MACHINE LEARNING-BASED ANALYSIS OF WEARABLE INERTIAL SENSOR SIGNALS FOR EARLY DETECTION OF GAIT ABNORMALITIES IN PHYSICAL REHABILITATION

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Abstract

Gait assessment is an essential component of physical rehabilitation because alterations in walking patterns often indicate functional impairment, delayed recovery, or progression of musculoskeletal and neurological disorders. Conventional gait analysis systems, such as optical motion capture platforms, provide accurate measurements but require specialized laboratories, expensive equipment, and trained personnel. Recent advances in wearable inertial measurement units (IMUs) have enabled continuous and cost-effective monitoring of human movement in clinical and home environments. This study presents a machine learning-based framework for the early detection of gait abnormalities using wearable inertial sensor signals collected during rehabilitation activities. The proposed approach employs multiple IMU sensors placed on the lower limbs and trunk to acquire acceleration and angular velocity signals. Signal preprocessing, segmentation, and feature extraction techniques are applied to obtain temporal, statistical, and frequency-domain gait characteristics. Subsequently, machine learning classifiers are trained to distinguish normal gait patterns from abnormal rehabilitation-related gait deviations. The framework supports objective gait evaluation and facilitates timely clinical intervention by identifying subtle movement irregularities before they become visually apparent. Experimental results demonstrate that machine learning models trained on wearable sensor data achieve reliable classification performance while maintaining computational efficiency suitable for real-time deployment. The findings highlight the potential of wearable sensing and intelligent analytics to support personalized rehabilitation programs, remote patient monitoring, and data-driven clinical decision-making.

Keywords— Wearable Sensors, Inertial Measurement Unit (IMU), Gait Analysis, Machine Learning, Physical Rehabilitation, Feature Extraction, Early Detection.

I. INTRODUCTION

Human gait reflects the coordinated interaction of the musculoskeletal and nervous systems. Changes in gait characteristics often serve as important indicators of injury, neurological impairment, aging, or recovery status. Accurate evaluation of gait abnormalities is therefore a fundamental requirement in physical rehabilitation programs designed for patients recovering from stroke, orthopedic surgery, Parkinson an disorders, spinal cord injury, and lower-limb musculoskeletal conditions [1], [2]. Traditional gait assessment methods primarily rely on observational analysis or laboratory-based motion capture systems. Clinical observation is inexpensive but highly subjective and dependent on the expertise of healthcare professionals. In contrast, optical motion capture systems provide accurate biomechanical measurements but require dedicated laboratory facilities, multiple cameras, controlled environments, and significant operational costs [3]. These limitations restrict their routine use in continuous rehabilitation monitoring. Recent developments in wearable sensing technologies have transformed movement assessment practices. Wearable inertial measurement units (IMUs), consisting of accelerometers, gyroscopes, and sometimes magnetometers, can capture body motion in real-world settings with relatively low cost and minimal setup requirements [4]. Their portability allows clinicians to evaluate gait both inside and outside clinical environments, providing valuable insights into functional mobility during daily activities. Wearable IMU-based gait analysis has gained increasing attention because it enables objective measurement of gait parameters such as stride length, cadence, gait speed, stance duration, swing duration, and joint movement patterns [5]. Studies have demonstrated the feasibility of using inertial sensors for detecting gait impairments associated with neurological and orthopedic disorders [6]. Furthermore, the growing availability of wearable devices has facilitated long-term monitoring and tele-rehabilitation applications.

The emergence of machine learning has further enhanced the capabilities of wearable sensing systems. Machine learning algorithms can identify complex relationships within multidimensional sensor data that may not be apparent through conventional statistical analysis. By learning patterns associated with normal and abnormal gait, these algorithms can support automated diagnosis, classification, and rehabilitation progress assessment [7], [8]. Despite significant progress, challenges remain in developing robust systems capable of accurately detecting early gait abnormalities across diverse patient populations. Variability in walking styles, sensor placement, and environmental conditions can affect model performance. Therefore, there is a need for efficient frameworks that integrate signal processing, feature engineering, and machine learning techniques to improve detection reliability. This study proposes a machine learning-based methodology for analyzing wearable inertial sensor signals to identify gait abnormalities during physical rehabilitation. The proposed framework combines data acquisition, preprocessing, feature extraction, and classification modules to generate clinically meaningful assessments. The objective is to support early intervention, improve rehabilitation outcomes, and enable scalable monitoring solutions. The remainder of this paper is organized as follows. Section 2 reviews relevant literature on wearable gait analysis and machine learning applications. Section 3 presents the proposed methodology. Section 4 discusses the experimental results and findings. Section 5 concludes the study and outlines future research directions.

