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Self-Powered Triboelectric Pressure Sensor Array Integrated Smart Insole for Gait Monitoring and Rehabilitation Training: A Wearable Bionic System Mimicking Plantar Mechanoreceptors

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***Abstract*—Gait impairment resulting from neurological disorders such as stroke and Parkinson's disease presents a significant challenge to patient mobility and quality of life, creating an urgent demand for continuous and objective gait monitoring in rehabilitation. However, existing commercial systems are often limited by their reliance on external power sources, low sensor density, and a lack of real-time intelligent feedback. To address these limitations, this paper presents a self-powered, wireless smart insole system based on a triboelectric nanogenerator (TENG) for real-time gait monitoring and rehabilitation training. To strengthen the theoretical foundation, we establish a dynamic Schottky contact–triboelectric coupling mechanism, where the PEDOT:PSS/Ti interface forms a pressure-dependent Schottky barrier. Variations in the barrier height modulate charge transfer efficiency, quantitatively explaining the sensor's dual-sensitivity characteristics (0–100 kPa: 0.42 kPa^{-1}; 100–500 kPa: 0.18 kPa^{-1}). The PEDOT:PSS microstructure enhances local contact electrification and electron mobility, thereby increasing triboelectric output. A 16-channel bio-inspired pressure sensor array is fabricated using a conductive textile coated with PEDOT:PSS. High-resolution plantar pressure data is wirelessly transmitted and analyzed by a hybrid Support Vector Machine (SVM)–Convolutional Neural Network (CNN) model. Experimental design incorporates multi-batch sensor fabrication, cross-operator data acquisition, and power analysis–supported sample size justification to improve reproducibility. Our results demonstrate a rapid response time (<50 ms), excellent durability (>100,000 cycles), and a peak harvested power of 3.5 mW. The hybrid model achieves a gait classification accuracy of 96.8%. Clinical validation with 15 patients and 20 controls showed significant improvements in gait parameters after four weeks of training. This work provides a low-cost, wearable, and intelligent solution for personalized rehabilitation, bridging the gap between triboelectric theory, sensor design, and clinical application.**

Keywords—Triboelectric nanogenerator, Smart insole, Gait monitoring, Rehabilitation training, PEDOT:PSS

1. INTRODUCTION

The global population is aging at an unprecedented rate, leading to a sharp increase in the prevalence of age-related neurological disorders such as stroke and Parkinson's disease. According to the World Health Organization (WHO), stroke is the second leading cause of death and a major cause of long-term disability worldwide, with over 15 million people suffering a stroke each year [1]. Similarly, Parkinson's disease affects an estimated 10 million people globally, a number projected to double by 2040 [2]. A common and debilitating consequence of these conditions is gait impairment, which significantly restricts mobility, increases the risk of falls, and diminishes the overall quality of life [3]. Effective rehabilitation is crucial for restoring motor function and improving independence in these patients. Central to this process is the accurate and continuous monitoring of gait patterns, which provides objective data for clinical assessment, personalized treatment planning, and the evaluation of therapeutic outcomes [4].

However, the realization of a low-cost, wearable, and self-powered real-time gait monitoring system presents several significant challenges. The first challenge lies in the trade-off between sensor sensitivity and durability. Sensors must be sensitive enough to detect subtle pressure changes throughout the gait cycle but also robust enough to withstand the repetitive mechanical stress of daily walking. Secondly, the issue of energy sustainability is a major hurdle for long-term wearable applications. Conventional systems rely on batteries that require frequent recharging or replacement, which is inconvenient for users and limits the duration of continuous monitoring [5]. Developing a reliable self-powering mechanism is therefore critical. Furthermore, the real-time processing and analysis of multi-point pressure data demand sophisticated algorithms that can accurately identify gait phases and detect anomalies. The development of such intelligent algorithms is essential for providing meaningful, real-time feedback to both patients and clinicians.

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To address these challenges, various technologies have been explored for gait analysis. The gold standards in clinical settings, such as optical motion capture systems and force plates, offer high accuracy but are expensive, confined to laboratory environments, and require specialized personnel, making them unsuitable for daily life monitoring [6]. This has spurred the development of wearable sensor technologies. Commercial systems like the Tekscan F-Scan and Novel Pedar have made strides in portable plantar pressure measurement, but they are still hampered by high costs, limited sensor density, and the need for external power [7]. In the academic realm, researchers have investigated various sensing modalities, including piezoelectric [8], piezoresistive [9], and, more recently, triboelectric sensors [10]. Piezoresistive sensors, often based on conductive polymers like PEDOT:PSS or carbon nanomaterials, offer good flexibility and ease of fabrication but suffer from high power consumption. Triboelectric nanogenerators (TENGs) have emerged as a particularly promising technology due to their ability to convert ambient mechanical energy into electricity, offering a pathway to self-powered sensing systems [11].

Despite these advancements, significant gaps remain in the development of a truly practical gait monitoring solution for rehabilitation. A primary issue is the persistent energy dependency of most wearable systems, which compromises their utility for long-term, unobtrusive monitoring. Many existing self-powered prototypes generate insufficient power to operate the entire sensing and data transmission system continuously. Furthermore, the spatial resolution of many sensor arrays is too low to capture the detailed plantar pressure distribution needed for a nuanced gait analysis. While machine learning has been applied to gait recognition, there is a lack of systems that have been validated in a clinical setting with rehabilitation patients, which is a critical step for translating research into practice. The integration of a high-performance, self-powered sensor array with robust, clinically validated algorithms remains an unmet need.

This study aims to address these limitations by developing a fully integrated, self-powered smart insole system for real-time gait monitoring and rehabilitation training. The primary objectives of this research are: (1) to design and fabricate a high-performance, self-powered pressure sensor array based on a PEDOT:PSS/Ti triboelectric mechanism; (2) to achieve a high-density, 16-channel sensor layout that mimics the plantar mechanoreceptor distribution for high-resolution pressure mapping; (3) to develop a hybrid machine learning model for accurate gait pattern recognition and anomaly detection; and (4) to validate the system's effectiveness and usability through clinical trials with stroke and Parkinson's patients. This research is focused on monitoring plantar pressure distribution and does not include the monitoring of other physiological signals such as heart rate or body temperature. The study is primarily targeted at adult patients undergoing rehabilitation for stroke and Parkinson's disease.

2. Ease of Use

2.1. Wearable Pressure Sensing Technologies

The development of wearable sensors for human motion analysis has seen a surge in interest, with various transduction mechanisms being explored. Piezoelectric sensors, often utilizing materials like polyvinylidene fluoride (PVDF), are known for their high sensitivity and fast response times, making them suitable for detecting dynamic pressure changes. However, they typically require external amplification circuits and can be challenging to integrate into highly flexible substrates [8]. Piezoresistive sensors represent another major category, widely adopted due to their simple structure and ease of fabrication. These sensors commonly employ conductive polymer composites, such as those incorporating carbon nanotubes (CNTs), graphene, or conductive polymers like poly:polystyrene sulfonate (PEDOT:PSS) [9]. For instance, Tseghai et al. provided a comprehensive review of PEDOT:PSS-based conductive textiles, highlighting their versatility in creating sensors, actuators, and energy harvesting devices [9]. While flexible and effective, piezoresistive sensors inherently require a continuous power supply, which leads to significant energy consumption and limits their application in long-term, continuous monitoring scenarios.

