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Development of Wearable Optical Fiber Sensors Integrated with Machine Learning Monitoring for Rehabilitation Gait Analysis

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ABSTRACT

A wearable optical fiber sensor system integrated with machine learning is developed to support rehabilitation gait analysis. Human gait monitoring plays a crucial role in evaluating the recovery progress of individuals with lower limb injuries or neurological disorders. Conventional gait analysis methods are often expensive, non-portable, and reliant on expert interpretation, which limits their practicality for continuous use. To overcome these challenges, a flexible insole embedded with six fiber optic pressure sensors is designed to capture plantar pressure data during walking. The collected data is wirelessly transmitted to a MATLAB interface, where it is processed and analysed using a decision tree classifier to identify gait phases and detect abnormalities. The output is visualized through graphical representations and classification trends, enabling clinicians to monitor and interpret patient progress effectively. This system enables the assessment of gait patterns in both healthy individuals and those undergoing rehabilitation. Expected outcomes include a cost-effective, portable, and intelligent solution capable of distinguishing between normal and abnormal gait patterns, identifying stages of rehabilitation, and offering interpretable feedback for improved clinical decision-making. The approach aims to advance non-invasive, automated, and personalized rehabilitation monitoring.

1. INTRODUCTION

Monitoring human gait is critical for understanding locomotor function, particularly in the context of rehabilitation for individuals recovering from lower limb injuries or neurological disorders. Gait abnormalities such as asymmetrical steps and inconsistent stride lengths can significantly affect mobility and reduce the overall quality of life [1], [2]. Traditional gait analysis tools such as force platforms and electromyography provide high precision but are often expensive, bulky, and limited to clinical settings. This restricts their usefulness for continuous or at-home monitoring of patients.

In response to these limitations, wearable technologies have gained attention as a more practical solution. Among these, fiber optic sensors have emerged as a promising option

due to their high sensitivity, flexibility, immunity to electromagnetic interference, and relatively low cost. These

sensors can be integrated into insoles to capture real-time pressure distribution data from the plantar surface of the foot, offering valuable insights into walking patterns and rehabilitation progress [3]. However, the challenge lies in the interpretation of the large volumes of data generated, especially during extended monitoring periods where manual analysis becomes laborious and inefficient.

Advancements in artificial intelligence, particularly in machine learning, have opened new possibilities for automating and enhancing data interpretation. Machine learning algorithms such as decision trees are capable of classifying gait phases, identifying walking anomalies, and visualizing recovery trends [4], [5]. This integration allows the transition from passive data recording to intelligent systems that produce actionable insights, improving the support provided during patient rehabilitation [6].

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Despite these developments, many existing gait analysis systems remain expensive, nonportable, and dependent on manual data interpretation. Wearable alternatives provide improved portability but still require extensive manual processing of collected data. The lack of integrated intelligent analysis tools limits their application in long-term rehabilitation monitoring outside of clinical environments.

This study addresses these challenges by focusing on the development of a wearable insole system embedded with fiber optic pressure sensors and integrated with machine learning based post processing tools. The system is designed to collect detailed plantar pressure data during walking and to support the analysis of rehabilitation progress in individuals recovering from lower limb injuries or surgeries. The study involves the design and fabrication of the insole system, the collection of gait data from both healthy individuals and patients undergoing rehabilitation, and the application of optimized machine learning algorithms for classifying gait phases and detecting abnormalities in walking patterns. The results are then visualized through pressure maps and recovery trend charts, making it easier for clinicians to interpret and assess progress.

It is important to note that the machine learning component of this project is implemented as a post processing tool rather than being embedded in the wearable device for real-time analysis. The focus of the study is limited to walking gait in controlled environments and does not extend to more dynamic activities such as running or stair climbing. This approach ensures that the system remains practical, accessible, and relevant for continuous rehabilitation monitoring.

2. LITERATURE REVIEW

A comprehensive overview of human gait analysis is also presented, including fundamental gait phases, metrics, and how variations can indicate specific musculoskeletal or neurological conditions. The integration of machine learning approaches, particularly decision tree algorithms is discussed due to their simplicity, interpretability, and effectiveness in handling biomedical data.

Additionally, the review evaluates the real-world and clinical implementation of these technologies, exploring how wearable systems facilitate remote rehabilitation monitoring, patient progress tracking, and clinical decision-making. Visual elements such as system diagrams, sensor layouts, and sample classification outputs are included to aid in understanding the technical and practical aspects discussed.

2.1 Innovations in Fiber Optic Sensor Technologies

Fiber optic sensors (FOSs) provide considerable advantages in biomechanics due to their inherent properties such as immunity to electromagnetic interference, high sensitivity to physical changes, flexibility, and compact design. These characteristics make them ideal for integration into wearable technology, where precise and real-time monitoring of biomechanical data is required. In recent years, their use in detecting pressure and strain in dynamic situations, such as during human locomotion, has established them as the preferred option for smart insole development and other portable health-monitoring devices. Among the different types of fiber optic sensors, the fiber bragg grating (FBG) sensor is frequently used because of its accurate ability to detect deformation and structural changes caused by external forces. Figure 1 depicts the fundamental structure and function of an FBG sensor, demonstrating how strain or temperature changes affect the reflected wavelength, which may then be detected and evaluated for biomechanical assessment [7].