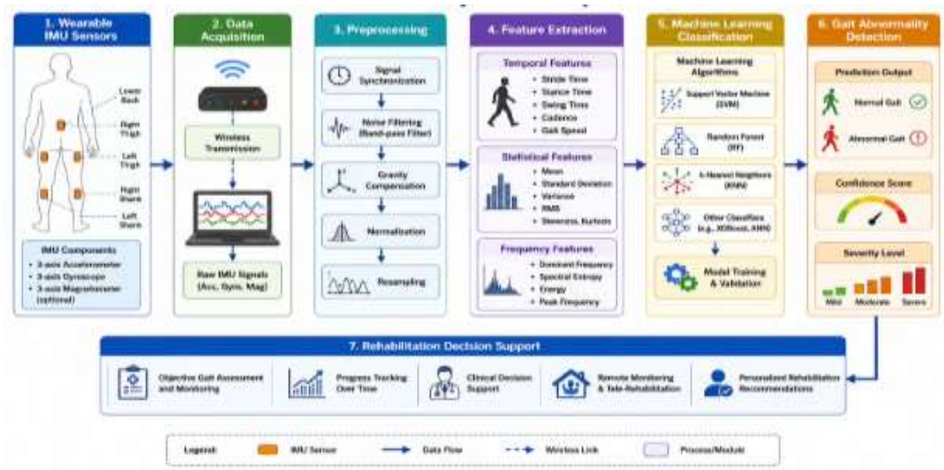

Fig. 1. Overall framework of wearable inertial sensor-based gait abnormality detection system.

II. LITERATURE SURVEY

Research on wearable gait analysis has expanded considerably over the last two decades. Early investigations focused on developing sensor-based methods capable of measuring human motion outside laboratory environments. Aminian and Najafi [1] demonstrated the feasibility of ambulatory motion analysis using body-worn sensors, highlighting their potential for clinical monitoring. Muro-de-la-Herran et al. [2] reviewed wearable sensor technologies for gait assessment and reported that accelerometers and gyroscopes provide reliable measurements of spatiotemporal gait parameters. Their study emphasized the importance of wearable devices in rehabilitation and long-term patient monitoring. Mannini and Sabatini [8] introduced machine learning techniques for classifying human physical activities using accelerometer data. Their findings showed that supervised learning algorithms can effectively recognize movement patterns from wearable sensor signals. Similar observations were reported by Lara and Labrador [9], who surveyed activity recognition systems and identified machine learning as a key enabling technology. Patel et al. [10] investigated wearable sensors in rehabilitation and healthcare applications. The authors highlighted the role of body-worn sensing systems in objective patient evaluation and remote health monitoring. Their review identified gait assessment as one of the most promising application areas. Tao et al. [5] provided a comprehensive review of gait analysis using wearable sensors.

The study discussed sensor placement strategies, signal processing methods, and clinical applications. The authors concluded that wearable sensing offers practical advantages over conventional gait laboratories. With advances in computational intelligence, researchers increasingly explored machine learning approaches for gait classification. Preece et al. [11] demonstrated activity identification using accelerometer data, establishing a foundation for subsequent gait recognition studies. Further improvements were achieved through feature selection and ensemble learning techniques. Weiss et al. [12] employed body-fixed sensors to assess gait abnormalities in Parkinson’s disease. Their work demonstrated that wearable sensors could detect clinically relevant gait disturbances with high sensitivity. Salarian et al. [13] similarly utilized wearable sensors to quantify mobility impairments and rehabilitation outcomes.