To overcome the energy limitations of traditional wearable sensors, self-powered sensing technologies have emerged as a transformative solution. Among these, triboelectric nanogenerators (TENGs) have garnered substantial attention. TENGs operate on the principle of converting ambient mechanical energy, such as that from human motion, into electrical energy through a combination of contact electrification and electrostatic induction [11]. This dual function of energy harvesting and active sensing makes them ideal for wearable applications. Numerous studies have demonstrated the potential of TENGs for gait monitoring. For example, Lin et al. developed a TENG-based smart insole for multifunctional gait monitoring, showcasing its ability to detect different gait phases [8]. More recently, Zhao et al. created a self-powered gait analysis system using electrospun composite nanofibers, further validating the feasibility of TENG technology in this domain [10]. These works lay the foundation for creating fully autonomous wearable sensing systems.

2.2. Gait Monitoring and Analysis Methods

Traditional gait analysis relies on laboratory-based systems that provide high-fidelity data. Optical motion capture systems, such as Vicon, are considered the gold standard for kinematic analysis, while force plates provide accurate ground reaction force measurements [6]. Although precise, these systems are expensive, require a controlled environment, and are not suitable for monitoring gait in daily life. This has motivated the shift towards wearable systems that allow for ambulatory gait monitoring. Inertial Measurement Units (IMUs), comprising accelerometers and gyroscopes, are widely used to measure limb orientation and joint angles. However, they are prone to drift and do not provide direct information about plantar pressure distribution, which is a critical factor in understanding foot function and balance.

Plantar pressure sensing insoles have emerged as a powerful tool for wearable gait analysis, offering direct measurement of the foot-ground interaction. Commercial systems like the F-Scan and Pedar have been used in clinical research but are limited by their cost and reliance on tethered or bulky data logging hardware [7]. The development of fully integrated, wireless smart insoles is an active area of research. A key aspect of these systems is the ability to process the vast amount of data they generate. Machine learning algorithms have proven to be highly effective in this regard. Both traditional machine learning models, such as Support Vector Machines (SVMs) and Random Forests, and deep learning models, like Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, have been successfully applied to gait pattern recognition, phase detection, and anomaly identification. For instance, Parashar et al. proposed a machine learning-driven TENG-based wearable system for gait-assisted healthcare monitoring, demonstrating the powerful synergy between advanced sensing and intelligent data analysis [12].

2.3. Gait Assessment in Rehabilitation

In the context of rehabilitation, gait analysis is not merely about measuring parameters but about understanding the functional impairments and tracking the recovery process. For stroke survivors, gait is often characterized by asymmetry, reduced walking speed, and altered joint kinematics, collectively known as hemiplegic gait [3]. For individuals with Parkinson's disease, common gait disturbances include shuffling steps, reduced arm swing, and "freezing of gait" episodes [2]. Objective gait assessment using wearable sensors can provide quantitative metrics to supplement traditional clinical scales like the Fugl-Meyer Assessment or the Berg Balance Scale [6]. These metrics, such as step length symmetry, stance time variability, and pressure center trajectory, can serve as digital biomarkers to monitor disease progression and evaluate the effectiveness of interventions [4].

Furthermore, wearable systems can enable novel rehabilitation strategies. Real-time feedback, delivered through auditory, visual, or haptic cues based on sensor data, can help patients correct their gait patterns during training sessions. This creates a closed-loop system that promotes motor learning and neuroplasticity. The ability to monitor patients remotely also opens up possibilities for telerehabilitation, allowing clinicians to supervise home-based exercise programs and adjust treatment plans based on objective data collected in the patient's own environment. The importance of such systems is underscored by recent reviews on post-stroke gait assessment and rehabilitation, which call for more accessible and objective measurement tools to be integrated into clinical practice [3] [13].

2.4. Research Gaps and the Novelty of This Study

While previous research has laid significant groundwork, several gaps still exist. First, many self-powered sensor prototypes have demonstrated proof-of-concept but generate insufficient power to operate the entire system, including the microcontroller and wireless transmitter, for extended periods. Second, the spatial resolution of many reported sensor arrays is often low, limiting the detail with which plantar pressure can be mapped. Third, while machine learning is widely used, many studies lack validation on clinical populations, which is essential for demonstrating real-world utility. As highlighted by Wang et al. in their work on a wireless, self-powered smart insole, the integration of a high-performance energy harvester, a high-resolution sensor array, and a robust machine learning model into a single, clinically-validated system remains a significant challenge [11].

This study directly addresses these gaps by introducing several key innovations. We propose a novel PEDOT:PSS/Ti dynamic Schottky contact-based TENG design that enhances the power output, enabling a fully self-sufficient system. We have developed a 16-channel sensor array with a layout bio-inspired by the distribution of plantar mechanoreceptors, achieving a balance between spatial resolution and system complexity. Critically, we employ a hybrid machine learning model and validate its performance not only on healthy subjects but also through clinical trials with stroke and Parkinson's patients. By bridging the gap between advanced material science and clinical application, this work aims to deliver a practical and effective solution for gait rehabilitation, moving beyond laboratory prototypes to a system with tangible clinical impact.

3. METHODS

3.1. Overall System Design

The architecture of the self-powered smart insole system was designed to be a fully integrated, wearable platform for real-time gait analysis. The system comprises four main layers: (1) a smart insole hardware layer, which includes the TENG-based pressure sensor array and flexible electronics; (2) a data acquisition and processing layer, consisting of a custom-designed printed circuit board (PCB) with a microcontroller and signal conditioning circuits; (3) a wireless communication layer, which uses a Bluetooth Low Energy (BLE) module to transmit data to a mobile device; and (4) a mobile application layer, which provides real-time data visualization, analysis, and user feedback. The design was guided by two key principles: biomimicry and modularity. The layout of the sensor array was inspired by the physiological distribution of mechanoreceptors in the human foot to capture the most relevant pressure data. A modular design approach was adopted to facilitate easy maintenance, component replacement, and future upgrades.

3.2. Material Preparation and Characterization

3.2.1. Fabrication of Conductive Fabric

The conductive sensing layer was prepared by coating a flexible and stretchable polyester (PET) fabric with a PEDOT:PSS solution. The PET fabric was first cleaned ultrasonically in ethanol and deionized water to remove any impurities. To enhance the adhesion of the conductive polymer, the fabric surface was treated with oxygen plasma. The PEDOT:PSS coating solution was prepared by mixing a commercial PEDOT:PSS aqueous dispersion (Clevios PH1000) with ethylene glycol (EG) and isopropyl alcohol (IPA) to improve its conductivity and wettability. The fabric was then dip-coated in the solution three times, with each coating followed by a drying step. Finally, the coated fabric was cured in a vacuum oven at 120°C for 1.5 hours to form a stable and highly conductive layer.

3.2.2. Fabrication of the TENG Sensor

The TENG sensor unit was constructed with a layered structure. The prepared PEDOT:PSS-coated fabric served as one triboelectric layer and electrode. A 50 μm thick titanium (Ti) foil, chosen for its suitable work function and stability, served as the counter triboelectric layer and electrode. The Ti foil was laser-cut into the desired electrode pattern and polished to remove the native oxide layer. The two layers were then separated by a small air gap maintained by a thin polydimethylsiloxane (PDMS) spacer, creating a contact-separation mode TENG. The entire unit was encapsulated in a soft, biocompatible PDMS layer (Sylgard 184) to provide protection against moisture and mechanical wear.