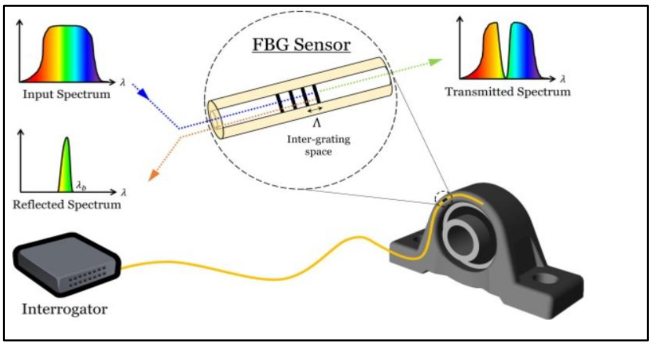

Fig. 1. Fiber Bragg Grating Sensor for Strain Sensing [8].

Polymer optical fibers and polydimethylsiloxane (PDMS)-based sensors have emerged as promising candidates for enhanced wearable sensing systems in biomedical applications, according to recent research. These materials have distinct characteristics, including mechanical flexibility, durability, and biocompatibility, making them excellent for continuous monitoring in dynamic situations such as human gait study. A PDMS-based fiber optic pressure sensor with high sensitivity and outstanding repeatability was successfully developed, making it ideal for integration into wearable platforms such as smart insoles [9].The inclusion of such sensors into insoles allows for accurate and targeted pressure measurement across multiple parts of the foot while walking or standing. Figure 2 depicts a detailed cross-section of the PDMS-based optical pressure sensor, highlighting the internal structure and design features that contribute to its operation and performance.

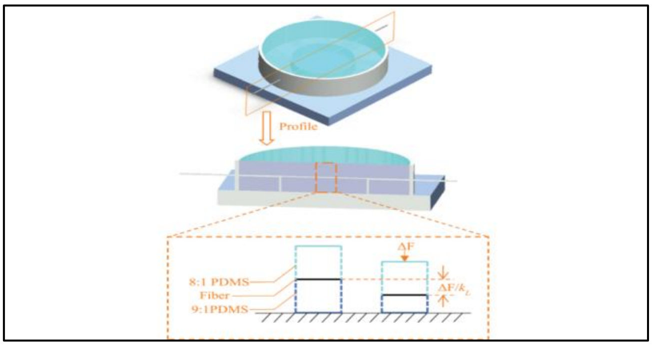

Fig. 2. Cross-Section of Polydimethylsiloxane-Based Optical Pressure Sensor [9].

2.2 Smart Insole Systems and Vertical Ground Reaction Force (vGRF)

A systematic approach was proposed for the design and characterization of a smart insole specifically aimed at sensing vertical ground reaction force (vGRF), a critical parameter for analyzing the biomechanical dynamics of human gait [10]. In clinical settings, accurate vGRF measurements are critical for studying load distribution, diagnosing gait problems, and assessing rehabilitation progress. The suggested insole design strategically integrates fiber optic sensors and force-sensitive resistors (FSRs) to improve the precision and reliability of pressure detection throughout the gait cycle.

Figure 3 shows the insole's precise layout, including the appropriate positioning of both fiber optic and FSR sensors to provide complete foot coverage and data collection. Meanwhile, Figure 4 shows the equivalent gait cycle readings for the left and right feet acquired from the FSR sensors, which provide visual insight into the temporal distribution and amplitude of pressure during walking activities. This combination of sensor technologies creates a robust system for real-time gait monitoring and analysis, which supports both clinical diagnosis and rehabilitation tracking.

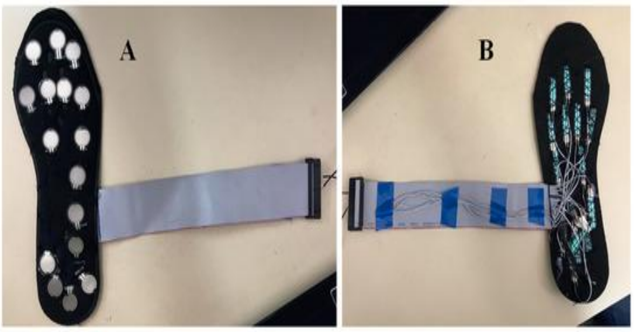

Fig. 3. Smart Insole Layout with Embedded Sensors [10].

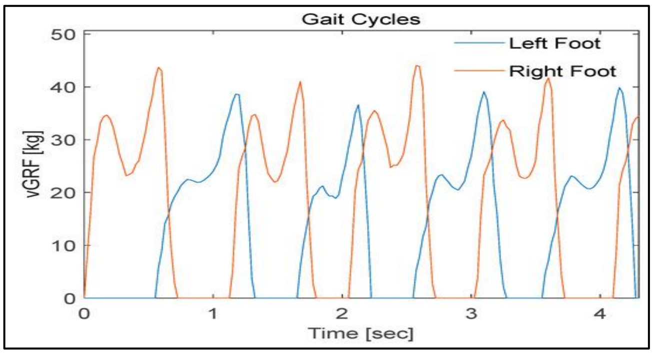

Fig. 4. Left and Right Foot Gait Cycle Readings from FSR Sensors [10].

2.3 *Wearable Sensor Technology in Clinical Gait Monitoring*

Wearable sensor technology has evolved as an effective and non-invasive method for continually gathering gait-related data over long periods of time, making it ideal for clinical and at-home rehabilitation monitoring. These devices provide the ability to capture movement in naturalistic environments, which improves the ecological validity of gait analysis when compared to standard lab-based examinations. As shown in Figure 5 and Figure 6, a variety of sensor types including FSR pressure sensor and inertial sensors are commonly embedded into wearable platforms such as insoles, shoes, or wearable bands to capture multidimensional data with regard to movement, orientation, and pressure distribution [11].