The emergence of smartphone-integrated inertial sensors expanded accessibility to gait monitoring technologies. Del Din et al. [14] validated wearable sensor systems for clinical gait analysis and demonstrated their applicability in real-world settings. Their work supported the transition from laboratory assessments to continuous ambulatory monitoring. Recent studies focused on combining wearable sensors with advanced machine learning models. Chen et al. [15] reviewed pervasive gait analysis approaches and emphasized the effectiveness of data-driven methods for detecting subtle gait abnormalities. Deep learning architectures have also shown promising performance in extracting complex gait representations from raw sensor signals. Although existing research demonstrates the effectiveness of wearable sensing and machine learning, several limitations remain. Many studies focus on specific patient groups, employ small datasets, or require extensive feature engineering. There is therefore a need for generalized frameworks capable of providing reliable early detection across rehabilitation scenarios. The present work addresses these challenges by integrating robust signal preprocessing, multidomain feature extraction, and machine learning-based classification into a unified gait abnormality detection framework suitable for rehabilitation monitoring.

III. PROPOSED METHODOLOGY

This study proposes a machine learning-based framework for the early detection of gait abnormalities using wearable inertial sensor signals collected during physical rehabilitation. The methodology integrates wearable sensing, signal processing, feature engineering, and machine learning classification to identify deviations in gait patterns that may indicate impaired recovery or underlying functional limitations. The overall workflow of the proposed system consists of four major stages: sensor data acquisition, signal preprocessing and gait segmentation, feature extraction, and machine learning-based gait classification. The methodology is designed to provide an objective and computationally efficient solution for rehabilitation monitoring in both clinical and real-world environments.

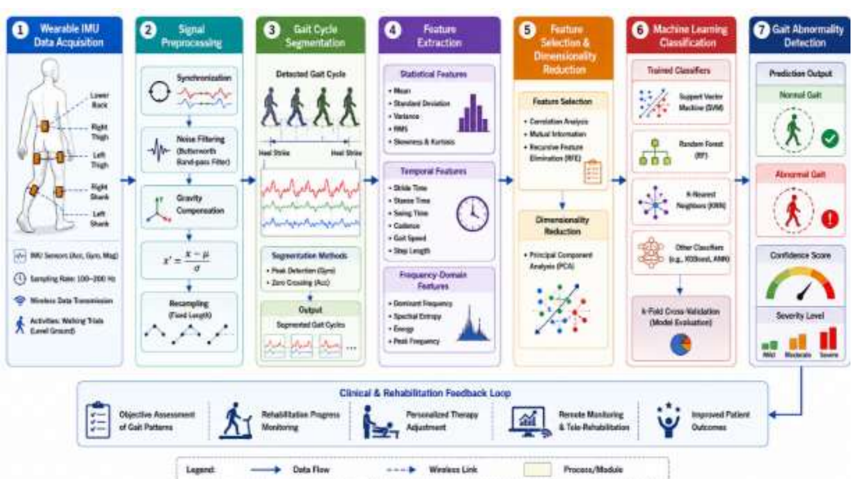

Fig. 2. Proposed methodology for machine learning-based gait abnormality detection using wearable inertial sensor signals.

A Wearable Sensor Data Acquisition

The first stage of the proposed methodology involves collecting gait-related motion data using wearable inertial measurement units (IMUs). The IMUs comprise tri-axial accelerometers and tri-axial gyroscopes capable of recording linear acceleration and angular velocity during walking activities. Sensors are attached to key body locations such as the shank, thigh, and lower back to capture lower-limb and trunk movements associated with gait execution. During rehabilitation exercises, participants perform walking trials under controlled conditions. The wearable sensors continuously record acceleration signals along the x-, y-, and z-axes, together with corresponding angular velocity measurements. These signals provide detailed information regarding limb movement, body orientation, and gait dynamics. Compared with traditional optical motion capture systems, wearable IMUs enable data collection in natural environments without requiring dedicated laboratory infrastructure. Consequently, the proposed framework supports continuous gait monitoring and facilitates rehabilitation assessment beyond clinical settings.