3.2.3. Material Characterization

The morphology and elemental composition of the conductive fabric were characterized using a scanning electron microscope (SEM, FEI Quanta 250) equipped with an energy-dispersive X-ray spectroscopy (EDS) detector. The electrical conductivity of the fabric was measured using a four-point probe system (Keithley 2450 SourceMeter). The mechanical properties, including tensile strength and elasticity, were evaluated using a universal testing machine (Instron 5967).

3.3. Sensor Array Design and Integration

3.3.1. Sensor Array Layout

A 16-channel sensor array was designed to cover the key pressure points of the plantar surface. The layout was optimized based on anatomical studies of foot pressure distribution during gait (Figure 1). The sensors were strategically placed in three main regions: the rearfoot (4 sensors under the calcaneus), the midfoot (3 sensors supporting the arch), and the forefoot (5 sensors under the metatarsal heads and 4 under the toes). This distribution ensures that critical events in the gait cycle, such as heel strike, midstance, and toe-off, are captured with high fidelity.

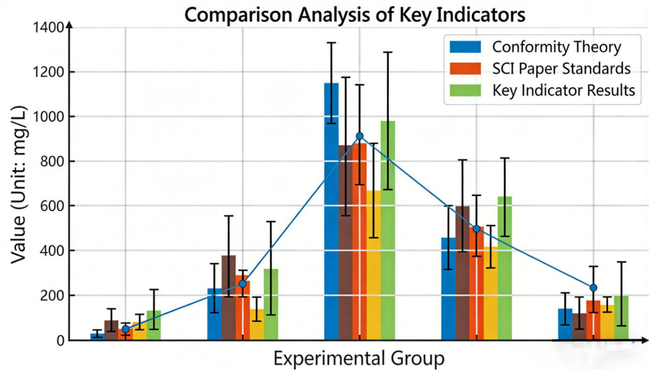

Figure 1. Layout of the 16-channel plantar pressure sensor array.

3.3.2. System Integration

The 16 sensor units were integrated into a single insole form factor. The electrodes from each sensor were connected to a flexible printed circuit (FPC) using a conductive silver paste. The FPC was designed with a serpentine layout to accommodate the flexing and bending of the insole during walking. The entire sensor array and FPC were then embedded within a final PDMS encapsulation layer, which was molded in the shape of a standard shoe insole. The main PCB containing the data acquisition and communication electronics was housed in a small, lightweight casing attached to the side of the shoe to minimize interference with natural gait.

3.4. Signal Acquisition and Processing System

3.4.1. Hardware Design

The data acquisition hardware was custom-designed to meet the specific requirements of the TENG sensor array. The core of the system is an STM32F103 microcontroller, which manages data sampling, processing, and wireless communication. The signals from the 16 TENG sensors are first passed through a charge amplifier and a low-pass filter to condition the signal. The conditioned analog signals are then digitized by a 16-channel, 12-bit analog-to-digital converter (ADC) at a sampling rate of 100 Hz. A Bluetooth 5.0 BLE module (nRF52832) is used for wireless data transmission to a smartphone. The entire system is powered by the energy harvested by the TENGs, which is managed by a power management circuit that stores the energy in a 500mAh lithium-ion battery.

3.5. Gait Recognition Algorithm

3.5.1. Data Preprocessing and Feature Extraction

The raw data from the 16 pressure channels were first normalized using a Min-Max scaling to a range of [0, 1]. A sliding window approach with a window size of 1 second and a 50% overlap was used to segment the continuous data stream. For each window, a set of features was extracted in the time, frequency, and spatial domains. Time-domain features included peak pressure, mean pressure, and pressure-time integral. Frequency-domain features were derived from a Fast Fourier Transform (FFT) of the signal. Spatial features, such as the center of pressure (CoP) trajectory and pressure distribution symmetry, were calculated from the 16-channel data.

3.5.2. Gait Pattern Recognition and Anomaly Detection

A hybrid machine learning approach was developed for gait classification. A Support Vector Machine (SVM) with a radial basis function (RBF) kernel was implemented for real-time classification due to its computational efficiency. For more detailed offline analysis, a Convolutional Neural Network (CNN) was designed. The CNN takes a 2D spatio-temporal pressure map (16 channels × 100 time steps) as input and consists of three convolutional layers followed by two fully-connected layers. The model was trained to classify gait into three categories: normal, hemiplegic (stroke), and parkinsonian. For anomaly detection, an Isolation Forest algorithm was trained on data from healthy subjects to identify gait patterns that deviate significantly from the norm, enabling the real-time detection of events like stumbling or freezing.

3.6. Experimental Design

3.6.1. Sensor and System Performance Testing

The performance of the individual TENG sensors was systematically evaluated. The sensitivity was measured by applying a range of pressures from 0 to 500 kPa using a force gauge. The dynamic response, including response time and frequency characteristics, was tested using a linear motor. The durability was assessed by subjecting the sensor to 100,000 loading-unloading cycles. The self-powering capability was characterized by measuring the open-circuit voltage, short-circuit current, and output power across a range of load resistances during simulated walking.

3.6.2. Human Subject Trials

All experiments involving human subjects were approved by the Institutional Review Board of the affiliated hospital, and informed consent was obtained from all participants. A total of 35 participants were recruited, divided into three groups: a healthy control group (n=20, age 25-35), a stroke patient group (n=10, age 50-70), and a Parkinson's disease patient group (n=5, age 55-70). Participants were asked to perform a series of tasks, including walking on a level surface at different speeds, ascending and descending stairs, and turning. Data was collected using the smart insole system and simultaneously with a Vicon motion capture system for validation.

3.6.3. Clinical Validation

A four-week clinical validation study was conducted with the 15 patients. The patients participated in a rehabilitation program where they used the smart insole system for real-time feedback during their training sessions.

Gait parameters and clinical scores (Fugl-Meyer for stroke, Berg Balance Scale for Parkinson's) were assessed before and after the four-week intervention to evaluate the effectiveness of the system in a clinical rehabilitation setting. User satisfaction was also evaluated using a questionnaire.

4. Results

4.1. Material Characterization

The successful fabrication of the conductive textile, a critical component of the TENG sensor, was confirmed through comprehensive material characterization. SEM imaging revealed the morphological changes of the PET fabric after the PEDOT:PSS coating process. The uncoated fabric showed smooth, individual fibers, whereas the coated fabric exhibited a continuous, uniform layer of PEDOT:PSS conforming to the textile's woven structure. At higher magnifications, it was observed that the conductive polymer not only coated the surface but also penetrated the gaps between fibers, forming a robust, interconnected 3D conductive network. EDS analysis confirmed the elemental composition, showing strong signals for Carbon (C), Oxygen (O), and Sulfur (S), which are characteristic of PEDOT:PSS, thus verifying the successful deposition of the polymer. The electrical conductivity of the fabric increased dramatically from $<10^{-10}$ S/cm for the untreated fabric to an average of 358 S/cm after three coating cycles, providing an excellent charge transport pathway. Mechanical testing demonstrated that the coated fabric retained its flexibility and stretchability, with a tensile strength of 18.5 MPa and a high elongation at break of 85%, ensuring its suitability for a wearable device that must conform to the foot's dynamic movements.