These integrated sensor systems can provide real-time input to both patients and physicians, which is particularly useful in rehabilitation settings involving stroke survivors, patients with orthopedic injuries, or individuals recovering from lower limb surgeries. Wearable sensors' real-time data processing and feedback mechanisms have been demonstrated to improve therapeutic outcomes, increase patient involvement, and enable tailored treatment programs [12]. The advancement of these technologies is a big step toward decentralized and patient-centered therapy in gait rehabilitation.

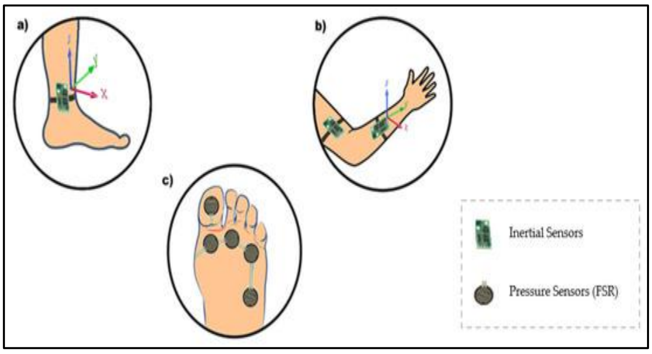

Fig. 5. Wearable Sensor Integration in Rehabilitation Monitoring [13].

Fig. 6. Physical Therapy Using Gait Monitoring Systems [14].

2.4 *Integration of Machine Learning in Gait Assessment*

The integration of machine learning (ML) techniques into gait assessment has fundamentally altered how human walking patterns are examined, evaluated, and classified. Traditionally, gait analysis needed human interpretation by professionals, which was time-consuming and inconsistent. However, ML algorithms have enabled automation and increased accuracy in recognizing and classifying complicated gait patterns, resulting in faster and more objective assessments. Sensor-generated data, such as that acquired from accelerometers, gyroscopes, and pressure sensors, can be used to train ML models to spot tiny changes in gait that may signal certain musculoskeletal or neurological diseases. In particular, the use of supervised learning techniques like as decision trees, support vector machines (SVMs), and artificial neural networks has shown tremendous promise in the field of biomechanical evaluation [15, 16].

These models can handle big datasets and understand complex patterns, making them appropriate for clinical situations where accurate gait characterization is required for diagnosis and rehabilitation monitoring. Furthermore, the ability of these models to provide real-time feedback and adaptive learning makes them more useful in wearable devices, enabling continuous and tailored gait training therapies for those recuperating from diseases such as stroke or injury.

2.5 Decision Tree Algorithms for Classification and Monitoring

Decision tree algorithms have grown in favor in biomedical signal classification applications, particularly gait analysis and rehabilitation monitoring, due to its simplicity, ease of implementation, and excellent interpretability. Unlike more sophisticated models, decision trees provide a clear, logical flow of decisions that physicians and researchers can comprehend and trace, making them ideal for applications that require transparency and explainability. Furthermore, their low computing complexity permits real-time data processing, which is essential for integration into wearable health monitoring systems.

In a review, various decision tree designs and their usefulness in diagnosing gait disorders based on sensor-derived data were discussed, highlighting their potential to enhance diagnostic precision in clinical gait analysis [17]. Similarly, the real-time deployment of decision tree models on wearable platforms was investigated, demonstrating how these algorithms can support continuous monitoring and adaptive feedback in rehabilitation settings [18]. The findings highlight the decision tree's capacity to perform quick and accurate classifications even on devices with low computing power. Figure 7 depicts the layout of a basic decision tree used for gait classification, demonstrating how sensor input features are used to journey through decision nodes to get a final classification result. This structure forms the foundation for more complex decision systems used in smart wearable technology today.

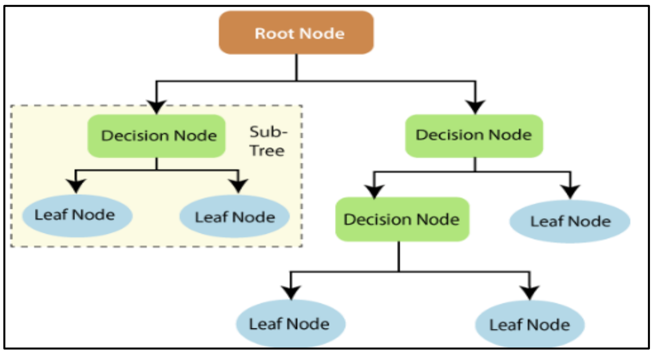

Fig. 7. Structure of a Simple Decision Tree for Gait Classification [18].

Ensemble decision tree models have been introduced to support the identification of neuromuscular diseases [19], while decision trees have also been applied in post-stroke rehabilitation to assess a patient's level of gait independence [20], [21]. These machine learning approaches demonstrated strong performance in distinguishing between normal and abnormal gait patterns by generating clear, interpretable decision rules. Their application in clinical environments has helped enhance patient monitoring and treatment evaluation over time. The decision tree used to predict gait recovery stages is shown in Figure 8.

