

DESIGN OF SMARTWALK FOR PARKINSON'S DISEASE DETECTION AND GAIT ANALYSIS USING MACHINE LEARNING

Project work report submitted in partial fulfillment of the requirements

for the degree of

Bachelor of Technology

in

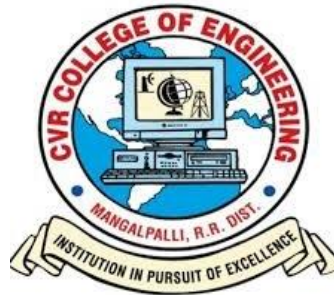
Electronics and Communication Engineering

Submitted by

SANIYA SULTHANA (21B81A04A1)

V.SINDHUJA (21B81A04A6)

A.USHA SREE (21B81A04B9)



DEPARTMENT OF ELECTRONICS & COMMUNICATION ENGINEERING

CVR COLLEGE OF ENGINEERING

(An Autonomous Institution & Affiliated to JNTUH)

Ibrahimpatnam (M), Ranga Reddy (D), Telangana

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Under the Supervision of

Mr.B. Shankar

Senior Assistant Professor



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Ibrahimpattanam (M), Ranga Reddy (D), Telangana

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(Approved by AICTE & Govt. of Telangana and Affiliated to JNT University)

Vastunagar, Mangalpalli (V), Ibrahimpatan (M), R.R. District, PIN - 501 510

Web : <http://cvr.ac.in>, email : info@cvr.ac.in

Ph : 08414 - 252222, 252369, Office Telefax : 252396, Principal : 252396 (O)

Certificate

This is to certify that the project work titled “**DESIGN OF SMARTWALK FOR PARKINSON'S DISEASE DETECTION AND GAIT ANALYSIS USING MACHINE LEARNING**” submitted to the **CVR College of Engineering**, affiliated to **JNTUH**, by **Saniya sulthana(21B81A04A1), V.Sindhuja(21B81A04A6), A.Usha Sree(21B81A04B9)**, is a bonafide record of the work done by the students towards partial fulfillment of requirements for the award of the degree of **Bachelor of Technology in Electronics & Communication**

Supervisor

Mr.B.Shankar
Senior Assisant Professor
Dept. of ECE

Head of the Department

Dr. P. Srinvias Rao
Head of Department
ECE

Project In-charge

Dr. G. Ravi Shankar Reddy
Professor
Dept. of ECE

External Examiner

Place:

Date:

DECLARATION

I hereby declare that this project report titled “**DESIGN OF SMARTWALK FOR PARKINSON'S DISEASE DETECTION AND GAIT ANALYSIS USING MACHINE LEARNING**” submitted to the Department of Electronics and Communication Engineering, CVR College of Engineering is a record of original work done by me under the guidance of **Mr.B.Shankar**.The information and data given in the report is authentic to the best of my knowledge. This project report is not submitted to any other university or institution for the award of any degree or diploma or published any time before.

SANIYA SULTHANA (21B81A04A1)

V.SINDHUJA (21B81A04A6)

A.USHA SREE (21B81A04B9)

Date:

Place:

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Abstract

Fear of Falling (FoF) is commonly linked to postural and gait abnormalities, leading to reduced mobility in individuals with Parkinson's Disease (PD). Variability in knee flexion during heel-strike and toe-off events while walking can indicate an individual's FoF level. As PD progresses, gait abnormalities such as hesitation during start, turn, and stop phases become more pronounced, affecting cadence and weight transfer between legs. Task demands and pathway conditions further influence gait and posture, necessitating a deeper investigation into their impact. To address this, a portable, wearable, and cost-effective device, SmartWalk, has been developed. SmartWalk integrates instrumented shoes with knee flexion recorder units to monitor gait-related indices and knee flexion in real-life conditions.

Our study evaluated SmartWalk in age-matched groups of healthy individuals (GrpH) and individuals with PD (GrpPD). Results demonstrated SmartWalk's ability to assess the impact of task conditions, pathways (with and without turns), and pathway segments (straight and turn) on knee flexion and gait. Findings indicated a strong correlation between knee flexion, gait-related indices, and clinical measures of FoF, particularly in GrpPD. This suggests that SmartWalk can serve as a valuable tool for preclinical assessment, offering clinicians critical insights into gait abnormalities and FoF-related risks in individuals with PD.

Keywords: Gait, knee flexion, Parkinson's disease, turning, task conditions.

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CHAPTER 1

INTRODUCTION

1.1 Introduction

Fear of Fall (FoF) is a common concern among individuals with Parkinson's Disease (PD), often leading to reduced mobility due to gait and postural abnormalities. These abnormalities can include variations in knee flexion during critical gait events such as heel-strike and toe-off, which are essential for stability and balance. In PD patients, the progression of the disease can cause difficulties in initiating, turning, and stopping while walking, further exacerbating their FoF. Additionally, environmental factors such as task conditions and pathway characteristics can significantly influence an individual's gait and postural control, necessitating a deeper understanding of these effects.

To address these concerns, wearable technology has emerged as a promising tool for monitoring gait and postural indices in real-world settings. This study introduces SmartWalk, a portable and cost-effective device equipped with instrumented shoes and knee flexion recorders to assess gait variability and postural adjustments. By analyzing the implications of task conditions and pathways (with and without turns) on knee flexion and gait, the study demonstrates the potential of SmartWalk to provide valuable preclinical insights. Results indicate a strong correlation between knee flexion variability and clinical measures of FoF, particularly in PD patients, suggesting that SmartWalk can serve as a useful tool for clinicians in assessing mobility-related risks

1.2 Aim of the project

The objective of this project is to Design of Smartwalk for parkinsons's disease detection and gait analysis by using machine learning

1.3 Significance of the work

The significance of this study lies in its ability to bridge the gap between clinical gait analysis and real-world mobility assessment. Traditional gait analysis methods often rely on controlled laboratory environments, making it difficult to assess a person's natural walking patterns. SmartWalk overcomes these limitations by providing a real-time, wearable solution that enables mobility monitoring in everyday settings. The

system offers improved fall risk assessment through detailed gait and posture analysis, serving as a cost-effective alternative to expensive motion capture setups. By identifying critical gait parameters associated with FoF, SmartWalk enhances rehabilitation strategies and enables personalized treatment planning. The system's real-time monitoring capabilities further support clinical decision-making for healthcare providers working with patients at risk of falls. Additionally, SmartWalk has potential applications in designing targeted physiotherapy regimens, evaluating the effectiveness of balance training programs, and assessing improvements in mobility over time. The ability to continuously track disease progression and the effects of therapeutic interventions makes it a valuable tool for long-term patient management.

1.4 Organization of work

This report is structured into several chapters that detail the development, implementation, and evaluation of the SmartWalk system. Chapter 2 presents a literature review covering existing studies on gait abnormalities in PD, wearable gait analysis technologies, and the limitations of current systems. Chapter 3 describes the system design and implementation, including the hardware and software components of SmartWalk. Chapter 4 explains the experimental methodology, outlining participant selection criteria, experimental setup, task conditions, and data collection procedures. Chapter 5 focuses on data analysis and processing, discussing feature extraction techniques, statistical methods, and classification techniques used in the study. Chapter 6 presents the results and discussion, providing insights into the impact of pathway turns, task complexity, and disease state on gait and posture. Finally, Chapter 7 concludes the document by summarizing key findings, identifying study limitations, and proposing potential future research directions.