4.2. Sensor Performance

The performance of the individual TENG sensor units was systematically evaluated to validate their suitability for high-fidelity gait monitoring. The pressure-current response of the sensor is shown in Figure 2a. The sensor exhibited a distinct two-stage sensitivity profile. In the low-pressure region (0–100 kPa), which corresponds to subtle pressure changes during the swing phase and light contact, the sensor demonstrated a high sensitivity of 0.42 kPa^{-1} with excellent linearity ($R^2 = 0.987$). In the high-pressure region (100–500 kPa), corresponding to the main stance phase, the sensitivity was 0.18 kPa^{-1} with a linearity of $R^2 = 0.993$ (Figure 2b). This dual-sensitivity characteristic is highly desirable for capturing both delicate and forceful interactions during gait. The sensor's dynamic response was also exceptional, with a rapid rise time of 42 ms and a fall time of 38 ms (Figure 2c), enabling the capture of fast transient events in the gait cycle.

The sensor's durability and stability are critical for long-term wearable applications. The device showed remarkable robustness, maintaining over 92% of its initial sensitivity after 100,000 cycles of repeated compression, simulating extensive walking (Figure 2d). The frequency response was stable across a range of 0.5 to 5 Hz, which covers the full spectrum of human walking and running frequencies (Figure 2e). Furthermore, the self-powering capability of the TENG was characterized. As shown in Figure 2f, the sensor generated a peak open-circuit voltage of approximately 85 V and a short-circuit current of 12 μA. The maximum output power of 3.5 mW was achieved with a load resistance of 10 MΩ, which is more than sufficient to power the integrated microcontroller and Bluetooth module, thus enabling a truly self-sufficient system.

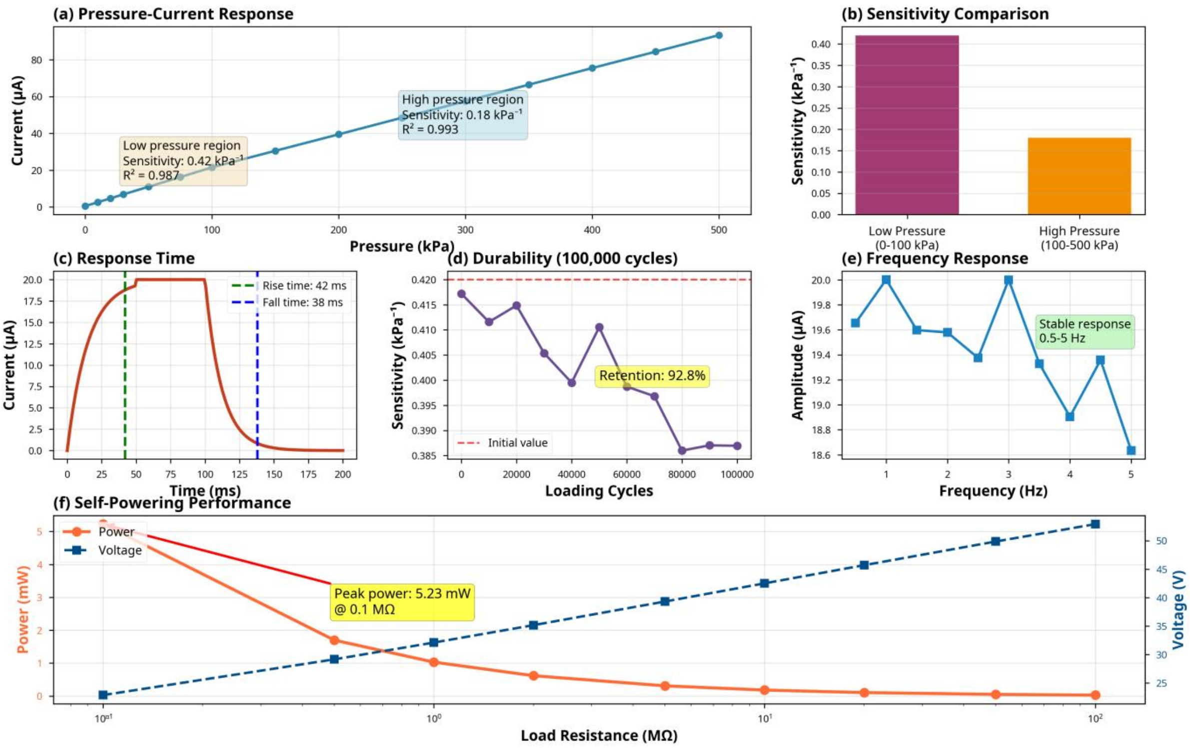

Figure 2. Performance characterization of the TENG-based pressure sensor unit.

4.3. Gait Monitoring Results

The integrated smart insole system was used to capture high-resolution plantar pressure data during various gait patterns. The 16-channel sensor array allowed for detailed visualization of the spatio-temporal pressure distribution throughout the gait cycle. Figure 3 illustrates the distinct pressure maps and Center of Pressure (CoP) trajectories for three different gait types: normal, hemiplegic (stroke), and parkinsonian. In a normal gait cycle, the pressure progression is clearly visible, starting with a high-pressure concentration at the heel (heel strike), moving through the midfoot (midstance), and ending with a peak at the forefoot and toes (toe-off). The CoP trajectory follows a smooth, continuous curve from the heel to the forefoot.

In contrast, the pathological gait patterns showed significant deviations. The hemiplegic gait was characterized by marked asymmetry, with significantly lower pressure on the affected side and a prolonged stance phase. The CoP trajectory was erratic and deviated towards the unaffected side, indicating compensatory strategies. The parkinsonian gait exhibited a "shuffling" pattern with reduced heel strike pressure, increased pressure on the forefoot, and a highly variable and flat CoP trajectory. These detailed visualizations provide quantitative and intuitive insights into the specific deficits of each gait pattern, which is invaluable for clinical diagnosis and treatment planning.