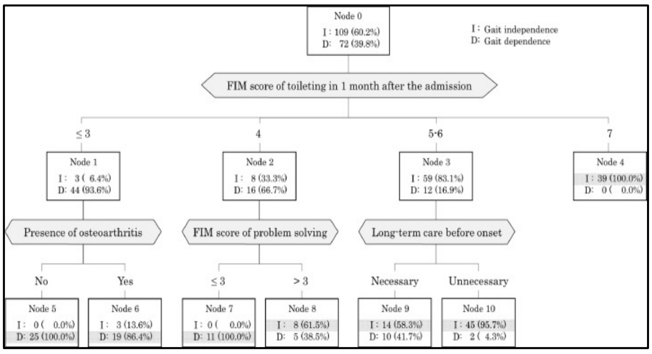

Fig. 8. Decision Tree Used to Predict Gait Recovery Stages [22].

2.6 Gait Subphases and Balance Estimation.

The human gait cycle is divided into various subphases, including first contact, loading response, midstance, terminal stance, pre-swing, starting swing, mid-swing, and terminal swing, which together provide important insights into walking stability, postural control, and locomotor efficiency. Each subphase is associated with particular biomechanical functions and transitions in the lower limb joints, as well as muscle activation. Accurate detection and analysis of these subphases is critical for recognizing gait irregularities and monitoring balance, especially in people undergoing rehabilitation or suffering from neuromuscular illnesses.

Pressure distribution analysis can successfully record these gait phases by embedding sensor arrays in smart insoles, particularly those positioned under the heel, midfoot, and forefoot. Monitoring the time and amplitude of pressure alterations across these key locations allows us to estimate the subject's gait dynamics and balance control throughout the walking cycle. Analysing leg orientation and body equilibrium during these subphases provides useful information for evaluating gait patterns and diagnosing potential instabilities [23]. Figure 9 depicts the functional phases of the human gait cycle, emphasizing the order and features of each subphase. This information serves as a foundation for developing algorithms that classify gait stages and estimate dynamic balance in real time, contributing to more personalized and effective rehabilitation strategies.

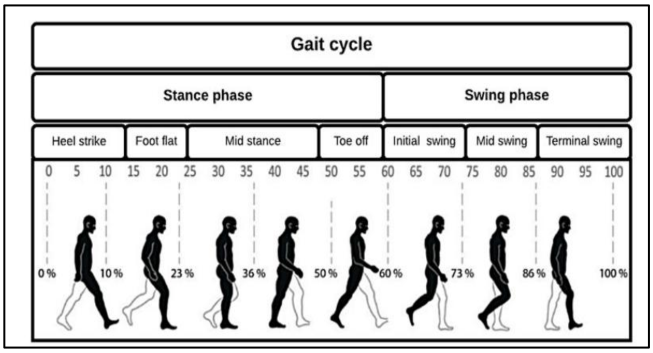

Fig. 9. Functional Phases of the Human Gait Cycle [23].

3. METHODOLOGY

This section details the methodology implemented to develop the wearable fiber optic insole system, collect gait data, and perform machine learning-based analysis. The process includes hardware design, sensor calibration, data acquisition through MATLAB, feature extraction, and classification using a decision tree algorithm. The methodology builds on a previously developed fiber-optic-based insole, now enhanced with intelligent post-processing for rehabilitation gait analysis.

3.1 Flowchart of the Project

Figure 10 shows the flowchart of the project that provides a visual representation for operational process of the wearable optical fiber. It begins with the user wearing the optical fiber, which contains embedded fiber optic pressure sensors. These sensors detect pressure changes during walking. The sensed data is transmitted to the microcontroller (ESP32 and Arduino Uno), where it is collected and forwarded wirelessly to a computer. In the next stage, the data is processed in MATLAB software and passed into a decision tree classifier, which analyzes the gait and determines whether it is normal or abnormal. Finally, the classified output is visualized as graphs to support rehabilitation assessment and monitoring.

3.2 System Architecture

The system comprises three major components consisting of (1) a custom-designed insole embedded with six optical fiber sensors, (2) an embedded controller (NodeMCU or Arduino Uno) that transmits data wirelessly to a computer, and (3) a MATLAB interface for data processing, visualization, and integration with a decision tree model. The circuit diagram is visualized in Figure 11.

3.3 Fabrication of the Insole Sensor System

A flexible silicone insole is embedded with six fiber optic sensors using PMMA plastic optical fibers. They are placed at key anatomical regions of the foot which is the heel (sensors 2 and 4), forefoot (sensors 1, 3, and 6), and midfoot arch (sensor 5). This configuration enables comprehensive detection of pressure distribution across various phases of the gait cycle. These fibers are enclosed within transparent silicone tubes to protect them from damage and to ensure consistent pressure transmission. One end of each fiber is connected to a red laser diode, and the other to a photodiode. Pressure applied to the