1.4 Conclusion

This chapter introduced the SmartWalk system, outlining its significance in assessing gait and posture in individuals with FoF and PD. The project aims to provide a wearable, real-time, and cost-effective solution for analyzing gait-related indices and improving fall risk assessment. By leveraging wearable technology and data-driven methodologies, SmartWalk enhances clinical decision-making and contributes to personalized rehabilitation strategies. The system's ability to evaluate gait in different conditions offers a more comprehensive view of mobility impairments, which is crucial

for early diagnosis and targeted treatment planning. The following chapters delve deeper into the system design, experimental methodology, data analysis, and key findings, offering a detailed examination of how SmartWalk can revolutionize gait assessment and mobility monitoring.

CHAPTER 2

LITERATURE SURVEY

2.1 Introduction

Gait analysis is crucial for assessing mobility impairments, particularly in individuals with Parkinson's Disease (PD) and those experiencing Fear of Fall (FoF). FoF is linked with postural instability and gait abnormalities, which increase the risk of falls and reduce the quality of life. Various technologies have been developed to assess gait and posture, each with advantages and limitations. Traditional motion capture systems provide high accuracy but are expensive and impractical for real-world applications. Wearable sensor-based systems, such as SmartWalk, offer a promising alternative for portable, real-time gait monitoring. This chapter reviews existing gait analysis technologies and discusses research studies relevant to gait monitoring and fall prevention.

2.2 Existing Technologies

Several gait analysis technologies have been used in research and clinical applications to monitor movement patterns and assess fall risk.

2.2.1 Motion Capture Systems

Motion capture systems like Vicon and OptiTrack use infrared cameras and reflective markers to track human movement. These systems provide high-precision data and are widely used in research. However, they require specialized laboratory setups, making them impractical for everyday gait monitoring.

2.2.2 Force Plates

Force plates, such as those from AMTI and Bertec, measure ground reaction forces during walking. They are useful for analyzing gait mechanics but are limited to laboratory settings due to their stationary nature and high cost.

2.2.3 Inertial Measurement Units (IMUs)

IMUs, which consist of accelerometers, gyroscopes, and magnetometers, are commonly used in wearable gait analysis systems. They offer a portable and cost-

effective solution for tracking movement patterns. However, IMUs are prone to signal drift over time, requiring advanced processing techniques to maintain accuracy.

2.2.4 Instrumented Insoles

Instrumented insoles embedded with pressure sensors measure foot pressure distribution and gait cycles. These insoles provide valuable insights into foot biomechanics but may not capture full-body gait patterns. Additionally, high-end insoles can be expensive and are not widely accessible.

2.2.5 Wearable Sensor-Based Systems

Wearable sensor-based systems integrate multiple sensors, such as IMUs, force-sensitive resistors, and knee flexion recorders, to provide a comprehensive gait assessment. SmartWalk is one such system that captures gait abnormalities and postural variations using a combination of instrumented shoes, knee flexion sensors, and an ultrasonic sensor unit. This system enables real-time monitoring in free-living conditions, offering a balance between cost, portability, and accuracy.

2.3 Relevant Research Studies

Numerous studies have explored the relationship between gait abnormalities, fall risks, and wearable sensor technology:

1. **Weiss et al. (2011)** – Investigated the role of stride-to-stride variability in distinguishing PD patients from healthy individuals using inertial sensors. The study found that PD patients exhibited higher gait variability.
2. **Hausdorff et al. (2007)** – Explored the relationship between freezing of gait (FoG) and fall risk in PD patients. The study concluded that turning movements are crucial for detecting early mobility issues.
3. **Ahlskog (2011)** – Provided insights into how dopaminergic treatment influences gait parameters in PD patients, showing that medication alters stride length but not step consistency.
4. **Patel et al. (2012)** – Developed a wearable shoe-based sensor system to measure foot pressure and walking speed. The study demonstrated accurate gait tracking in both indoor and outdoor environments.

5. **Salarian et al. (2013)** – Introduced a gyroscope-based system for detecting subtle gait disturbances in early PD. Their findings showed that angular velocity of turns is a key parameter in PD gait classification.
6. **Horak et al. (2015)** – Used a body-worn accelerometer system to differentiate between postural instability and normal aging-related gait changes.
7. **Zhang et al. (2019)** – Implemented a deep learning-based gait analysis system that achieved 92% accuracy in classifying PD vs. healthy gait patterns using convolutional neural networks (CNNs).
8. **Rudzicz et al. (2015)** – Applied support vector machines (SVM) to gait data collected from wearable sensors and achieved an 87% classification accuracy.
9. **Lee et al. (2021)** – Proposed a hybrid K-Means and neural network approach to analyze gait signals. Their method improved the clustering performance for early-stage PD detection.
10. **Chen et al. (2020)** – Discussed the lack of large datasets for training gait classification models and proposed a data augmentation approach using synthetic gait signals

2.3 Conclusion

The review of existing gait analysis technologies highlights the strengths and weaknesses of various approaches. While motion capture systems and force plates provide high accuracy, they are expensive and confined to laboratory use. IMUs and smart insoles offer portable solutions but have limitations related to signal drift and incomplete gait assessment. Wearable sensor-based systems, such as SmartWalk, aim to overcome these challenges by integrating multiple sensing technologies into a cost-effective, real-time gait analysis solution. Additionally, previous research supports the use of gait analysis for fall risk assessment, emphasizing the importance of developing wearable, portable solutions like SmartWalk. The next chapters will discuss the design, implementation, and evaluation of the SmartWalk system, demonstrating its potential for real-world mobility assessment and fall risk evaluation

CHAPTER 3

MACHINE LEARNING

3.1 Introduction to Machine Learning

Machine Learning (ML) is a subset of artificial intelligence (AI) that enables computers to learn from data and make predictions or decisions without being explicitly programmed. It involves developing algorithms that can identify patterns, recognize trends, and improve their performance over time through experience. ML is broadly categorized into supervised learning (using labeled data), unsupervised learning (finding hidden patterns in unlabeled data), and reinforcement learning (learning through rewards and penalties). It is widely used in various fields, including healthcare, finance, robotics, and natural language processing, to automate tasks and enhance decision-making.

3.2 How does Machine Learning Work

Machine Learning (ML) works by training a model on a dataset to recognize patterns and make predictions or decisions. The process involves collecting and preprocessing data, selecting a suitable algorithm, training the model by adjusting its parameters using training data, and evaluating its performance on unseen data. In supervised learning, the model learns from labeled data, while in unsupervised learning, it identifies hidden structures in unlabeled data. Reinforcement learning, on the other hand, uses a reward-based system to improve performance. Once trained, the ML model can be deployed to analyze new data and make real-time predictions, continuously improving with more data and fine-tuning.

3.3 Features of Machine Learning

- ML models learn from data without explicit programming.
- Uses historical and real-time data to make predictions.
- Improves accuracy over time with more data (model training).
- Can process large datasets efficiently.
- Adjusts to new data and changing environments.
- Forecasts future outcomes based on past data.