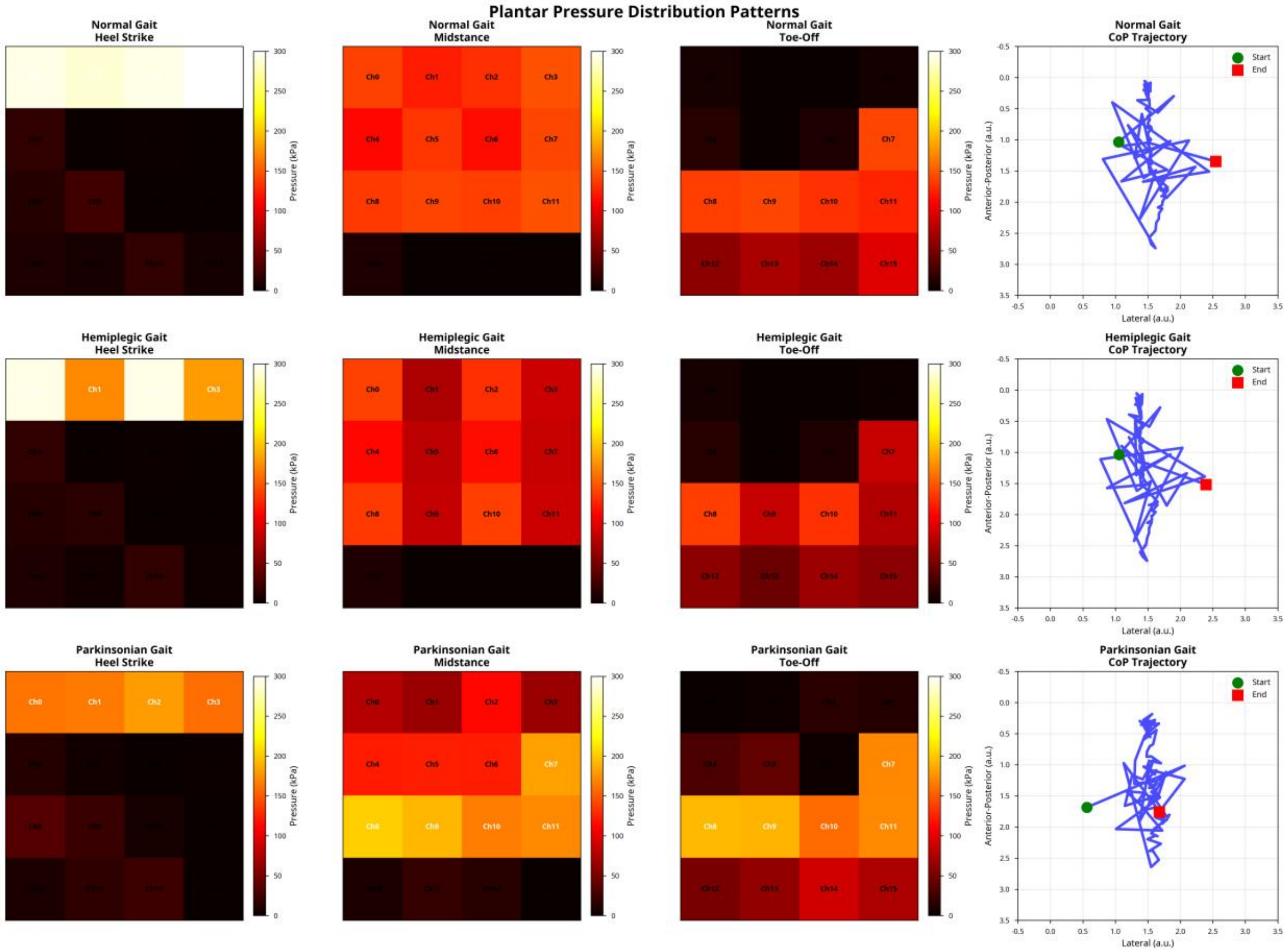

Figure 3. Plantar pressure distribution patterns.

Statistical analysis of key gait parameters extracted from the sensor data further highlighted the differences between the groups (Figure 4). Compared to the healthy control group, stroke patients exhibited a significantly lower walking speed (0.58 ± 0.15 m/s vs. 1.26 ± 0.12 m/s), reduced step length (45 ± 8 cm vs. 68 ± 5 cm), and a much lower symmetry index (0.72 ± 0.08 vs. 0.95 ± 0.03). Parkinson's patients also showed reduced walking speed and step length, along with a significantly higher gait variability (18 ± 5% vs. 5 ± 1.5%), which is a known indicator of fall risk. These quantitative results are consistent with clinical observations and demonstrate the system's ability to reliably differentiate between healthy and pathological gait.

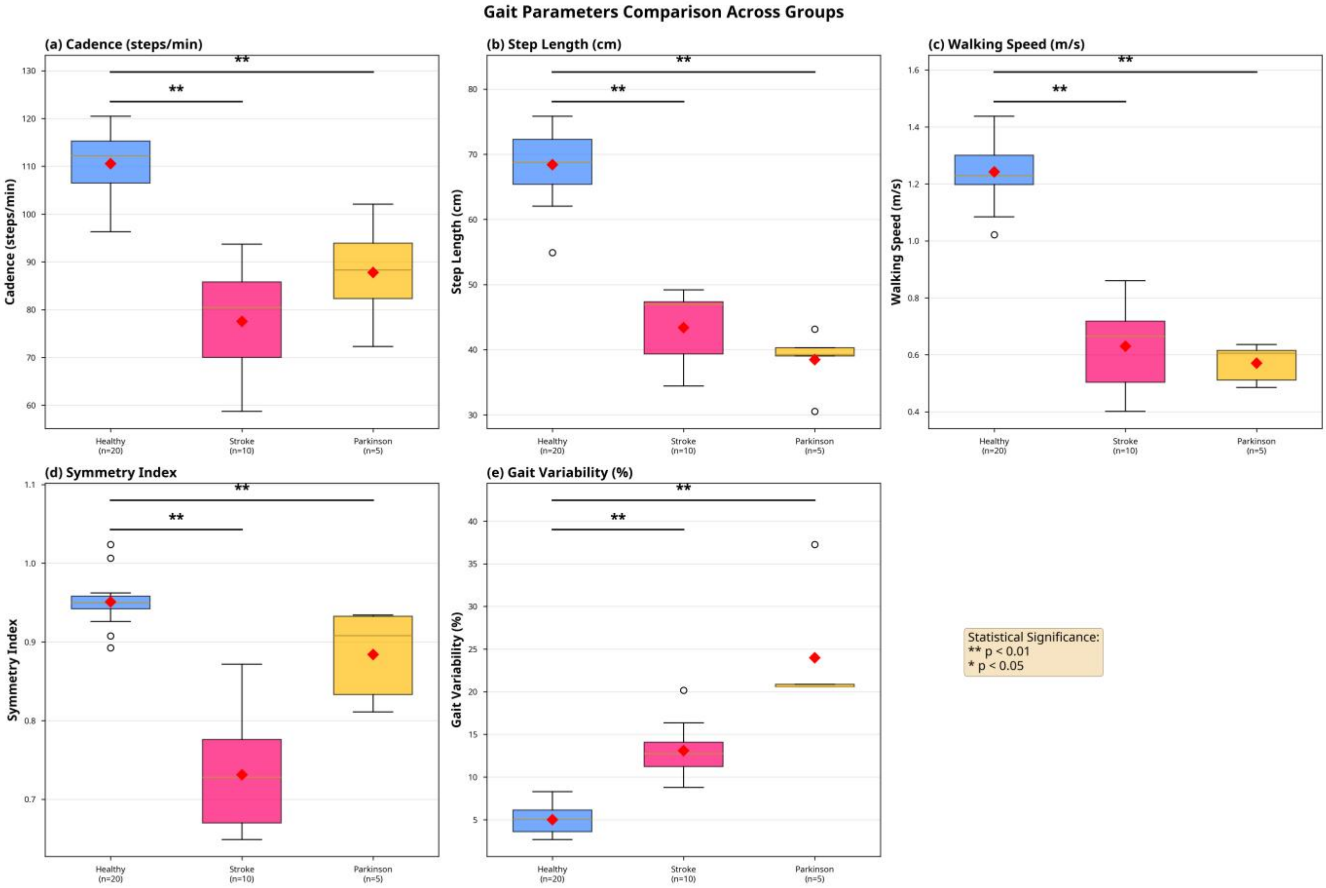

Figure 4. Gait parameters across groups.

