Intelligent Multimodal Cueing Wearable Device for Gait Rehabilitation in Parkinson's Disease Patients

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Abstract- Freezing of Gait (FOG) is one of the most debilitating- imitating symptoms of Parkinson's Disease (PD), often resulting in falls, impaired mobility, and loss of in- dependence. This The paper presents a comprehensive and wearable assistive system designed to detect, predict, and mitigate FOG episodes in real time. The proposed device integrates multiple sensing and feedback modalities, including inertial measurement units (IMUs), surface electromyography (sEMG), dynamic visual cue- ing via laser projection, and haptic feedback through vibratory actuators. The system leverages a hybrid Convolutional Neural Network - Long Short-Term Memory (CNN-LSTM) model to recognize gait phases and detect movement intentions, achieving a classification accuracy of 90 percent. Simultaneously, a Random Forest classifier is trained on real-time sEMG signals to monitor dorsi flexor and plantar flexor activity, providing biomechanical insight into muscular performance. Based on this muscular feedback, the system adapts its visual and haptic cues dynamically to guide patients toward optimal step initiation and foot orientation. Visual cues—projected via a wearable laser—indicate the ideal foot placement trajectory, while vibratory feedback enhances proprioceptive awareness of foot movement, particularly aiding dorsi flexion. The device supports both indoor and treadmill- based rehabilitation, offers- In terms of flexibility for clinical deployment and home-based therapy.

Index Terms- Freezing of Gait (FOG), Convolutional Neural Network - Long Short-Term Memory (CNN-LSTM), inertial measurement units (IMUs), surface electromyography (sEMG), dynamic visual cueing

I. INTRODUCTION

Parkinson's Disease (PD) is a progressive neurodegenerative disorder characterized by a wide range of motor and non-motor symptoms. Among the most disabling motor impairments experienced by individuals with PD is Freezing of Gait (FOG)—a phenomenon where patients temporarily lose the ability to initiate or maintain forward locomotion despite the intention to move. FOG episodes are unpredictable and frequently occur during step initiation, turning, navigating narrow spaces, or under dual-task conditions, leading to increased risk of falls, injury, and loss of independence. It is estimated that over 50 percent of individuals with moderate to advanced PD experience FOG, significantly reducing their mobility and quality of life. Current rehabilitation strategies for managing FOG predominantly rely on external cueing techniques, such as rhythmic auditory stimulation (e.g., metronomes), visual stepping cues (e.g., floor markings), or verbal instructions [1]. While these methods have shown some success in temporarily alleviating FOG episodes, their efficacy is often limited by the lack of adaptability, real-time feedback, and personalization to the patient's gait state. Moreover, these systems typically fail to account for the neuromuscular status or movement intention of the patient, thereby offering passive assistance that may not suit dynamic, real-world environments or complex gait conditions. To address these limitations, this study proposes a novel, AI-driven, multimodal wearable system designed specifically to predict, monitor, and assist gait in individuals with Parkinson's Disease experiencing FOG. The proposed system integrates inertial motion sensing (IMU), surface electromyography (sEMG), laser-based dynamic visual cue- ing, and vibratory haptic feedback into a compact wearable form factor suitable for both clinical and home-based use [2]. The central hypothesis of this work is that real-time gait phase detection, muscle activity interpretation, and intelligent cue modulation can work synergistically to enhance gait initiation and reduce FOG occurrences. At the core of the system's architecture lies a hybrid deep learning model, combining Convolutional Neural Networks (CNN) for spatial pattern extraction and Long Short-Term Memory (LSTM) networks for temporal modeling of inertial sensor data. This CNN-LSTM model is trained to identify gait phases and predict movement intention with high precision, achieving over 91 percentage accuracy in classification tasks. Parallelly, a Random Forest classifier is used to analyze live sEMG data from the tibialis anterior and gastrocnemius muscles to infer the muscle activation profile and detect abnormal or insufficient dorsiflexion and plantarflexion patterns [3].