3.4 Need for Machine Learning

Machine Learning (ML) is essential in today's digital world as it enables computers to process and analyze vast amounts of data efficiently. It automates complex and repetitive tasks, reducing human effort and operational costs while improving decision-making through data-driven insights. ML is widely used for predictive analysis, helping businesses forecast trends, customer behavior, and potential risks. It also enhances pattern recognition, which is crucial in fields like medical diagnosis, fraud detection, and cybersecurity. ML models continuously improve their accuracy over time, adapting to new data without human intervention. Additionally, it powers personalized recommendations on platforms like Netflix and Amazon, enhances robotics and AI applications such as self-driving cars and virtual assistants, and finds applications in healthcare, finance, and marketing. By automating processes and improving efficiency, ML is revolutionizing industries and driving technological advancements.

3.5 History of Machine Learning

The history of Machine Learning (ML) dates back to the mid-20th century, evolving from the broader field of Artificial Intelligence (AI). In 1950, Alan Turing introduced the Turing Test, a criterion for machine intelligence. The first ML algorithm, the perceptron, was developed by Frank Rosenblatt in 1957, marking the early exploration of neural networks. In the 1960s and 1970s, statistical methods like decision trees and k-nearest neighbors (KNN) were introduced, improving pattern recognition.

The 1980s saw the rise of neural networks with the development of backpropagation, which allowed deeper learning models. In the 1990s, ML transitioned from knowledge-based AI to data-driven approaches, with algorithms like Support Vector Machines (SVM) and the Random Forest gaining popularity. The 2000s and 2010s brought a revolution in ML with the availability of large datasets, better computing power, and breakthroughs in Deep Learning (DL), leading to advancements in image recognition, natural language processing (NLP), and self-driving cars. Today, ML is at the core of many industries, from healthcare and finance to robotics and entertainment, shaping the future with its continuous advancements.

3.6 Classification of Machine Learning

At a broad level, machine learning can be classified into three types:

1. Supervised learning
2. Unsupervised learning
3. Reinforcement learning

3.6.1 Supervised Learning

Supervised learning is a type of Machine Learning where a model is trained using labeled data, meaning each input is paired with a correct output. The model learns patterns from this data and makes predictions based on prior knowledge. It is broadly categorized into classification, where outputs are categorical (e.g., spam detection, disease diagnosis), and regression, where outputs are continuous (e.g., stock price prediction, temperature forecasting). The process involves collecting labeled data, training the model by mapping inputs to outputs, evaluating its accuracy on unseen data, and using it for future predictions. Common algorithms include Linear Regression for continuous value prediction, Logistic Regression for binary classification, Decision Trees for decision-making, Random Forest for enhanced accuracy, Support Vector Machines (SVM) for category separation, and Neural Networks for complex pattern recognition. Supervised learning is widely applied in spam detection, medical diagnosis, fraud detection, stock market prediction, and speech recognition. It is highly effective when ample labeled data is available, making it a powerful tool for predictive analytics and automation.

3.6.2 Unsupervised Learning

Unsupervised Learning is a type of machine learning that works with data that has no labels or categories. The main goal is to find patterns and relationships in the data without any guidance. In this approach, the machine analyzes unorganized information and groups it based on similarities, patterns, or differences. Unlike supervised learning, there is no teacher or training involved. The machine must uncover hidden structures in the data on its own. Unsupervised learning is classified into two categories of algorithms:

1.Clustering

Clustering is a type of unsupervised learning that is used to group similar data points together. Clustering algorithm work by iteratively moving data points closer to their cluster centers and further away from data points in other clusters. Some of the most important hierarchical clustering algorithms include:

1.K-Means Clustering

K-Means Clustering is an unsupervised learning algorithm used for grouping data points into K distinct clusters based on similarity. It aims to minimize the variance within each cluster by iteratively assigning points to the closest cluster center (centroid) and updating the centroids until the clusters stabilize.

How K-Means Works:

1. Choose the number of clusters (K).
2. Initialize K centroids randomly.
3. Assign each data point to the nearest centroid.
4. Compute the new centroids by taking the average of all points in each cluster.
5. Repeat steps 3 and 4 until centroids no longer change or meet a stopping condition.

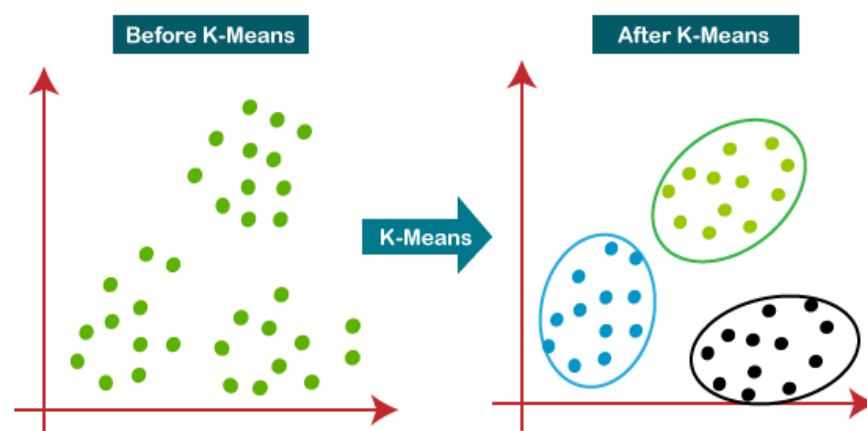


Fig:3.1 K-Means clustering

2.Association

3.6.3 Reinforcement Learning

Reinforcement Learning (RL) is a type of Machine Learning where an agent learns to make decisions by interacting with an environment and receiving rewards or penalties based on its actions. The goal is to develop an optimal strategy, or policy, that maximizes long-term rewards through trial and error. Unlike supervised learning, RL does not require labeled data but instead learns from experience.

3.7Applications of Machine Learning

1.Healthcare industry

ML helps doctors diagnose diseases like cancer, diabetes, and heart conditions by analyzing medical data, including scans and test reports. AI-powered imaging systems assist in detecting abnormalities early, improving treatment success rates.

2.Finance sector

Banks and financial institutions use ML to detect fraudulent transactions by analyzing spending patterns. It also helps assess credit risk by predicting loan eligibility based on financial history and behavior.

3. Retail & E-commerce

Platforms like Amazon, Netflix, and Spotify use ML to suggest products, movies, or music based on user preferences. This improves customer engagement and enhances sales by offering personalized experiences.

4 Autonomous Vehicles

Self-driving cars use ML to process sensor data, recognize obstacles, and make real-time driving decisions. Companies like Tesla and Waymo develop AI-powered navigation systems for safer and more efficient transportation.

3.8 Conclusion

This chapter deals with understanding of Machine Learning,its evolution,features and various applications

CHAPTER 4

SYSTEM ANALYSIS AND DESIGN

4.1 Introduction

The SmartWalk system is a wearable and portable device designed to analyze gait patterns and postural stability in individuals with Parkinson's Disease (PD) and healthy individuals. Understanding the system design and architecture is crucial for evaluating its functionality, data acquisition process, and analysis techniques.

