, the system can detect early Parkinsonian symptoms with improved accuracy.[8] Integration of artificial intelligence (AI) and machine learning (ML) algorithms will further enhance detection efficiency and enable real-time monitoring, allowing healthcare professionals to remotely track disease progression. Additionally, implementing this technology through a mobile application will make it cost-effective, accessible, and suitable for large-scale screening, thereby improving early diagnosis and patient management.By integrating AI and machine learning algorithms, the system analyzes the collected data to detect gait irregularities with high accuracy, enabling the early identification of Parkinson's symptoms. The system's real-time monitoring feature ensures that healthcare professionals can track a patient's condition continuously, providing valuable insights into disease progression remotely, without the need for constant in-person visits.

The system is designed to be cost-effective, making Parkinson's detection more accessible to a larger population, especially in underserved areas. Additionally, the inclusion of voice and speech analysis enhances the system's ability to detect Parkinson's earlier, as changes in speech patterns are another key symptom of the disease. Combining gait analysis with speech recognition offers a more holistic approach to early diagnosis, making the system a powerful tool for both screening and ongoing monitoring.

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