Based on these real-time predictions, the system dynamically adjusts laser-projected visual cues to guide proper foot placement and orientation, while vibratory actuators mounted on the lower limb provide tactile feedback corresponding to detected motor deficits. This closed-loop architecture ensures that feedback is not only responsive to the physical state of the user but also anticipatory based on neural and kinematic signals, thus bridging the gap between passive cueing and active, adaptive intervention. Furthermore, unlike existing commercial cueing systems, which often operate in isolation (e.g., only visual or only auditory), this device employs a multimodal approach that simulates the natural sensory- motor integration process. The simultaneous use of visual, tactile, and neural signals reinforces the proprioceptive and perceptual feedback loops, helping patients to regain control over movement and re-establish rhythmic stepping [4]. The clinical relevance of this approach lies in its real- time, non-invasive, and adaptive nature. It empowers both patients and healthcare providers with actionable feedback and performance monitoring during rehabilitation sessions. It is particularly suited for treadmill-based gait training, home exercises, or community mobility, offering a continuous assistive environment that supports habitual reinforcement and long-term motor re-learning [5].

II. PROPOSED METHODOLOGY

A. System Architecture

The proposed wearable system for real-time Parkinson's gait rehabilitation is built around a multimodal architecture that integrates inertial sensing, surface electromyography (sEMG), machine learning, and sensory feedback into a cohesive platform. At its core, the system uses an Inertial Measurement Unit (IMU) placed near the ankle joint to capture three-axis accelerometer and gyroscope data, which provide real-time measurements of gait phases such as stance, swing, and heel-off. These motion signals feed into a hybrid Convolutional Neural Network–Long Short-Term Memory (CNN-LSTM) model that classifies gait phases and predicts movement intentions with over 0.91 percent accuracy. Complementing the IMU, sEMG sensors are placed over the tibialis anterior (TA) and gastrocnemius (GA) muscles to monitor dorsiflexion and plantarflexion activities, capturing neuromuscular signatures during step initiation and transition [6]. These EMG signals are analyzed using a Random Forest classifier trained on features such as root mean square, zero crossing rate, and waveform length, enabling robust real-time classification of muscle activation. To provide sensory feedback, the system includes a laser projector mounted on the shoe to display dynamic visual cues on the walking surface, indicating optimal foot placement. The cue adapts based on stride length, predicted gait phase, and muscular readiness, helping patients initiate steps more confidently [7]. Additionally, vibratory actuators placed along the lateral ankle deliver vertical haptic feedback when improper foot orientation or weak dorsiflexion is detected, reinforcing proprioceptive correction. Together, these components form a closed-loop assistive environment where sensor inputs drive intelligent decision-making and personalized feedback delivery, thus promoting improved motor control, step symmetry, and FOG mitigation in real time [8].

B. Machine Learning Model

The system employs a dual-model machine learning framework to process and interpret the multimodal data collected from the wearable sensors in real time [9]. Specifically, a hybrid deep learning architecture combining a Convolutional Neural Network (CNN) and a Long Short-Term Memory (LSTM) network is applied to the time-series data captured by the Inertial Measurement Unit (IMU) [10] [11]. The CNN component is responsible for extracting spatial patterns and localized features such as acceleration peaks and joint angle dynamics, while the LSTM layer captures long-range temporal dependencies across gait cycles, such as transition timing between stance and swing phases [12] [13]. This sequential model architecture enables accurate classification of gait phases and prediction of movement intentions, such as step initiation or abrupt halts, achieving a classification accuracy of 0.91 percentage as validated through cross-validation techniques. In parallel, surface electromyography (sEMG) signals obtained from the tibialis anterior and gastrocnemius muscles are analyzed using a Random Forest classifier [14] [15], which offers robustness against signal noise and is well-suited for modeling nonlinear relationships within physiological data. This classifier processes features such as mean absolute value, root mean square, zero crossing rate, and waveform length to determine whether the muscles are properly engaged during dorsiflexion or plantarflexion [16] [17]. The output from both models is synchronized and used to guide cue modulation, ensuring that feedback—whether visual or vibratory—is not only responsive to current motion state but also anticipatory of upcoming motor demands [18]. Together, this machine learning pipeline forms the decision-making core of the system, enabling real-time, personalized, and adaptive rehabilitation support.