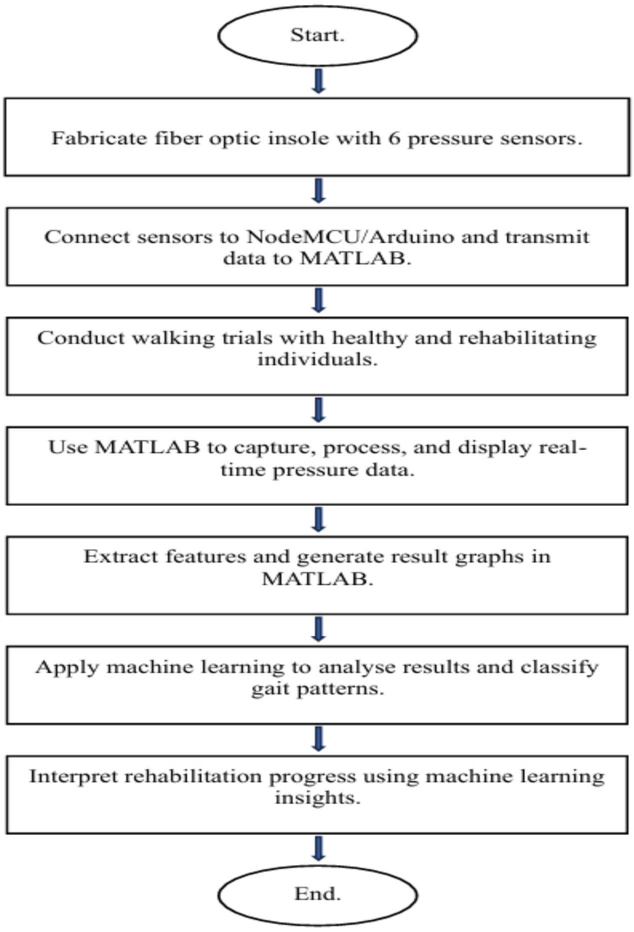

Fig. 10. System Flowchart from Sensor Input to Machine Learning Output

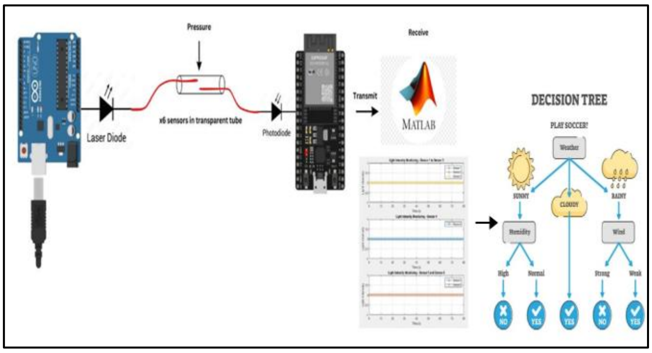

Fig. 11. Circuit Diagram.

insole modulates light transmission through the fiber, which is then interpreted as a voltage drop. The sensor placement and anatomical mapping of foot regions is shown in Figure 12 and Figure 13.

Forefoot (Sensors 1, 3, and 6): These sensors are positioned in the forefoot to assess pressure distribution over the front. This area usually bears a lot of weight during the pushoff phase of walking and running. Monitoring the pressure in the forefoot can provide information on the subject's balance and propulsive force.

Midfoot (Sensor 5): Sensor 5, located in the midfoot region, is essential for monitoring pressure distribution in the arch of the foot. During movement, the midfoot serves as a stabilizer and a shock absorber. Analyzing pressure here aids in determining total arch support and load distribution, which is critical for identifying abnormalities such as flat feet or high arches.

Hindfoot (Sensor 2 and 4): These sensors are located in the hindfoot, specifically at the heel. This area receives the initial touch during the heel-striking phase of walking. Monitoring pressure in the hindfoot is critical for determining impact force and distribution, which can reveal both the effectiveness of the heel strike and potential concerns such as overpronation or supination.

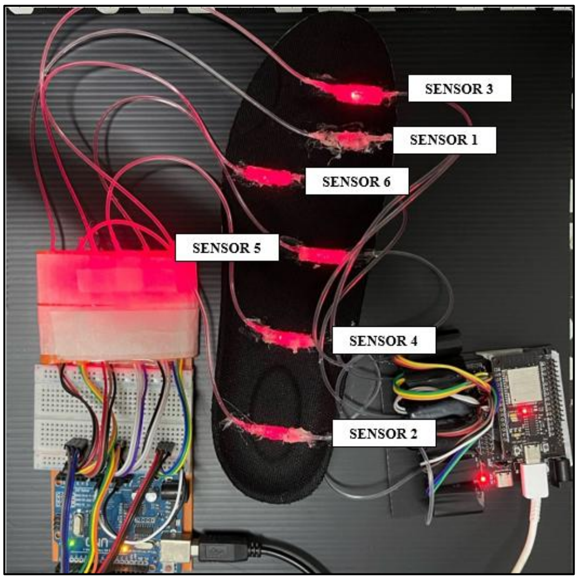

Fig. 12. Sensor Configuration on the Insole [24].

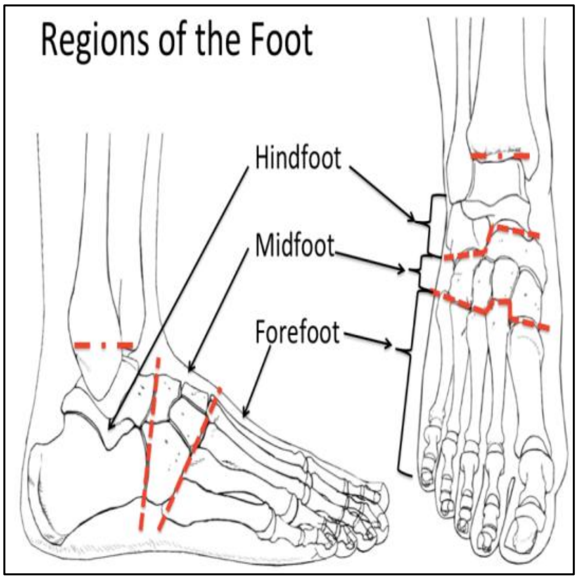

Fig. 13. Region of the Foot [25].

3.4 Data Acquisition using MATLAB

The output from the photodiodes is digitized by the microcontroller and transmitted via Wi-Fi to MATLAB. MATLAB's interface plots real-time voltage readings for each sensor, allowing users to observe pressure distribution across the foot. Sample plots include stride length, contact timing, and pressure force trends.