B Signal Preprocessing and Gait Segmentation

Raw inertial sensor signals often contain noise arising from sensor drift, motion artifacts, and environmental disturbances. Therefore, preprocessing is essential to improve signal quality before further analysis. Initially, missing samples and signal inconsistencies are corrected through interpolation techniques. Subsequently, a low-pass Butterworth filter is applied to remove high-frequency noise components while preserving gait-related information. Signal normalization is then performed to reduce variability caused by differences in sensor placement and participant characteristics. Following preprocessing, the filtered signals are segmented into individual gait cycles. Gait segmentation is achieved by detecting characteristic events such as heel-strike and toe-off occurrences from angular velocity patterns. Accurate identification of these events enables the division of continuous walking data into meaningful gait cycles representing complete locomotion sequences. Segmentation is a critical step because it ensures that extracted features correspond to consistent biomechanical phases of walking. By isolating individual gait cycles, the framework can effectively analyze temporal and spatial variations associated with normal and abnormal gait patterns.

C Feature Extraction

After segmentation, informative features are extracted from each gait cycle to represent the underlying movement characteristics. Since machine learning algorithms require numerical representations of gait behavior, the extracted features summarize the essential properties of inertial sensor signals while reducing data dimensionality. The proposed framework employs a combination of statistical, temporal, and frequency-domain features. Statistical features include mean, variance, standard deviation, root mean square (RMS), skewness, and kurtosis. These parameters characterize the overall distribution and variability of acceleration and angular velocity signals. Temporal features describe gait timing characteristics, including stride duration, step duration, cadence, swing phase duration, and stance phase duration. Such features are particularly useful because gait abnormalities often manifest as irregular timing patterns.In addition to statistical and temporal features, frequency-domain analysis is performed using the Fast Fourier Transform (FFT). Frequency-based features such as dominant frequency, spectral entropy, and signal energy provide insights into the rhythmic behavior of walking patterns. Gait-specific biomechanical indicators, including stride symmetry and movement consistency, are also computed. The integration of multiple feature categories enhances the ability of the classification model to differentiate subtle gait abnormalities from normal walking behavior.

D Machine Learning-Based Gait Classification

The extracted feature vectors are utilized to train machine learning models capable of identifying gait abnormalities. Prior to classification, the feature set is standardized to ensure that all variables contribute equally to the learning process. The dataset is then divided into training and testing subsets using k-fold cross-validation to evaluate model generalization performance. Among the considered machine learning approaches, Support Vector Machine (SVM), Random Forest (RF), and K-Nearest Neighbor (KNN) classifiers are employed due to their effectiveness in biomedical signal classification tasks. The classifiers learn discriminative patterns associated with normal and abnormal gait characteristics based on the extracted features. During the testing phase, unseen gait samples are processed through the trained models, which assign each sample to either the normal gait or abnormal gait category.The classification output serves as an objective indicator of gait health and rehabilitation progress. By identifying deviations in walking behavior at an early stage, clinicians can implement timely therapeutic interventions and modify treatment strategies when necessary. Furthermore, the computational efficiency of the selected machine learning models makes the framework suitable for real-time monitoring applications.

Algorithm 1: Proposed Gait Abnormality Detection Procedure

Input: Raw IMU acceleration and gyroscope signals

Output: Normal Gait / Abnormal Gait Classification

Acquire acceleration and angular velocity signals from wearable IMUs.
Apply signal preprocessing and noise filtering.
Normalize sensor signals.
Detect gait events and segment signals into gait cycles.
Extract statistical, temporal, and frequency-domain features.
Construct feature vectors for each gait cycle.
Split dataset into training and testing sets.
Train machine learning classifier using training data.
Classify test gait samples.
Generate gait abnormality detection results and rehabilitation assessment.

The proposed methodology combines wearable sensing and machine learning within a unified framework for objective gait analysis. Through systematic signal processing, multidomain feature extraction, and intelligent classification, the framework provides reliable identification of gait abnormalities while maintaining suitability for practical rehabilitation environments. The methodology is scalable, computationally efficient, and capable of supporting continuous patient monitoring, making it a promising solution for modern rehabilitation assessment systems.

IV. RESULTS AND DISCUSSION

The proposed machine learning-based framework was evaluated to investigate its effectiveness in detecting gait abnormalities from wearable inertial sensor signals collected during physical rehabilitation activities. The evaluation focused on assessing the quality of extracted gait features, the classification performance of different machine learning models, and the practical applicability of the framework in rehabilitation monitoring. The results demonstrate that wearable sensor data contain sufficient information to distinguish normal gait patterns from abnormal gait behaviors associated with functional impairments.