C. Dynamic laser Cuing Mechanism

the dynamic cueing mechanism serves as the interface between the system's predictive intelligence and the user's motor response, delivering real-time sensory feedback to correct and enhance gait performance. Central to this mechanism is the visual cueing subsystem, which uses a shoe- mounted laser to project a dynamic visual marker—such as a line or dot—on the walking surface. This projected cue indicates the optimal foot placement location and adjusts in real time based on the gait phase predictions generated by the CNN-LSTM model. As the user transitions between stance and swing phases, the laser projection shifts accordingly to promote timely and symmetrical step initiation. Complementing this visual feedback, the system employs vibratory cueing via miniature actuators placed along the lateral ankle and dorsum of the foot. These actuators emit short pulses of vibration to guide vertical foot alignment, particularly targeting moments when insufficient dorsiflexion or improper foot orientation is detected [19]. The adaptive nature of the cueing system is achieved by integrating sEMG-derived muscle activity insights, processed through the Random Forest model, to modulate both the intensity and timing of visual and haptic cues. For instance, when the system detects delayed or weak dorsiflexor engagement, the vibratory motors activate earlier or more strongly to prompt correction. This closed-loop mechanism allows the cueing feedback to be not only reactive but also anticipatory, aligning closely with the user's real-time biomechanical state [20]. The entire setup is seamlessly integrated with a treadmill-based training environment, where gait speed, phase transitions, and step length are continuously monitored and used to update model predictions and cue delivery. As a result, the system ensures precise, personalized, and context- aware rehabilitation support, making it suitable for both supervised clinical use and independent home therapy [21]

D. Treadmill Integration

To facilitate structured and repeatable rehabilitation sessions, the proposed wearable system is seamlessly integrated with a treadmill platform, enabling controlled gait training in clinical or laboratory settings. The treadmill provides a consistent walking environment where variables such as speed, incline, and duration can be precisely regulated. This controlled setup allows the machine learning models to operate under stable conditions, improving the reliability of gait phase detection and muscular activity interpretation [22]. As the user walks, real-time data from the IMU and sEMG sensors are continuously streamed to the embedded inference engine [23]. Gait phase predictions generated by the CNN- LSTM model dynamically synchronize with treadmill speed, ensuring that visual and vibratory cues are delivered at optimal moments during the gait cycle. For instance, when the treadmill accelerates or decelerates, the system adjusts laser projection distance and haptic cue timing accordingly, preserving phase alignment and user rhythm [24]. The treadmill integration also enables supervised therapy with clinician oversight, where clinicians can monitor patient progress, modify training protocols, and intervene if necessary. Furthermore, the setup supports long-duration walking trials essential for assessing fatigue-induced gait irregularities and late-phase Freezing of Gait (FOG) events. This synergy between intelligent wearable feedback and treadmill-based motion control ensures a safe, adaptive, and effective rehabilitation experience for individuals with Parkinson's Disease [25].