3.5 Feature Extraction

From the raw time-series data, key gait metrics are extracted, including:

i. Peak pressure points per sensor.
ii. Temporal symmetry between left and right foot
iii. Arch pressure variability (sensor 5)

These metrics are essential for evaluating walking performance and detecting abnormalities.

3.6 Machine Learning Integration: Decision Tree Classifier

In this study, the Statistics and Machine Learning Toolbox™ in MATLAB was utilized to support the implementation and evaluation of machine learning algorithms, specifically for gait classification using decision tree models. The toolbox offers a comprehensive suite of functions and interactive apps designed for data preprocessing, modeling, and evaluation. It was employed to perform descriptive statistical analysis, data visualization, and feature exploration, which aided in understanding the structure and variability within the collected gait data. The labeled dataset is prepared using trials from both healthy and rehabilitating subjects. The classifier is trained to distinguish between:

i. Normal gait with normal arch (Sensor 5 inactive)
ii. Normal gait with flat foot (Sensor 5 active)
iii. Abnormal gait due to injury (high heel pressure, irregular stride)
iv. Progressive recovery stages (based on sensor activity and rhythm)

The decision tree model selects features (e.g., pressure peak values, gait symmetry index) and recursively splits them to form interpretable rules.

The Classification Learner app was used to interactively train and validate decision tree classifiers based on labeled gait phase data. This tool facilitated model training by allowing for visual inspection of classification performance metrics such as accuracy, confusion matrices, and ROC curves. Additionally, programmatic tools within the toolbox supported automation of model development and testing.

For feature selection and dimensionality reduction, the toolbox provided functions such as principal component analysis (PCA) and regularization techniques, enabling the identification of the most relevant input variables contributing to accurate gait classification. These features helped to enhance the model's generalization ability while minimizing overfitting.

Moreover, the toolbox's support for supervised learning alongside capabilities for semi-supervised and unsupervised methods offered flexibility for potential future extensions of this system. Although this study focused primarily on decision tree classifiers due to their interpretability and low computational requirements, other algorithms such as support vector machines (SVMs), ensemble models, and clustering methods (e.g., k-means) are also available and can be considered in subsequent research phases for comparative analysis or performance enhancement.

3.7 Classification Output and Visualization

In this study, the output of the Decision Tree classifier is visualized using time-series line plots combined with categorical labels indicating gait status over the rehabilitation period. This approach enhances the interpretability of the classification results for both technical and clinical stakeholders.

The Decision Tree model produces binary gait classification results, categorizing each rehabilitation session as either "Normal" or "Abnormal." These labels are plotted against the rehabilitation timeline, with the x-axis representing the rehabilitation day and the y-axis representing the gait classification outcome. Categorical mapping is applied, where numerical classifier outputs (e.g., 0 and 1) are translated into descriptive terms to improve readability and facilitate clinical interpretation.

The visualization provides an intuitive and immediate understanding of the patient's gait recovery trajectory. For example, periods marked as "Abnormal" followed by a transition to "Normal" indicate positive rehabilitation progress, whereas persistent "Abnormal" classifications may signal the need for adjusted treatment strategies. In contrast, fluctuations between "Normal" and "Abnormal" could reflect inconsistent gait patterns, prompting further clinical assessment.

By using a Decision Tree model, the classification process remains interpretable, as the decision boundaries and criteria are based on a structured, rule-based approach. This aligns well with clinical needs, where explainability and transparency of AI outputs are crucial for informed decision-making. The tree structure enables clinicians to trace back the reasoning behind each classification, supporting confidence in the system's recommendations.

Moreover, this visual representation acts as a valuable feedback tool for both patients and healthcare providers. It enables monitoring of rehabilitation effectiveness over time, facilitates early detection of setbacks, and supports data-driven adjustments to personalized rehabilitation plans.

4. RESULTS AND DISCUSSION

4.1 Normal Gait Patterns

Two categories were studied under normal gait:

i. Subject 1 (Normal Arch): Subjects exhibited steady stride rhythm. Forefoot sensors (1, 3, 6) and heel sensors (2, 4) showed balanced activation. Sensor 5 showed negligible response, indicating a well-formed arch which is shown in Figure 14.

ii. Subject 2 (Flat Foot): Sensor 5 recorded consistent midfoot pressure, distinguishing flat-footed gait. Despite flat arches, stride rhythm remained consistent and efficient which is shown in Figure 15.

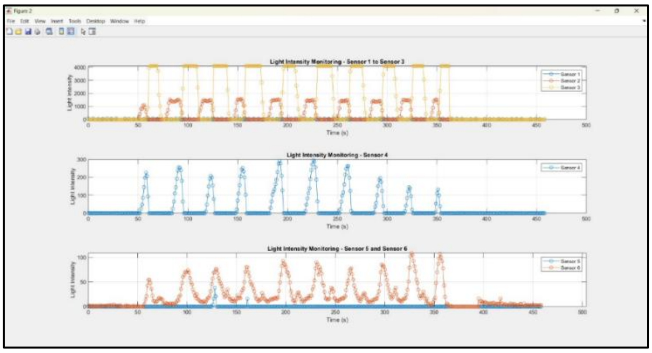

Fig. 14. Normal Gait Pattern (Subject 1 with Normal Arch).