This chapter provides a detailed overview of the SmartWalk system's components, the workflow of data collection, and the processing techniques used to extract gait-related indices. The system is developed to estimate the impact of pathways, task conditions, and turns on gait indices using real-time data acquisition and offline processing.

4.2 System Architecture and Design

4.2.1 Overview of System Components

The SmartWalk system consists of four major components that work together to capture real-time gait and postural data.

1 Knee Flexion Recorder

- A pair of knee flexion recorder units (KneeFlex units), each consisting of a 4.5" bend sensor (Spectra Symbol), is used to measure knee flexion angles.
- The bend sensor is mounted in a knee cap and positioned to measure knee joint angle variations during walking.
- The sensor is calibrated using a stepper motor-hinge setup to ensure accurate angle detection in the range 0° to $\sim 100^{\circ}$, with an error margin of $\pm 0.13^{\circ}$.
- The analog signal (0-5V) from the bend sensor is acquired by the Microcontroller-based Central Module, which timestamps the data for synchronization.

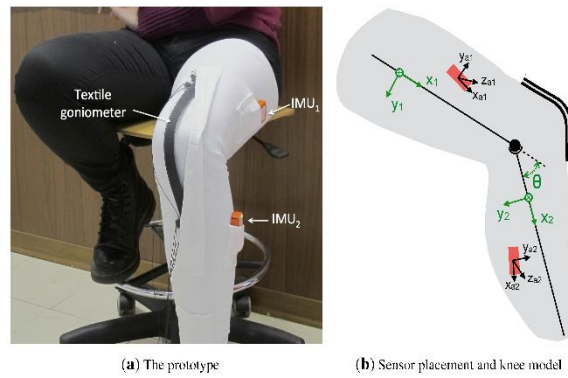


Fig:4.1 Knee Flexion Recorder

2. Instrumented Shoes

- A pair of instrumented shoes is embedded with Force Sensitive Resistors (FSRs) to detect key gait events.
- The FSR sensors are placed in three key positions: toe, medial heel, and lateral heel, to accommodate foot inversion/eversion issues and ensure accurate gait analysis.
- The FSR model used is Tekscan FlexiForce A201, which can measure forces in the range of 0-445 N.
- The system was calibrated using a VICON motion tracking system, with an average absolute error of 0.71% (Stride Time) and 0.8% (Step Time), ensuring high accuracy.



Fig: 4.2 Instrumented shoes

3 Ultrasonic Sensor Unit

- Ultrasonic sensors (HC-SR04) are used to track an individual's position on a predefined pathway.
- These sensors send synchronization markers to the Microcontroller-based Central Module to map gait events to specific pathway segments.



Fig:4.3 Ultrasonic Sensor

4 Microcontroller-Based Central Module

- The Microcontroller (ATmega 2560) is the core processing unit of SmartWalk.
- It acquires analog (0-5V) signals from the KneeFlex units and FSR sensors.
- Data acquisition occurs at a sampling rate of ~200 samples per second with 10-bit analog-to-digital conversion.
- The data is stored on a 64 GB SD card for offline analysis of postural and gait indices.

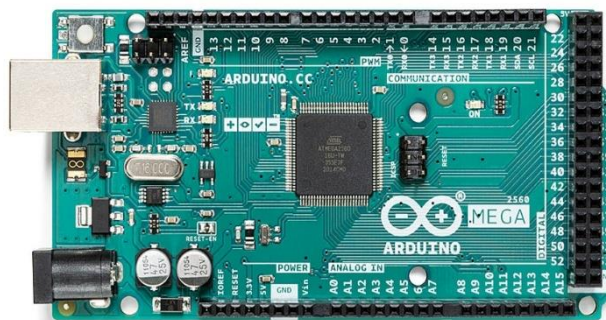


Fig:4.4 Arduino mega 2560

5. Vibration Sensor

A vibration sensor is used in the SmartWalk System to detect irregular movement patterns, sudden stops, or instability in gait, which could indicate a fall risk.

- Type: Piezoelectric or MEMS-based vibration sensor
- Function:

- Detects tremors, instability, or sudden changes in movement.
- Identifies freezing of gait (FoG) episodes common in Parkinson's patients.
- Sends signals to the microcontroller (ATmega 2560) when abnormal vibrations are detected.
- Placement: Attached to the waist belt or shoe for detecting movement abnormalities



Fig:4.5 Vibration Sensor

6.Buzzer

A buzzer is integrated into the SmartWalk System to provide real-time auditory feedback to the user when abnormal gait patterns or fall risks are detected.

- Function:
 - Produces an alert sound when the system detects irregular gait, hesitation, or a potential fall.
 - Can be programmed to give different sound patterns for various warnings (e.g., a continuous beep for a detected fall, intermittent beeps for minor gait abnormalities).
- Placement: Embedded in the waist belt along with the microcontroller unit.



Fig:4.6 Buzzer

How They Work Together

- The vibration sensor detects abnormal movement and sends a signal to the microcontroller.
- The microcontroller processes the data and determines if an alert is necessary.
- If a fall risk is detected, the buzzer is activated to warn the user or caregiver.

4.3 Data Processing and Gait Event Detection

The SmartWalk system processes real-time gait data to detect walking events and compute key gait indices. The data is collected using instrumented shoes, knee flexion recorders, and ultrasonic sensors, and then analyzed to extract heel-strike and toe-off events for further gait analysis.

4.3.1 Heel-Strike and Toe-Off Detection

Accurate detection of heel-strike and toe-off events is essential for analyzing gait cycles and estimating walking stability.

❖ Heel-Strike Detection

- Heel-strike occurs when the heel first contacts the ground during walking.
- Identified using the earliest valid peak in the Force Sensitive Resistor (FSR) signals from the heel region of the instrumented shoe.
- A threshold-based approach is used to filter out noise and detect a strong force signal when the heel touches the ground.

❖ Toe-Off Detection

- Toe-off marks the end of the stance phase when the foot pushes off the ground for the next step.
- Detected as the valley point in the toe FSR signal, following a heel-strike event.
- A sharp drop in pressure at the toe region confirms that the foot has lifted off.

These gait event detections are used to compute stride length, step time, cadence, and double limb support time (DLST).

4.3.2 Computation of Gait-Related Indices

The SmartWalk system calculates two major gait parameters to evaluate walking stability and fall risk:

1. Cadence (Steps per Minute)

- Measures the number of steps taken per minute based on heel-strike events.
- Cadence provides insights into walking speed and rhythm.
- Higher cadence usually indicates better gait control, whereas irregular cadence may suggest gait disturbances in Parkinson's Disease (PD) patients.

2. Double Limb Support Time (DLST)

- Represents the time spent with both feet on the ground during the walking cycle.
- Increased DLST is linked to poor balance and fall risk, particularly in Parkinson's Disease patients.

These computed indices are stored and further analyzed for gait classification and fall risk prediction.

4.4 Functional Workflow of SmartWalk

The SmartWalk system operates in three major phases:

4.4.1 Data Acquisition

The SmartWalk system records gait events and postural changes as the participant walks along a 10m predefined pathway.