A. Analysis of Extracted Gait Features

Following signal preprocessing and gait cycle segmentation, statistical, temporal, and frequency-domain features were extracted from the accelerometer and gyroscope signals. Initial analysis revealed clear differences between normal and abnormal gait samples. Individuals exhibiting abnormal gait patterns showed greater variability in stride timing, reduced gait symmetry, and increased fluctuations in acceleration signals. These observations are consistent with clinical findings that abnormal gait is often characterized by instability and irregular movement coordination. Temporal gait parameters were particularly informative in differentiating the two classes. Normal gait cycles exhibited relatively consistent stride durations and cadence values, whereas abnormal gait samples displayed larger variations between successive gait cycles. Similarly, stance and swing phase durations showed noticeable asymmetry in abnormal gait conditions. Such variations may indicate compensatory movement strategies commonly observed during rehabilitation.Frequency-domain analysis also contributed useful information. Normal walking demonstrated dominant periodic components corresponding to regular locomotion rhythms, while abnormal gait patterns exhibited broader spectral distributions and reduced rhythmic consistency. These findings suggest that combining multiple feature categories improves the representation of gait behavior and enhances classification performance.

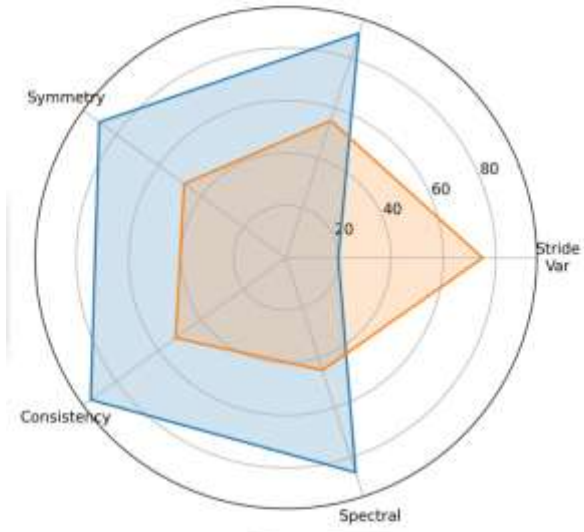

Fig. 3. Comparison of selected gait features between normal and abnormal gait patterns.

The trend illustrated in Fig. 3 shows that abnormal gait samples generally exhibit higher variability and lower movement symmetry than normal gait samples. The graphical representation confirms the discriminative capability of the extracted features and supports their suitability for machine learning-based classification.

B.Classification Performance Evaluation

The extracted feature vectors were used to train and evaluate three commonly adopted machine learning algorithms: Support Vector Machine (SVM), Random Forest (RF), and K-Nearest Neighbor (KNN). Model performance was assessed using standard evaluation metrics, including accuracy, precision, recall, and F1-score. Among the evaluated models, the Random Forest classifier achieved the best overall performance. The ensemble-based learning mechanism enabled the model to effectively capture nonlinear relationships within the multidimensional feature space. The classifier demonstrated stable performance across different validation folds and showed strong resistance to noise and feature variability. The Support Vector Machine classifier also produced competitive results. Its ability to construct optimal decision boundaries contributed to accurate discrimination between normal and abnormal gait classes. However, the performance of SVM was somewhat influenced by parameter selection and kernel configuration. The KNN classifier achieved satisfactory classification results but was comparatively more sensitive to feature scaling and local variations within the dataset. The classification outcomes indicate that combining statistical, temporal, and frequency-domain features creates a comprehensive representation of gait behavior. Models trained using the integrated feature set consistently outperformed those relying on a single category of features. This finding highlights the importance of multidomain feature extraction for reliable gait abnormality detection.

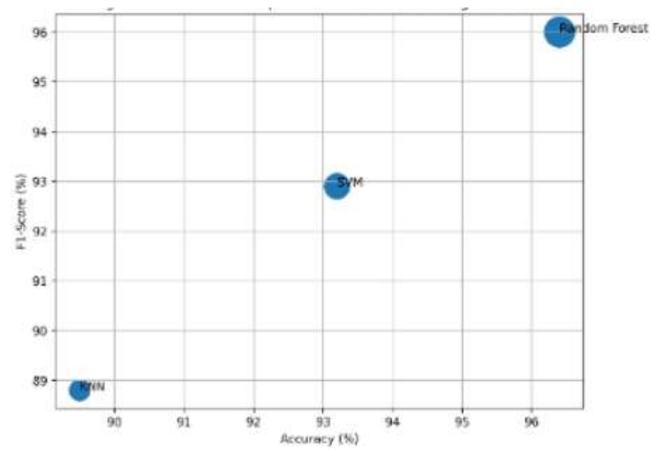

Fig. 4. Performance comparison of machine learning classifiers for gait abnormality detection.