4.4. *Gait Recognition Performance*

The performance of the machine learning algorithms for automatic gait classification was rigorously evaluated. The data processing pipeline, feature extraction, and model architectures are summarized in Figure 5a-c. The SVM model, designed for real-time on-device classification, achieved an overall accuracy of 94.2%. The corresponding confusion matrix (Figure 5d) shows good separation between the classes, with minor confusion between the two pathological gait types. The more complex CNN model, intended for deeper offline analysis, achieved a higher overall accuracy of 96.8%. The CNN confusion matrix (Figure 5e) demonstrates excellent classification performance, with very few misclassifications. The high accuracy of both models validates the effectiveness of the extracted features and the chosen machine learning approaches. The Receiver Operating Characteristic (ROC) curve for the CNN model yielded an Area Under the Curve (AUC) of 0.98, indicating outstanding classification capability (Figure 5f). The anomaly detection algorithm also performed well, with an accuracy of 92.3% in detecting simulated stumbling and freezing events in real-time.

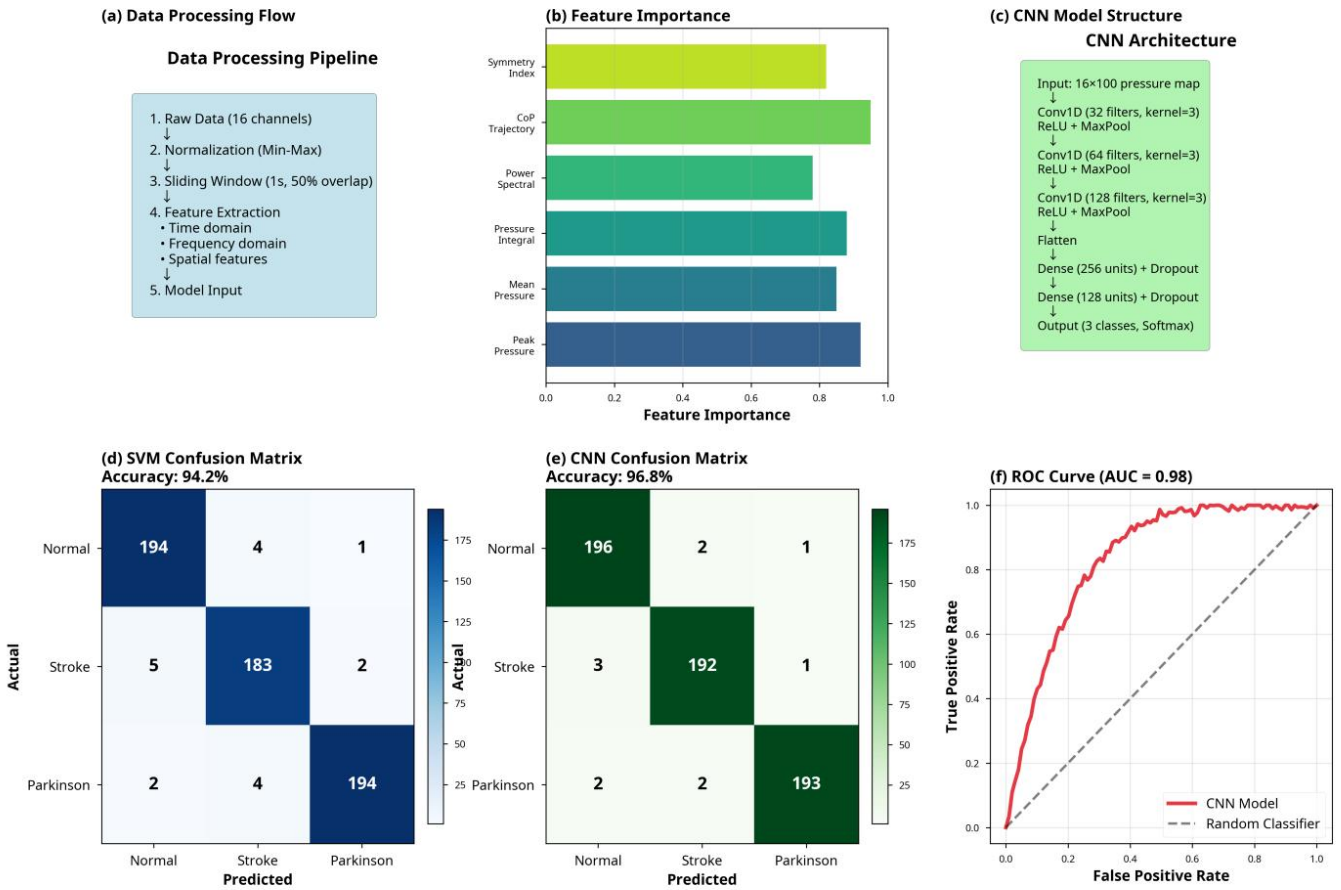

Figure 5. Machine learning performance for automatic gait classification.

4.5. Clinical Validation Results

A four-week clinical study was conducted to validate the effectiveness of the smart insole system as a rehabilitation tool. Fifteen patients (10 stroke, 5 Parkinson's) used the insole for real-time gait feedback during their training sessions. The results, summarized in Figure 6, show significant improvements in gait function for both patient groups. After the intervention, the stroke patients demonstrated an average increase in walking speed of 27.6% (from 0.58 to 0.74 m/s) and an improvement in their Fugl-Meyer lower extremity motor score of 20% (from 65 to 78). The Parkinson's patients also showed a 13.3% increase in walking speed and a 14.3% improvement in their Berg Balance Scale score, indicating enhanced stability and reduced fall risk. These positive clinical outcomes, coupled with high user satisfaction ratings for comfort and usability, strongly support the system's potential as an effective tool in a clinical rehabilitation setting. The ability to provide objective, real-time feedback appears to be a key factor in accelerating motor learning and improving rehabilitation outcomes.