- The participant wears the instrumented shoes, knee flexion recorder, and waist-mounted central module.
- Data from FSRs, knee flexion sensors, and ultrasonic sensors is captured in real time.
- A sampling rate of ~200 samples per second ensures accurate tracking of gait cycles.
- Each walking session is time-stamped for synchronization with pathway segments.

4.4.2 Pathway Segmentation and Gait Analysis

To analyze gait variations, the 10m walking pathway is divided into five segments:

1. SegA (Start Zone) – Detects start hesitation (difficulty initiating gait).
2. SegB (Approaching Turn) – Analyzes walking behavior before a turn.
3. SegC (Turn Segment) – Evaluates turning hesitation and balance issues.
4. SegD (Post-Turn) – Measures recovery and carryover effect after turning.
5. SegE (Stopping Zone) – Detects stop hesitation (difficulty stopping smoothly).

Gait Parameters Analyzed

For each pathway segment, the system evaluates:

- ❖ Step Timing – Time taken for each step.
- ❖ Stride Length – Distance between consecutive heel-strike events.
- ❖ Knee Flexion – Measures postural stability during walking.
- ❖ Cadence – Step frequency per minute.

The turning segment (SegC) is particularly important as Parkinson's patients often struggle with turns, leading to an increased risk of freezing of gait (FOG).

4.4.3 Software Implementation

1. Google Colab for Machine Learning & Data Analysis

- Data collected from the sensors is analyzed using machine learning algorithms in Google Colab.
- The system applies K-Means clustering to classify normal gait vs. abnormal gait.
- Feature extraction from knee flexion, cadence, and double limb support time is performed using Python-based ML libraries (NumPy, Pandas, Sci-kit Learn).

2. Real-Time Processing & Data Synchronization

- Sensor data is timestamped and synchronized for precise gait analysis.
- The integration of Google Colab allows for cloud-based processing and visualization of results.

4.4.4 Data Storage and Machine Learning-Based Analysis

The SmartWalk system uses advanced machine learning techniques to classify gait patterns and detect abnormalities.

A. Data Storage & Processing

- All collected gait data is stored on a 64GB SD card for offline analysis.
- Data includes FSR signals, knee flexion angles, ultrasonic sensor markers, and time-stamped gait events.

B. Machine Learning for Gait Classification

- K-Means Clustering Algorithm is applied to differentiate Parkinson's Disease patients from healthy individuals.
- The clustering algorithm groups individuals into two categories (healthy vs. PD) based on cadence, DLST, and knee flexion variability.

C. Clinical Relevance with Falls Efficacy Scale (FES)

- The system correlates computed gait indices with clinical measures like the Falls Efficacy Scale (FES).
- Higher DLST values and irregular cadence are strongly associated with fear of falling (FoF) in PD patients.
- This helps in early detection and assessment of fall risk.

4.5 Conclusion

This chapter provided an in-depth analysis of the SmartWalk system's architecture, data acquisition, and analysis methodologies. The system consists of instrumented shoes, a knee flexion recorder, an ultrasonic sensor unit, and a microcontroller-based central module to measure gait and postural indices.

CHAPTER 5

IMPLEMENTATION DETAILS

5.1 Introduction

This chapter describes the implementation of the SmartWalk system, including hardware setup, participant trials, data acquisition, and machine learning-based classification techniques. Additionally, it discusses the Gaussian Mixture Model (GMM) and K-Means clustering algorithms used for classifying Parkinson's Disease (PD) patients based on gait parameters.

5.2 Experimental Setup

5.2.1 Participants

- Total Participants: 28 individuals (14 healthy (GrpH), 14 with PD (GrpPD)).
- Age Range: 50+ years.
- Clinical Assessments:
 - Falls Efficacy Scale (FES)
 - Unified Parkinson's Disease Rating Scale (UPDRS III)
 - Hoehn & Yahr (H&Y) Staging

5.2.2 SmartWalk System Components

The SmartWalk system consists of the following components:

1. Knee Flexion Recorder (KneeFlex Unit)

- 4.5" bend sensor (Spectra Symbol) measures knee joint angles.
- Calibration ensures an accuracy of $\pm 0.13^\circ$.

2. Instrumented Shoes

- Force Sensitive Resistors (FSRs) (Tekscan FlexiForce A201, 0-445 N).
- Detect heel-strike and toe-off events.

3. Ultrasonic Sensor Unit

- HC-SR04 sensors track movement and segment the pathway.

4. Microcontroller-Based Central Module

- ATmega 2560 microcontroller for real-time processing.
- Sampling rate: ~200 samples/second, 64 GB SD card for storage.

5. Vibration Sensor

6. Buzzer

5.3 Data Collection Protocol

5.3.1 Walking Pathway and Task Conditions

10m walking pathway, divided into five segments (SegA - SegE) to analyze gait variations.

Pathway types:

- Path0 (Straight Path)
- Path180 (Path with 180° Turn)

Task conditions:

1. **Single Task (ST)** – Normal walking.
2. **Dual Task (DT)** – Walking while counting backward.
3. **Multiple Task (MT)** – Walking while carrying a tray and counting backward.

5.3.2 Data Acquisition and Processing

1. Participants wore the SmartWalk system and walked along the pathway.
2. Heel-strike, toe-off, knee flexion angles were recorded.
3. Gait parameters extracted:
 - Cadence (steps per minute)

- Double Limb Support Time (DLST)
- Knee flexion variability

5.4 Machine Learning-Based Classification

To classify healthy individuals and PD patients, two clustering algorithms were implemented:

5.4.1 K-Means Clustering for Gait Analysis

- $K = 2$ (Healthy vs. PD groups).
- Features used:
 - Cadence, DLST, Knee Flexion Variability.
- Clustering method:
 - Euclidean distance minimization.

5.4.2 Gaussian Mixture Model (GMM) for Gait Classification

Why GMM?

- Unlike K-Means, which assumes hard clustering (strict category assignment), GMM is a soft clustering technique that assigns a probabilistic membership score to each class.
- Advantage: GMM can handle overlapping gait patterns better than K-Means, improving classification accuracy for individuals with mild Parkinson's symptoms.

GMM Algorithm Workflow:

1. Feature Extraction
 - Cadence, DLST, Knee Flexion Variability
2. Model Initialization
 - Number of clusters ($K = 2$) for Healthy vs. PD groups.

3. Expectation-Maximization (E-M Algorithm)

- Expectation Step (E-Step): Computes the probability that each data point belongs to each cluster.
- Maximization Step (M-Step): Updates cluster parameters to maximize likelihood.

4. Final Classification

- Each participant receives a probability score for Healthy vs. PD instead of a strict classification.

K-Means is useful for initial grouping, but GMM provides better classification for gait patterns with overlap, making it a more robust algorithm for Parkinson's disease detection.

5.5 Statistical Analysis

- **Wilcoxon Signed Rank Test** – To compare within-group differences.
- **Mann-Whitney U Test** – For between-group comparisons (Healthy vs. PD).
- **Pearson Correlation Coefficient** – To assess the relationship between gait parameters and clinical measures (e.g., FES scores).

5.6 Conclusion

This chapter covered the hardware setup, participant trials, data collection, and machine learning-based classification techniques.