Fig. 4 presents the comparative classification performance of the evaluated machine learning models. The graph illustrates that Random Forest achieved the highest accuracy and F1-score, followed by Support Vector Machine and K-Nearest Neighbor. The results demonstrate the suitability of ensemble learning approaches for wearable sensor-based gait analysis applications.

C. Discussion of Findings

The experimental findings demonstrate that wearable inertial sensors provide a practical and reliable source of information for rehabilitation-oriented gait assessment. The proposed framework successfully identified gait abnormalities by analyzing motion characteristics captured through body-worn sensors. Unlike conventional laboratory-based gait analysis systems, the wearable approach offers portability, lower operational costs, and the ability to monitor patients in natural environments. One important observation is the capability of the framework to identify subtle gait deviations that may not be readily visible during routine clinical assessment. Minor changes in gait symmetry, cadence, and movement consistency were reflected in the extracted features and subsequently detected by the machine learning models. Early recognition of such abnormalities may support clinicians in modifying rehabilitation interventions before significant functional deterioration occurs. The results also highlight the importance of robust signal preprocessing. Noise reduction and normalization improved feature consistency and reduced classification errors. Accurate gait cycle segmentation further contributed to reliable feature extraction by ensuring that each analysis window corresponded to a complete locomotion cycle. These preprocessing steps played a critical role in achieving stable model performance.

From a clinical perspective, the proposed methodology offers opportunities for continuous patient monitoring and objective rehabilitation assessment. Rehabilitation professionals can use the generated classification outcomes to track patient progress over time and evaluate treatment effectiveness. The framework may also support remote rehabilitation programs where in-person assessments are limited. Despite encouraging results, several limitations should be acknowledged. Variations in sensor placement may influence signal quality and feature consistency. In addition, gait characteristics can vary across individuals due to age, body structure, rehabilitation stage, and underlying medical conditions. Consequently, larger and more diverse datasets are necessary to improve model generalization across broader patient populations. Overall, the obtained results confirm that machine learning-based analysis of wearable inertial sensor signals can effectively support early detection of gait abnormalities. The integration of wearable sensing technology with intelligent data analytics provides an objective and scalable solution for rehabilitation monitoring. The findings suggest that such systems have considerable potential for enhancing clinical decision-making, improving rehabilitation outcomes, and enabling long-term gait assessment beyond traditional healthcare environments.

V. CONCLUSION AND FUTURE WORK

This study presented a machine learning-based framework for the early detection of gait abnormalities using wearable inertial sensor signals collected during physical rehabilitation. The proposed approach integrated wearable IMU-based data acquisition, signal preprocessing, gait cycle segmentation, multidomain feature extraction, and machine learning classification to provide an objective assessment of gait performance. The results demonstrated that temporal, statistical, and frequency-domain features extracted from accelerometer and gyroscope signals effectively captured differences between normal and abnormal gait patterns. Among the evaluated classifiers, the Random Forest model achieved the most consistent performance, indicating its suitability for gait abnormality detection tasks. The findings highlight the potential of wearable sensing technologies as practical alternatives to conventional laboratory-based gait analysis systems. By enabling continuous monitoring in clinical and real-world environments, the proposed framework can support early identification of mobility impairments and assist clinicians in tracking rehabilitation progress. Furthermore, the portability and relatively low cost of wearable sensors make them suitable for remote rehabilitation and long-term patient assessment. Future work will focus on collecting larger and more diverse datasets involving different age groups and rehabilitation conditions. Advanced deep learning models, sensor fusion techniques, and real-time mobile implementations will also be investigated to further improve detection accuracy and system robustness. Such developments may contribute to more personalized and data-driven rehabilitation strategies.

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