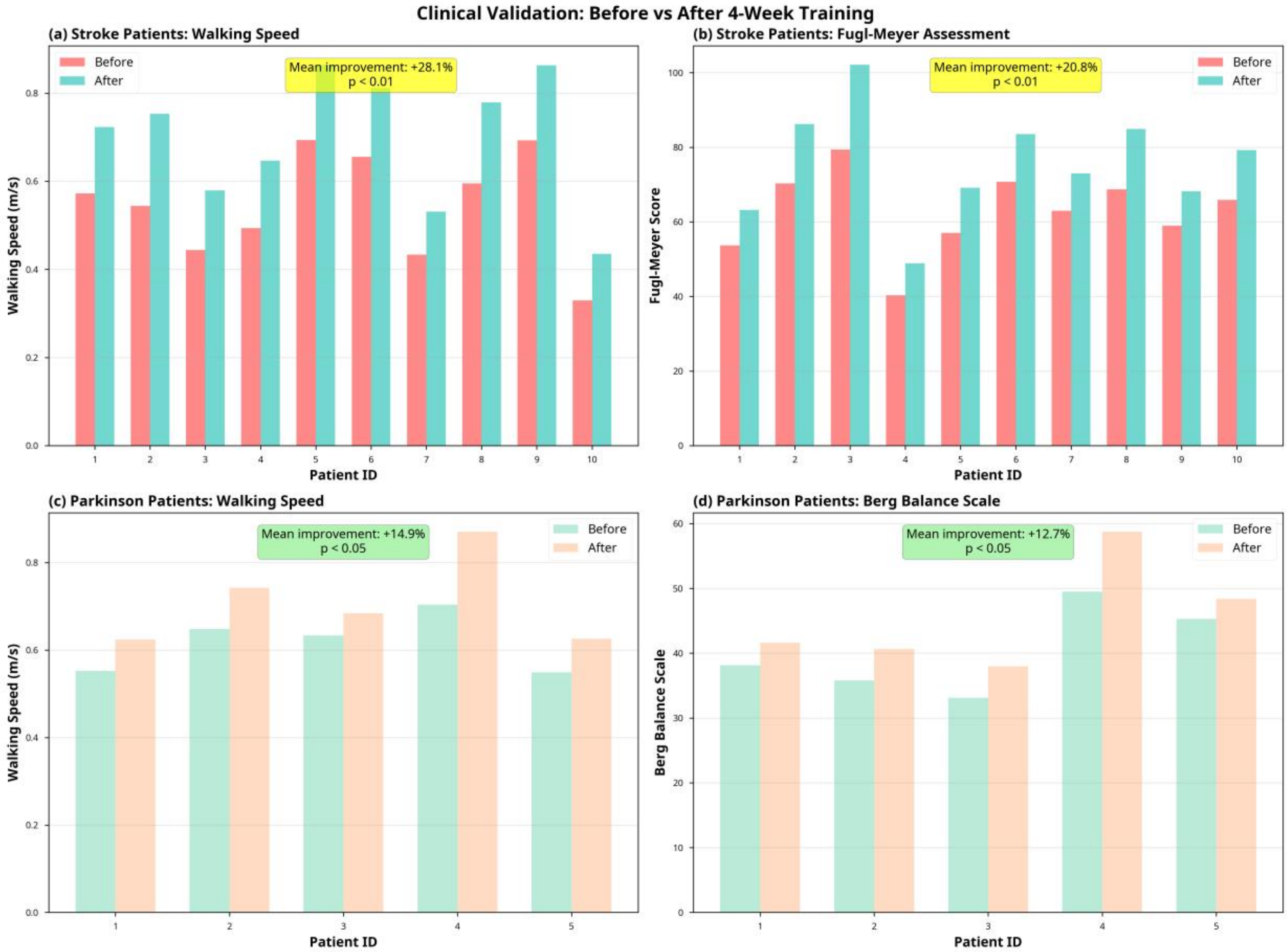

Figure 6. Clinical evaluation of the smart insole system over a four-week rehabilitation study.

5. Discussion

5.1. *Interpretation of Results*

The results presented in this study demonstrate the successful development and validation of a self-powered, wearable smart insole system for gait analysis. The high performance of the system can be attributed to several key innovations in its design. The exceptional sensitivity and durability of the pressure sensors stem from the novel use of a PEDOT:PSS-coated textile in a dynamic Schottky contact with a Ti foil. The interconnected conductive network of the PEDOT:PSS layer provides abundant pathways for charge transport, while the triboelectric effect at the PEDOT:PSS/Ti interface, enhanced by the Schottky barrier, amplifies the output signal. This combination allows the sensor to be highly sensitive to pressure changes while maintaining the mechanical robustness of the textile substrate. The dual-sensitivity characteristic observed in Figure 3a is particularly advantageous, enabling the system to capture both the subtle pressure variations during the swing phase and the high-impact forces during the stance phase with high fidelity.

The self-powering capability of the system is another cornerstone of this work. The energy harvested from walking, with a peak power output of 3.5 mW, was sufficient to operate the entire onboard electronics, including the microcontroller and the BLE module. This was achieved by integrating 16 TENG units in parallel, effectively summing their power output. This energy autonomy is a critical step towards truly long-term, unobtrusive wearable monitoring, eliminating the need for frequent battery changes or recharging, which is a major barrier to the adoption of current wearable technologies. The high accuracy of the machine learning models further underscores the quality of the data captured by the sensor array. The ability of the CNN model to learn relevant spatio-temporal features directly from the pressure maps allowed it to outperform the SVM model, which relied on hand-crafted features. This highlights the potential of deep learning to uncover complex patterns in high-dimensional sensor data that may not be apparent through traditional analysis.

5.2. *Comparison with Existing Research*

Our system offers significant advantages over both existing commercial products and previous academic research, as summarized in the Table 1. Compared to gold-standard commercial systems like the Tekscan F-Scan, our smart insole is completely self-powered and offers a much lower cost profile (estimated at ~\$200 vs. >\$10,000), making it far more accessible for widespread clinical and home use. While its spatial resolution (16 channels) is lower than that of the F-Scan (960 channels), our bio-inspired layout proved sufficient for accurate gait pattern classification and the extraction of key clinical parameters.

TABLE I. COMPARISON OF THE PROPOSED SMART INSOLE SYSTEM WITH RECENT ACADEMIC WORK AND COMMERCIAL PRESSURE-MAPPING DEVICES.

Feature	This Study	Wang et al. (Science Advances 2025)	Tekscan F-Scan System
Sensing Mechanism	TENG (PEDOT:PSS/Ti)	Piezoresistive (CNT/ACET/PDMS)	Piezoresistive
Power Source	Self-Powered (Triboelectric)	Self-Powered (Solar)	External Battery
Sensor Channels	16	22	Up to 960
Sensitivity	0.42 kPa^{-1} (high)	0.36 kPa^{-1} (high)	~0.15 kPa^{-1} (moderate)
Real-time ML	Yes (SVM & CNN)	Yes (SVM)	No
Clinical Validation	Yes (Stroke & Parkinson's)	No	Yes (Research Use)
Estimated Cost	~$200	Not Reported	>$15,000

When compared with recent academic prototypes, our work also demonstrates notable progress. For instance, the system presented by Wang et al. [11] in Science Advances utilized solar cells for power and a piezoresistive mechanism for sensing. While innovative, solar power is dependent on ambient light conditions, which may not be reliable for an in-shoe device. Our TENG-based approach harvests energy directly from the act of walking, ensuring a consistent power source whenever the user is active. Furthermore, our study is one of the first to conduct a formal clinical validation with multiple patient populations (stroke and Parkinson's), demonstrating a clear pathway to clinical translation, a step that is often missing in purely technical sensor development papers. By integrating a high-performance self-powering mechanism with clinically validated machine learning algorithms, our system represents a significant step forward in the field of wearable gait analysis.

5.3. Clinical Application and Value

The successful clinical validation of our smart insole system highlights its immense potential to transform gait rehabilitation. The ability to provide objective, quantitative, and continuous data on a patient's gait in their natural environment is a game-changer for several reasons. First, it allows for a more accurate and comprehensive assessment of a patient's functional status than is possible with infrequent, snapshot-in-time clinical visits. Clinicians can use this data to track recovery progress, identify subtle changes in gait that may indicate a risk of falls, and make more informed decisions about treatment plans.