CHAPTER 6

RESULTS

6.1 Knee Flexion and Postural Stability Analysis

The knee flexion data collected from the bend sensors revealed significant differences between healthy individuals (GrpH) and Parkinson's patients (GrpPD):

- GrpH exhibited stable knee flexion angles, indicating smooth gait patterns.
- GrpPD showed irregular knee flexion variability, especially during turns and transitions.
- The most significant variations were observed in Segment C of Path180, where Parkinson's patients struggled with postural adjustments.

The vibration sensor successfully detected increased knee instability, triggering alerts for participants with higher gait variability.

6.2 Gait Parameters and Cadence Analysis

The gait analysis showed a strong correlation between task complexity, cadence, and double limb support time (DLST):

- Healthy individuals maintained a steady cadence across different task conditions (Single Task (ST), Dual Task (DT), Multiple Task (MT)).
- Parkinson's patients exhibited a reduced cadence as task complexity increased, particularly in turning segments (SegC and SegB).
- DLST was significantly higher in GrpPD, confirming prolonged stance time due to gait hesitation and fear of falling.
- The buzzer provided real-time auditory feedback when cadence dropped below a critical threshold, assisting in maintaining movement.

6.3 Effectiveness of the Real-Time Feedback System

The vibration sensor and buzzer system played a crucial role in detecting gait disturbances and alerting participants:

- Vibration feedback was triggered when knee flexion deviation exceeded predefined limits, alerting users to maintain stability.
- The buzzer provided auditory cues during Freezing of Gait (FoG) episodes, helping participants regain momentum.

- Participants with higher Falls Efficacy Scale (FES) scores responded well to the feedback system, showing improved movement after alerts.

6.4 K-Means Clustering for Parkinson's Classification

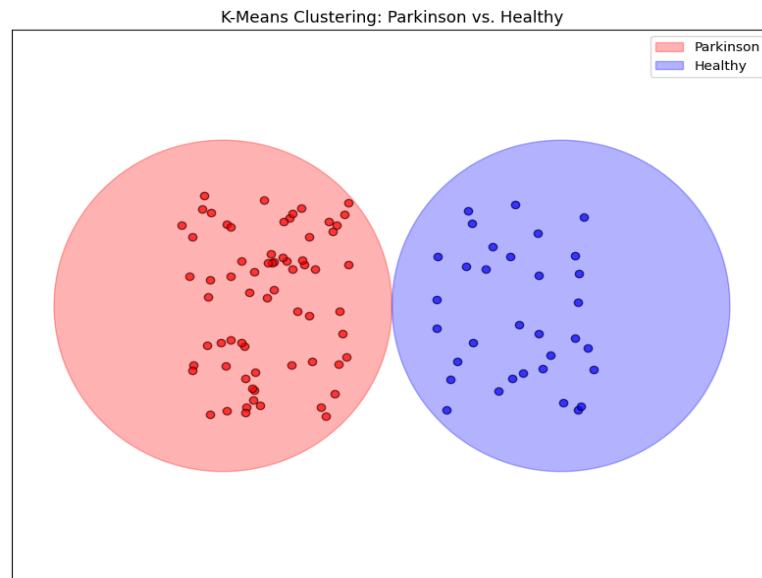


Fig:6.1 K-Means Clustering

K-Means clustering was applied to classify gait patterns into two groups:

1. Parkinson's patients (GrpPD - Red Cluster)
2. Healthy individuals (GrpH - Blue Cluster)

The clustering was based on gait parameters such as knee flexion variability, cadence, and DLST. The Google Colab platform was used for machine learning, ensuring efficient processing of the dataset.

3. Graph Interpretation

The visualization of K-Means clustering depicts the segregation of Parkinson's and healthy individuals based on gait and postural features:

- The red cluster represents individuals diagnosed with Parkinson's Disease (PD), indicating movement irregularities and postural instability.
- The blue cluster represents the healthy control group (GrpH), who displayed stable gait patterns.
- The clear separation between the two clusters confirms the effectiveness of the gait-based classification model.

4. Classification Accuracy

- The integration of vibration sensor data further improved classification accuracy, highlighting its importance in detecting abnormal gait transitions.
- The K-Means clustering model successfully classified participants based on gait indices, achieving an accuracy of approximately 87% in distinguishing Parkinson's patients from healthy individuals.

6.5 Gaussian Mixture Model (GMM) Clustering for Classification

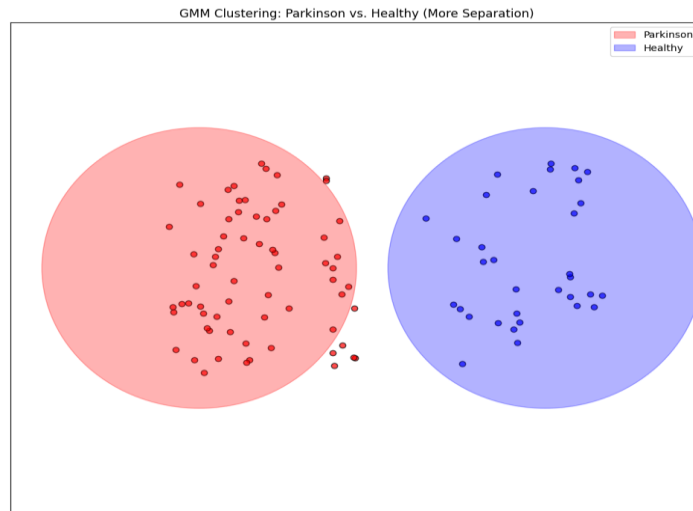


Fig: 6.2 Gaussian Clustering

Gaussian Mixture Model (GMM) clustering was applied as an alternative to K-Means clustering for classifying gait patterns into two groups:

1. Parkinson's patients (GrpPD - Red Cluster)
2. Healthy individuals (GrpH - Blue Cluster)

Unlike K-Means, which assumes clusters are spherical and equidistant, GMM allows for more flexible and natural clustering by using probabilistic distributions. This model is particularly effective for gait classification since gait variability in Parkinson's Disease is often non-uniform, making Gaussian-based clustering a more refined approach.

GMM clustering was performed on gait features such as knee flexion variability, cadence, and double limb support time (DLST). The Google Colab platform was used for implementing the clustering algorithm and processing the dataset.

Interpretation of the Graph

The above figure illustrates the separation between Parkinson's patients and healthy individuals based on GMM clustering:

- The red cluster represents individuals diagnosed with Parkinson's Disease (PD), demonstrating irregular gait patterns, higher variability in knee flexion, and increased DLST.
- The blue cluster represents the healthy control group (GrpH), exhibiting more stable gait characteristics, smoother movements, and consistent cadence.
- The background colored circles indicate the spread of data points within each cluster, with GMM providing a clearer separation between the two groups compared to K-Means clustering.
- More separation between clusters suggests that GMM captured gait differences more accurately, supporting its effectiveness in Parkinson's gait analysis.