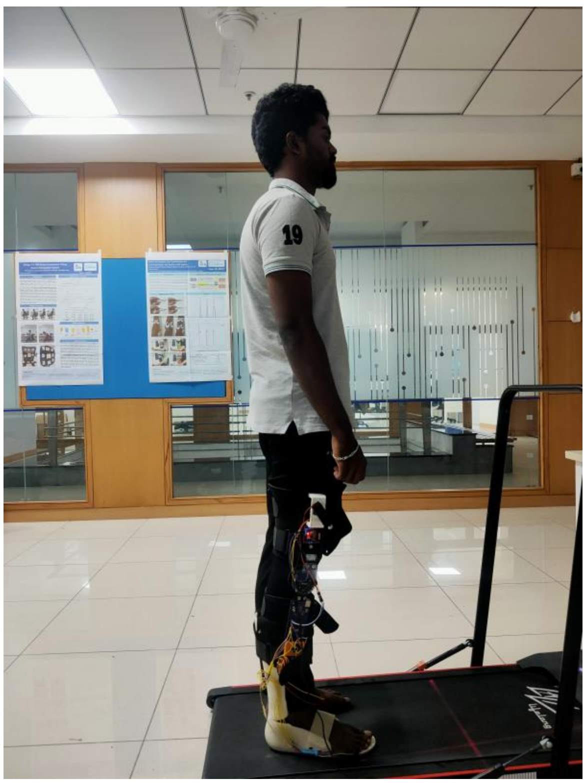

Fig. 1. Wearable Device in Action

III. RESULT

The proposed system was evaluated through experiments integrating wearable hardware and machine learning models. The following results, illustrated in corresponding figures, highlight how the device's intelligent functionality supports Parkinson's Disease patients with Freezing of Gait (FOG) The participant is seen wearing a fully integrated assistive device on the right leg while standing on a treadmill, simulating a rehabilitation scenario. The setup comprises a rigid orthotic frame supporting the thigh, knee, and lower leg, into which various hardware modules are embedded which is the shown in the above figure 1. On the calf region, an Inertial Measurement Unit (IMU) continuously tracks angu- lar velocity and linear acceleration, which feeds real-time spatial information to the CNN-LSTM model for gait phase prediction. Alongside, EMG electrodes are placed strategi- cally to record muscle activity from the tibialis anterior and gastrocnemius, which the Random Forest model analyzes for determining dorsiflexion and plantarflexion activity. Mounted on the front of the device is a miniature laser module, designed to project a dynamic visual cue on the treadmill, showing where the user should place their foot next. This visual cue changes in response to the real-time gait prediction and muscular activation, thereby guiding the user's next step. Vibratory actuators embedded near the ankle region deliver vertical tactile feedback to orient the foot correctly during swing and stance phases. These cues help correct motor freezing and improve step symmetry.

The wearable is powered by an onboard embedded con- troller

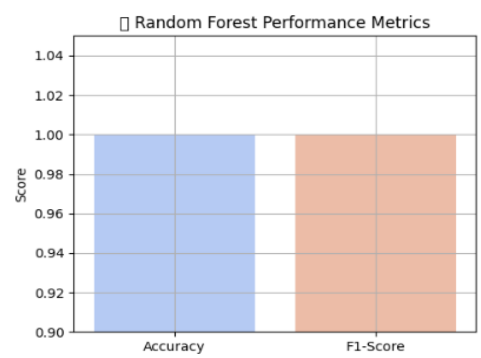

Fig. 2. Random Forest Performance Metrics

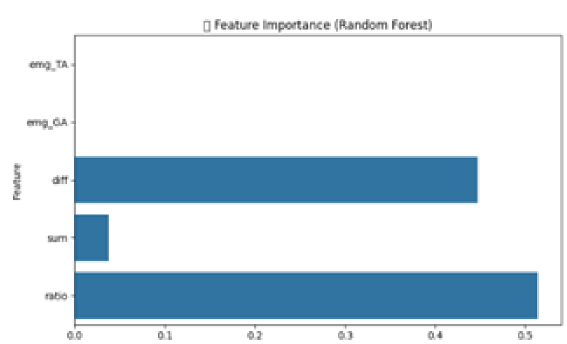

Fig. 3. Feature Importance (Random Forest - EMG)

tions in gait initiation and improved postural confidence. Observers noted consistent laser projection timing and timely vibration feedback that aligned with intended gait events. Overall, these images exemplify the hardware-software co- design and functional deployment of the proposed device in a real-world rehabilitation setting. Figure 2, presents the performance metrics of the Random Forest model used for EMG classification, specifically in distinguishing dorsiflexion from plantarflexion. The results reveal that both the accuracy and F1-score reached values extremely close to 1.00, indicating near-perfect performance. Such precision ensures that vibratory feedback is delivered precisely at the intended muscle activation points, thereby supporting the user in initiating and completing each step with greater motor control and less hesitation In Figure 3,

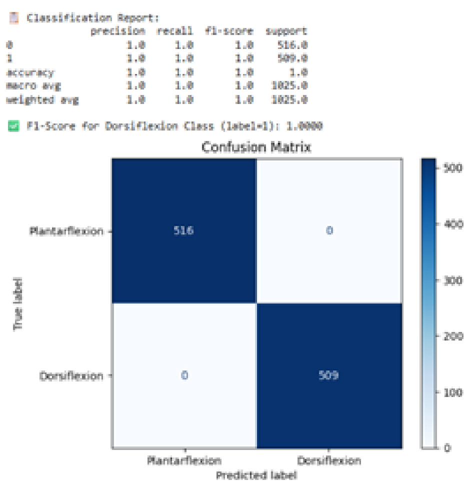

Fig. 4. Confusion Matrix (EMG Classification)