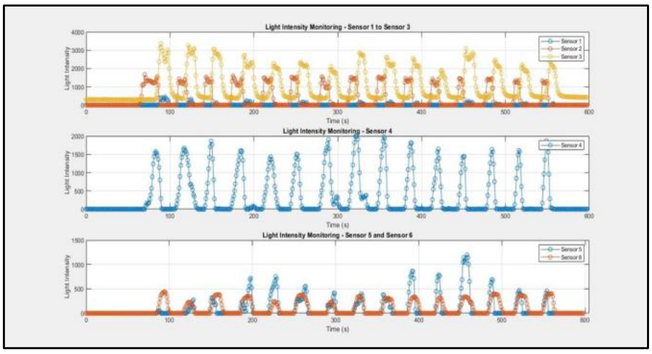

Fig. 15. Normal Gait Pattern (Subject 2 with Flat Foot).

4.2 Abnormal Gait and Rehabilitation Progress

Subject 3 is undergoing rehabilitation for tissue injury due to a motorcycle accident. The subject with a tissue injury demonstrated significant deviations from normal gait patterns during the early rehabilitation sessions, which were clearly captured by the wearable optical fiber sensors. In day 1, the subject exhibited an uneven stride and irregular walking rhythm, characteristic of impaired gait function. The pressure data indicated abnormally high readings from Sensors 2 and 4, located at the heel, while minimal pressure was detected across the forefoot sensors (Sensors 1, 3, 5, and 6). This pattern suggests that the subject was relying heavily on the heels for support, likely to avoid discomfort or instability in the forefoot. Additionally, the time-series plot revealed noticeable spikes in stride timing, indicating inconsistent step intervals and suggesting the presence of limping behaviour. This uneven loading pattern reflects the subject's compensation strategy to reduce discomfort or avoid placing pressure on the injured area. The abnormal pressure distribution during this initial session is illustrated in Figure 16, generated using MATLAB.

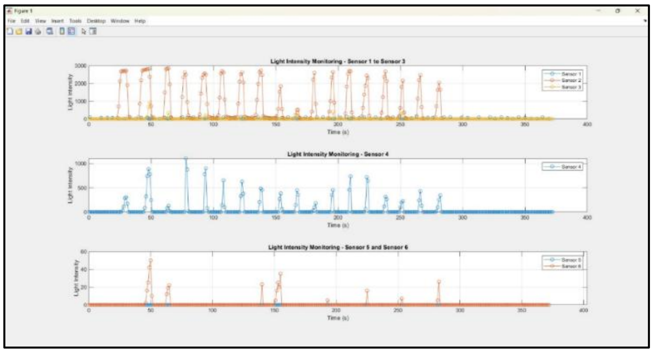

Fig. 16. Day 1 Walking Trial (Subject 3 with Tissue Injury).

In day 4, slight improvements were observed as the walking rhythm became more consistent, though the stride length remained shorter than normal. Despite some reduction in heel pressure, spike patterns in the stride timing persisted, indicating that the subject continued to limp, albeit with less severity compared to the first session. The pressure distribution, along with the reduced magnitude of stride spikes, is shown in Figure 17, highlighting early signs of rehabilitation progress.

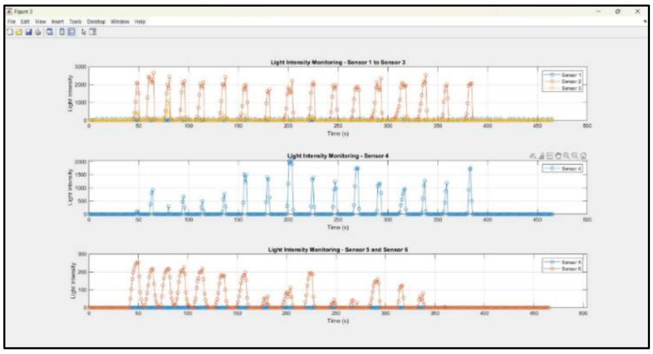

Fig. 17. Day 4 Walking Trial (Subject 3 with Tissue Injury).

By day 7, the subject's walking rhythm improved further, and an increase in stride length was noted. Importantly, the forefoot sensors began to register meaningful pressure responses, suggesting re-engagement of the forefoot during walking and reduced dependence on the heels. The reduction of stride spikes during this session indicates a decline in limping behaviour, demonstrating a positive recovery trend. This progress is visualized in Figure 18, showing forefoot activation and a more balanced pressure profile.

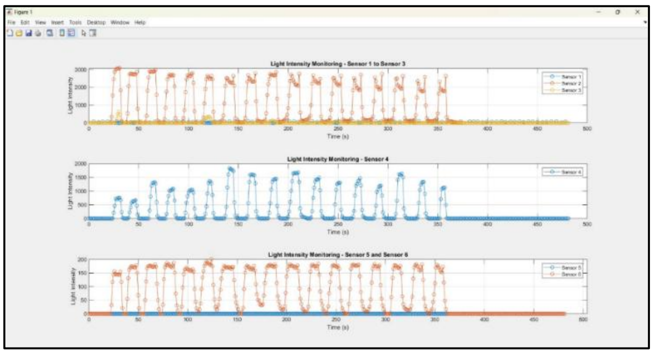

Fig. 18. Day 7 Walking Trial (Subject 3 with Tissue Injury).

In day 11, significant pressure was recorded by Sensor 3, located in the forefoot area, indicating full re-engagement of the forefoot in the gait cycle. The stride pattern appeared smoother, with the absence of spike anomalies, reflecting the subject's return to a more normal walking pattern. These improvements are evident in Figure 19, which presents the pressure profile and time-series data for the final rehabilitation session. Overall, the data reflects steady progress, with measurable reductions in limping and improvements in both pressure distribution and gait rhythm over time.