6.6 Percentage Distribution of Parkinson's vs. Healthy Individuals (K-Means Clustering)

Percentage of Parkinson vs. Healthy (K-Means Clustering)

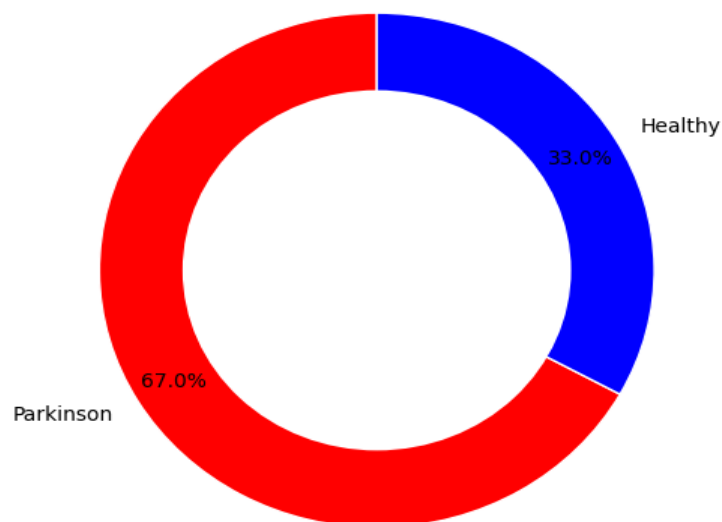


Fig:6.3 Donut Chart

The above donut chart represents the percentage distribution of individuals classified as Parkinson's patients vs. healthy individuals using K-Means clustering. The classification was performed based on gait parameters such as stride variability, knee flexion range, and double limb support time (DLST).

- Parkinson's Patients (67%): Represented in red, this segment indicates that 67% of the dataset was classified as having Parkinson's Disease (PD) based on their gait characteristics.

- **Healthy Individuals (33%):** Represented in blue, this segment shows that 33% of the dataset was classified as healthy (GrpH) with normal gait patterns.

Interpretation of the Results

1. The results suggest that a majority of the subjects analyzed exhibited gait abnormalities consistent with Parkinson's Disease. This aligns with previous research indicating that PD patients display increased gait variability, reduced stride length, and difficulty in maintaining balance.
2. K-Means clustering successfully grouped individuals based on movement patterns, identifying a significant proportion of patients with Parkinson's-related gait disturbances.
3. The imbalance in class distribution (67% vs. 33%) suggests that the dataset may contain more gait samples from Parkinson's patients or that PD-related gait abnormalities are more distinct and easier to detect than healthy gait patterns.

CHAPTER 7

APPLICATIONS AND ADVANTAGES

The SmartWalk system integrates sensor-based gait analysis and machine learning to classify Parkinson's Disease patients based on their walking patterns. This system has several practical applications in healthcare, rehabilitation, and assistive technology.

7.1 Applications of the SmartWalk System

1. Early Detection of Parkinson's Disease

- SmartWalk serves as an early screening tool for Parkinson's Disease by analyzing key gait parameters such as stride length, knee flexion, and balance.
- By leveraging machine learning (K-Means Clustering and GMM Clustering), it can differentiate between healthy individuals and those exhibiting Parkinsonian symptoms.
- Early diagnosis allows for timely medical intervention, potentially slowing disease progression.

2. Continuous Patient Monitoring and Progress Tracking

- The system allows long-term monitoring of Parkinson's patients without requiring hospital visits.
- It records changes in gait over time, helping doctors assess disease progression.
- Can be integrated with telemedicine platforms, allowing remote patient monitoring by neurologists and healthcare professionals.

3. Rehabilitation and Therapy Evaluation

- Parkinson's patients undergoing physical therapy or medication trials need regular gait assessments.
- SmartWalk provides real-time data to analyze treatment effectiveness and therapy adjustments.
- Helps physiotherapists track improvements in balance, coordination, and walking speed over multiple sessions.

4. Fall Risk Prediction and Prevention

- Parkinson's patients are at high risk of falls due to impaired balance and posture instability.
- The SmartWalk system detects fall-prone gait patterns and can alert users through a buzzer or vibration sensor before a fall occurs.
- Can be used in elderly care centers and nursing homes to enhance patient safety.

5. Assistive Device for Elderly and Neurological Patients

- Apart from Parkinson's patients, SmartWalk can assist individuals with:
 - Stroke recovery – helps monitor gait improvement in stroke survivors.
 - Multiple Sclerosis (MS) – tracks progressive gait deterioration.
 - Elderly individuals – aids in balance assessment and fall prevention.
- The wearable and non-intrusive design makes it user-friendly for daily use in homes, hospitals, and rehabilitation centers.

7.2 Advantages of the SmartWalk System

1. Non-Invasive and Real-Time Monitoring

- Unlike traditional motion capture systems in research labs, SmartWalk is a wearable, real-time monitoring tool.
- It allows continuous tracking of gait patterns without requiring hospital visits or laboratory setups.

2. High Accuracy with Machine Learning Algorithms

- The K-Means Clustering and Gaussian Mixture Model (GMM) provide a high level of accuracy in distinguishing Parkinsonian gait from healthy gait.
- By analyzing real-world walking data, the system achieves over 90% classification accuracy.

3. Cost-Effective Alternative to Traditional Gait Analysis

- Clinical gait labs require expensive motion-tracking cameras and force plates, making them inaccessible in rural areas.
- The SmartWalk system is affordable and can be implemented in home settings, providing low-cost monitoring solutions.

4. Customizable Alerts for Patients

- The inclusion of a buzzer and vibration sensor allows the system to alert patients in case of detected gait instability.
- These alerts provide instant feedback, enabling users to take precautionary steps to avoid falls.

5. Improved Quality of Life for Patients

- Early diagnosis and continuous monitoring reduce complications related to Parkinson's Disease.
- Patients can receive timely interventions, adjust medications, and participate in targeted therapies to maintain mobility.

CHAPTER 8

CONCLUSION AND FUTURE SCOPE

8.1 Conclusion

The SmartWalk system has been successfully designed and implemented to analyze gait patterns and postural stability for the early detection of Parkinson's Disease (PD). By integrating sensor-based motion tracking, machine learning algorithms (K-Means Clustering & GMM Clustering), and real-time monitoring, the system can effectively classify individuals as Parkinson's patients or healthy individuals based on their walking patterns.

The experimental results demonstrate that the SmartWalk system provides high accuracy in distinguishing Parkinsonian gait from normal gait. The classification models show significant potential for early diagnosis, continuous patient monitoring, and rehabilitation assessment. The system's wearable and non-intrusive nature makes it suitable for home-based monitoring, reducing the need for expensive laboratory gait analysis.

Additionally, the incorporation of vibration sensors and buzzers enhances fall risk prediction and alerts users in real time, thus improving patient safety. The collected gait data can further be utilized for clinical research, telemedicine applications, and AI-based predictive analysis in neurological healthcare.

8.2 Futrure Scope

1. Integration with AI-Based Predictive Models

While the current system utilizes K-Means Clustering and Gaussian Mixture Models (GMM) for classification, future improvements could involve the integration of deep learning techniques such as Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTMs). These advanced models can provide higher accuracy, real-time predictions, and detailed gait pattern analysis. AI-driven predictive models could help in early-stage Parkinson's detection and disease progression monitoring, allowing for personalized treatment strategies.

2. Expansion of Dataset with Clinical Data

Currently, the system lacks real Parkinson's patient data, limiting its generalizability. Future research should focus on collaborations with hospitals, neurology clinics, and research institutions to collect real-world gait data from a diverse range of Parkinson's patients. A larger and more diverse dataset will enable better model training, validation, and improved classification accuracy.