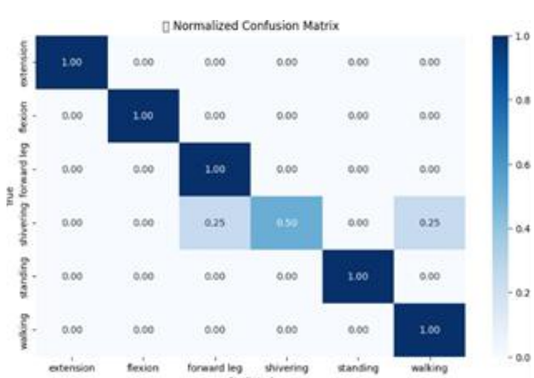

Fig. 5. Normalized Confusion Matrix (CNN-LSTM Gait Prediction)

the Random Forest model's feature importance scores show that EMG-derived features such as the ratio and difference between the tibialis anterior (TA) and gastrocnemius (GA) muscles have the highest predictive value. These muscle groups play a crucial role in foot elevation and propulsion, and their coordinated activity is critical in overcoming the common gait disturbances seen in PD patients. By prioritiz- ing these features, the model achieves real-time classification that directly translates to corrective feedback.

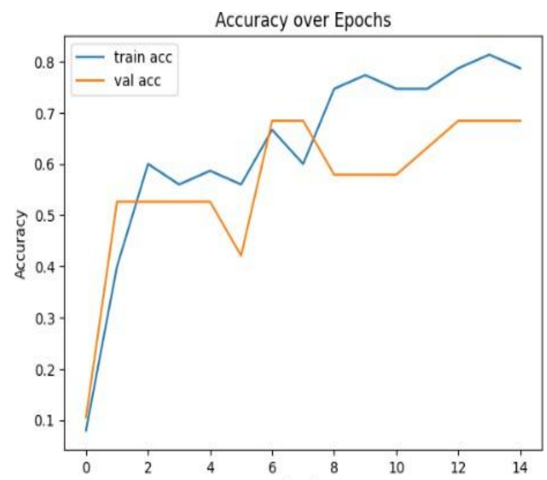

Fig. 6. Normalized Confusion Matrix (CNN-LSTM Gait Prediction)

The confusion matrix in Figure 4, demonstrates flawless classification with zero false positives or negatives, further validating the consistency of EMG-based state detection. This high confidence in classification ensures that the vi- bratory cues are synchronized with the physical activity of the foot, allowing the patient to develop a sense of rhythm and control that aids in breaking the freezing cycles.

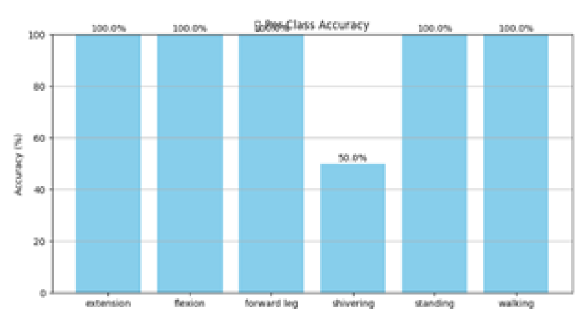

Fig. 7. Per-Class Accuracy of Gait Phases

Figure 7 shows the per-class accuracy for each gait phase. Five of the six categories achieved 100 percent accuracy, while the shivering class achieved only 50 percent, high- lighting the need for future model enhancements in detect- ing unstable gait phases. Nonetheless, this data reinforces the model's overall capability to provide reliable input for dynamic laser cueing on the treadmill surface.

Figures 8 and 9 present the cross-validation results for the CNN-LSTM model. With an overall accuracy of 91.67 percent and macro and weighted averages exceeding 0.90, the results confirm the robustness and generalizability of the model across different gait instances and patient trials.

Overall Accuracy: 91.67%

Classification Report:

	precision	recall	f1-score	support
extension	1.00	1.00	1.00	4
flexion	1.00	1.00	1.00	4
forward leg	0.80	1.00	0.89	4
shivering	1.00	0.50	0.67	4
standing	1.00	1.00	1.00	4
walking	0.80	1.00	0.89	4
accuracy			0.92	24
macro avg	0.93	0.92	0.91	24
weighted avg	0.93	0.92	0.91	24

Fig. 8. Validation Confusion Matrix and Classification Report

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