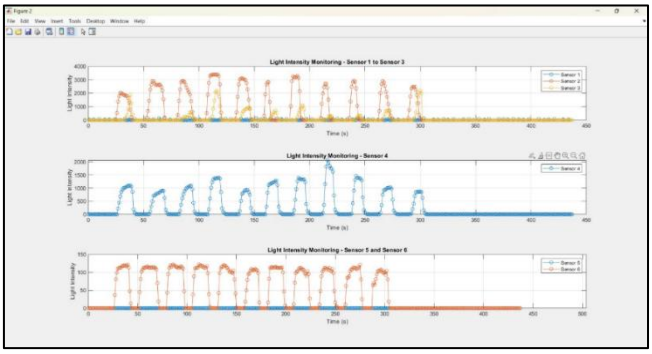

Fig. 19. Day 11 Walking Trial (Subject 3 with Tissue Injury).

4.3 Decision Tree Classification Accuracy

The decision tree classifier trained on these readings successfully identified and classified:

i. Gait phases
ii. Injury-induced abnormalities
iii. Recovery stages

Accuracy was measured against ground truth from physiotherapist evaluations. Classification accuracy was observed 80% for normal and recovering subjects. Figure 20 depicts the rehabilitation of Subject 3 throughout day 1 – day 11 from Decision Tree. Over the course of the rehabilitation period, the subject’s gait remained abnormal until Day 11. The output from the machine learning model can verify the results for Subject 3, confirming the progression and ensuring that the rehabilitation efforts are effectively on track to achieve the desired outcome by the end of the period. The 'normal' condition at Day 0 serves as the benchmark for recovery. This finding aligns with the goal of using the machine learning model to detect such abnormalities in real-time, which can be crucial for early detection and intervention in rehabilitation settings.

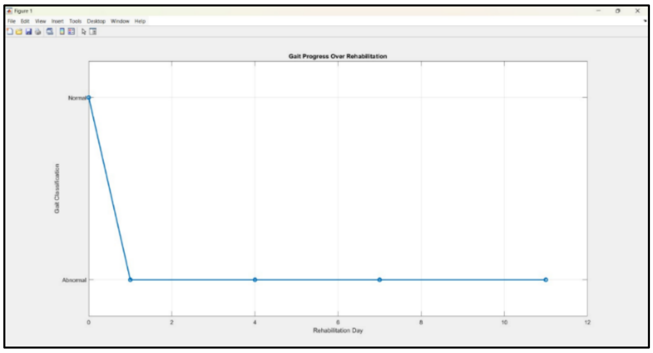

Fig. 20. Subject 3 Rehabilitation Progress from Decision Tree (Day 1 – Day 11).

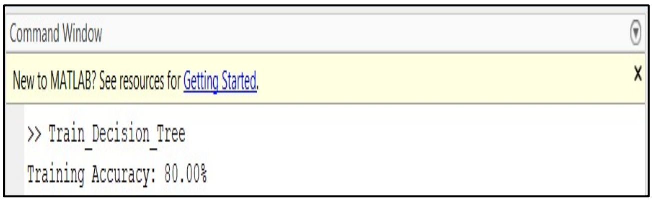

Fig. 21. Decision Tree Training Accuracy.

Figure 21 illustrates the decision tree training accuracy, which stands at 80%. This means that the model correctly predicted the gait classification (normal or abnormal) 80% of the time, reflecting its reliability in classifying the subjects' gait patterns. For the normal subjects, Subject 1 and Subject 2, multiple trial samples were utilized to train the model, capturing a broad range of movements and conditions. In contrast, for the abnormal subject (Subject 3), the model was trained using four trial samples taken from Day 1 to Day 11 of the rehabilitation period. This approach allowed the model to assess the progression of gait abnormalities over time and ensure accurate predictions based on different stages of rehabilitation. Improving the model's accuracy from 80% can be achieved through strategies like enhancing feature engineering, increasing data quality and quantity, using cross-validation, tuning hyperparameters, and exploring ensemble methods such as Random Forest or Gradient Boosting. By addressing these factors, the model's performance can be enhanced, resulting in more reliable gait classifications for effective rehabilitation monitoring.

5. Conclusion

The results of this study validated both the strategic placement of the fiber optic sensors within the insole and the effectiveness of the Decision Tree classification model in accurately identifying and categorizing different gait patterns. The fiber optic sensors demonstrated high sensitivity in capturing detailed pressure distribution across various regions of the foot, including the heel, arch, and forefoot areas, which provided reliable input data for gait analysis. The Decision Tree model successfully utilized this sensor data to differentiate between normal and abnormal gait with a high degree of accuracy, highlighting the model's suitability for real-world gait monitoring applications.

In addition, the inclusion of MATLAB-generated visual outputs, such as time-series plots and pressure distribution graphs, significantly enhanced the interpretability of the classification results. These visual tools provided clear, intuitive insights into gait abnormalities and rehabilitation progress, making it easier for clinicians, physiotherapists, and even patients to understand the recovery trajectory. The ability to track gait performance over multiple sessions illustrated the system's potential for continuous, objective rehabilitation monitoring outside of traditional clinical settings.

Overall, the study demonstrates that the integration of fiber optic sensor technology with machine learning and visual feedback tools offers a practical, portable, and non-invasive solution for long-term gait assessment and rehabilitation support in everyday environments.

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