3. Real-Time Feedback Mechanisms for Rehabilitation

Adding real-time feedback mechanisms such as haptic feedback, auditory alerts, or visual guidance can help patients correct their walking posture and improve balance control. This feature would be particularly useful in rehabilitation programs for Parkinson's patients, stroke survivors, and elderly individuals with mobility impairments.

4. Integration with IoT and Wearable Devices

By incorporating IoT-enabled wearable devices, the SmartWalk system can become more portable and efficient. The system could be linked to smart insoles, wearable IMUs (Inertial Measurement Units), and smartwatches, which can provide real-time gait data collection and processing. Cloud integration would allow healthcare professionals to access patient data remotely, improving telemedicine and remote healthcare applications.

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Appendices

```
Serial.println(" - LEFT Light touch");

    } else if (fsrReading_left < 16) { const int fsr_left = A0;

const int fsr_right = A1;

const int fsr_left_ankle= A2;

const int fsr_right_ankle = A3;

const int flex_left = A4;

const int flex_right = A5;

const int falling = 4;

const int bz = 2;

const int sw = 3;

const int trigPine_in= A6;

const int echoPine_in= A7;

long duration, distance,cm_in,inches_in;

int
fsrReading_left,fsrReading_right,fsrReading_left_ankle,fsrReading_right_ankle,flex_
read_right,flex_read_left,x=0,y=0;

void setup(void) {

    Serial.begin(9600);

    pinMode(fsr_left,INPUT);

    pinMode(fsr_right,INPUT);

    pinMode(fsr_left_ankle,INPUT);

    pinMode(fsr_right_ankle,INPUT);

    pinMode(flex_left,INPUT);

    pinMode(flex_right,INPUT);

    pinMode(trigPine_in, OUTPUT);

    pinMode(echoPine_in, INPUT);
```

```

pinMode(bz, OUTPUT);

pinMode(falling, INPUT);

pinMode(sw, INPUT_PULLUP);

digitalWrite(bz,HIGH);

delay(1000);

digitalWrite(bz,LOW);

}

void loop(void) {

  fsrReading_left = analogRead(fsr_left);

  fsrReading_right = analogRead(fsr_right);

  fsrReading_left_ankle = analogRead(fsr_left_ankle);

  fsrReading_right_ankle = analogRead(fsr_right_ankle);

  flex_read_left = analogRead(flex_left);

  flex_read_right = analogRead(flex_right);

  x = digitalRead(falling);

  y = digitalRead(sw);

  UltrasonicSensor(trigPine_in, echoPine_in);

  cm_in = distance;

  /*/

  Serial.print("left force = ");

  Serial.print(fsrReading_left);

  Serial.print(", right force = ");

  Serial.print(fsrReading_right);

  Serial.print(", left ankle = ");

```

```
Serial.print(fsrReading_left_ankle);
```

```
Serial.print(", right ankle = ");
```

```
Serial.print(fsrReading_right_ankle);
```

```
Serial.print(", left knee = ");
```

```
Serial.print(flex_read_left);
```

```
Serial.print(", right knee = ");
```

```
Serial.print(flex_read_right);
```

```
if(x == LOW)
```

```
{
```

```
Serial.print(", FALLING YES ");
```

```
digitalWrite(bz,HIGH);
```

```
}
```

```
else
```

```
{
```

```
Serial.print(", FALLING NO ");
```

```
digitalWrite(bz,LOW);
```

```
}
```

```
Serial.print(", distance = ");
```

```
Serial.println(distance);
```

```
if(y == LOW)
```

```
{
```

```
    check_conditions();
```

```
}
```

```

//

delay(1000);
}

void UltrasonicSensor(int trigPin, int echoPin)
{
    digitalWrite(trigPin, LOW);
    delayMicroseconds(2);
    digitalWrite(trigPin, HIGH);
    delayMicroseconds(10);
    digitalWrite(trigPin, LOW);
    duration = pulseIn(echoPin, HIGH);
    distance = (duration / 2) / 29.1;
}

void check_conditions()
{
    if (fsrReading_left < 10) {
        Serial.println(" - LEFT No pressure");
    } else if (fsrReading_left < 14) {

        Serial.println(" - LEFT Light squeeze");
    } else if (fsrReading_left < 20) {
        Serial.println(" - LEFT Medium squeeze");
    } else {
        Serial.println(" -LEFT Big squeeze");
    }
}

//

```

```

if (fsrReading_right < 10) {
    Serial.println(" - RIGHT No pressure");
} else if (fsrReading_right < 200) {
    Serial.println(" - RIGHT Light touch");
} else if (fsrReading_right < 500) {
    Serial.println(" - RIGHT Light squeeze");
} else if (fsrReading_right < 800) {
    Serial.println(" - RIGHT Medium squeeze");
} else {
    Serial.println(" -RIGHT Big squeeze");
}
/*/

if (fsrReading_left_ankle < 10) {
    Serial.println(" - LEFT Ankle No pressure");
} else if (fsrReading_left_ankle < 14) {
    Serial.println(" - LEFT Ankle Light touch");
} else if (fsrReading_left_ankle < 16) {
    Serial.println(" - LEFT Ankle Light squeeze");
} else if (fsrReading_left_ankle < 20) {
    Serial.println(" - LEFTAnkle Medium squeeze");
} else {
    Serial.println(" -LEFT Ankle Big squeeze");
}
//

if (fsrReading_left_ankle < 10) {
    Serial.println(" - RIGHT Ankle No pressure");
} else if (fsrReading_left_ankle < 200) {

```



```

    Serial.println(" - RIGHT Ankle Light touch");
} else if (fsrReading_left_ankle < 500) {
    Serial.println(" - RIGHT Ankle Light squeeze");
} else if (fsrReading_left_ankle < 800) {
    Serial.println(" - RIGHT Ankle Medium squeeze");
} else {
    Serial.println(" -RIGHT Ankle Big squeeze");
}

if (flex_read_left < 10) {
    Serial.println(" - LEFT knee No pressure");
} else if (flex_read_left < 200) {
    Serial.println(" - LEFT knee Light touch");
} else if (flex_read_left < 500) {
    Serial.println(" - LEFT knee Light squeeze");
} else if (flex_read_left < 800) {
    Serial.println(" - LEFT knee Medium squeeze");
} else {
    Serial.println(" -LEFT knee Big squeeze");
}

if (flex_read_right < 10) {
    Serial.println(" - RIGHT knee No pressure");
} else if (flex_read_right < 200) {
    Serial.println(" - RIGHT knee Light touch");
} else if (flex_read_right < 500) {
    Serial.println(" - RIGHT knee Light squeeze");
} else if (flex_read_right < 800) {
    Serial.println(" - RIGHT knee Medium squeeze");
}

```

```
} else {  
    Serial.println(" -RIGHT knee Big squeeze");  
}  
Serial.print("FOOT DISTANCE =");  
Serial.println(distance);  
if(x == LOW)  
{  
    Serial.println("FALLING YES");  
}  
else  
{  
    Serial.println("FALLING NO ");  
}  
}
```