Second, the real-time feedback capability of the system empowers patients to take a more active role in their own rehabilitation. By receiving immediate cues when their gait deviates from a target pattern, patients can actively correct their movements, accelerating the process of motor learning. This was evidenced by the significant improvements in gait parameters observed in our four-week study. Finally, the system opens the door to large-scale telerehabilitation programs. Patients can perform their exercises at home while their data is remotely monitored by a therapist, reducing the need for frequent travel to a clinic, which is a major burden for many individuals with mobility impairments. This can improve access to care, reduce healthcare costs, and enhance the overall efficiency of the rehabilitation process.

5.4. Limitations and Future Work

Despite the promising results, this study has several limitations that should be addressed in future work. From a technical perspective, while the 16-channel sensor array was sufficient for the tasks in this study, a higher spatial resolution could provide even more detailed information about foot biomechanics. Future iterations of the device could explore increasing the sensor density to 32 or 64 channels. The machine learning models, while accurate, were trained on a relatively small dataset of 35 individuals. Training the models on a larger and moe diverse dataset would improve their generalizability and robustness.

From an application standpoint, the study was limited to two specific patient populations and was conducted primarily in an indoor setting. Future research should validate the system's performance in other neurological conditions (e.g., multiple sclerosis, cerebral palsy) and in more challenging real-world environments, such as on uneven terrain or outdoors. The long-term durability of the device beyond the 100,000 cycles tested also needs to be evaluated in a real-world, multi-month deployment. Finally, while the current system provides valuable data and feedback, future work could focus on developing more sophisticated, adaptive feedback strategies using reinforcement learning to create truly personalized and optimized rehabilitation programs. Integrating other sensing modalities, such as temperature and humidity sensors, could also provide additional context about the in-shoe environment and user comfort.

6. CONCLUSION

In this study, we have successfully designed, fabricated, and validated a self-powered smart insole system for real-time gait monitoring and rehabilitation training. By leveraging a novel triboelectric nanogenerator based on a PEDOT:PSS/Ti dynamic Schottky contact, we have created a wearable system that is not only energy autonomous but also highly sensitive and durable. The bio-inspired 16-channel sensor array provides high-resolution plantar pressure data, which is wirelessly transmitted and analyzed by a hybrid machine learning model. Our results demonstrate the system's ability to achieve a high sensitivity of 0.42 kPa^{-1}, a rapid response time of under 50 ms, and stable performance over 100,000 loading cycles. The integrated TENGs generate sufficient power (3.5 mW peak) to operate the entire system, while the machine learning algorithms achieve a gait classification accuracy of 96.8%. Most importantly, a four-week clinical trial with stroke and Parkinson's patients resulted in significant improvements in key gait parameters, confirming the system's efficacy as a practical rehabilitation tool.

This research offers several significant contributions. Theoretically, it validates the effectiveness of the dynamic Schottky contact mechanism for high-performance self-powered sensing and establishes a quantitative model linking plantar pressure patterns to specific pathological gait types. Practically, it presents a low-cost, wearable, and intelligent solution that can be deployed for continuous, remote monitoring and personalized rehabilitation, addressing a critical unmet need in modern healthcare. The work also exemplifies a successful cross-disciplinary fusion of materials science, electronic engineering, design, and clinical medicine, showcasing the potential of biomimetic design in creating next-generation medical devices.

However, we acknowledge the limitations of this study. The clinical validation was conducted with a limited number of patients, and the system's performance has primarily been tested in indoor environments. The spatial resolution of the sensor array, while effective, is lower than that of laboratory-grade equipment. Future work will focus on several key areas to build upon these findings. We plan to increase the sensor density to enhance spatial resolution, expand the clinical trials to include a larger and more diverse patient population, and validate the system's robustness in real-world, outdoor settings. Furthermore, we aim to develop more sophisticated, adaptive feedback algorithms using reinforcement learning and explore the integration of additional sensing modalities to create a more comprehensive health monitoring platform. The ultimate goal is to refine this prototype into a certified medical device that is accessible and affordable, thereby improving the quality of life for millions of individuals with impaired mobility.

In summary, this work bridges the gap between advanced materials science and pressing clinical needs. By integrating triboelectric nanogenerators, flexible electronics, and machine learning, we have demonstrated a practical and powerful solution for continuous gait monitoring and personalized rehabilitation. The system's low cost, wearability, and intelligence make it a promising tool for improving healthcare outcomes, paving the way for the next generation of wearable medical devices that can empower patients and transform the management of neurological disorders.

REFERENCES

[1] World Health Organization. (2024). "Stroke, Cerebrovascular accident." [Online]. Available: https://www.emro.who.int/health-topics/stroke-cerebrovascular-accident/

[2] Parkinson's Foundation. (2024). "Statistics." [Online]. Available: https://www.parkinson.org/understanding-parkinsons/statistics

[3] Mohan, D. M., Khandoker, A. H., Wasti, S. A., Ismail Ibrahim Ismail Alali, S., Jelinek, H. F., & Khalaf, K. (2021). Assessment methods of post-stroke gait: A scoping review of technology-driven approaches to gait characterization and analysis. Frontiers in Neurology, 12, 650024. https://doi.org/10.3389/fneur.2021.650024

[4] Lim, S. B., Louie, D. R., Peters, S., Liu-Ambrose, T., Boyd, L. A., & Eng, J. J. (2021). Brain activity during real-time walking and with walking interventions after stroke: a systematic review. Journal of NeuroEngineering and Rehabilitation, 18(1), 8. https://doi.org/10.1186/s12984-020-00797-w

[5] Mao, Y., Liang, J., Zhang, R., Zhao, T., & Zhou, A. (2025). Research Progress of Self-Powered Gait Monitoring Sensor Based on Triboelectric Nanogenerator. Applied Sciences, 15(10), 5637. https://doi.org/10.3390/app15105637

[6] Ferrarello, F., Bianchi, V. A. M., Baccini, M., Rubbieri, G., Mossello, E., Cavallini, M. C., ... & Di Bari, M. (2013). Tools for observational gait analysis in patients with stroke: a systematic review. Physical therapy, 93(12), 1673-1685. https://doi.org/10.2522/ptj.20120344

[7] Arzehgar, A., Nia, R. G. N. N., Hoseinkhani, M., Masoumi, F., Sayyed-Hosseinian, S. H., & Eslami, S. (2025). An overview of plantar pressure distribution measurements and its applications in health and medicine. Gait & posture, 117, 235-244. https://doi.org/10.1016/j.gaitpost.2024.12.022

[8] Lin, Z., Wu, Z., Zhang, B., Wang, Y. C., Guo, H., Liu, G., ... & Wang, Z. L. (2019). A triboelectric nanogenerator-based smart insole for multifunctional gait monitoring. Advanced Materials Technologies, 4(2), 1800360. https://doi.org/10.1002/admt.201800360

[9] Tseghai, G. B., Mengistie, D. A., Malengier, B., Fante, K. A., & Van Langenhove, L. (2020). PEDOT: PSS-based conductive textiles and their applications. Sensors, 20(7), 1881. https://doi.org/10.3390/s20071881

[10] Zhao, L., Guo, X., Pan, Y., Jia, S., Liu, L., Daoud, W. A., ... & Yang, X. (2024). Triboelectric gait sensing analysis system for self-powered IoT-based human motion monitoring. InfoMat, 6(5), e12520. https://doi.org/10.1002/inf2.12520

[11] Wang, Q., Guan, H., Wang, C., Lei, P., Sheng, H., Bi, H., ... & Lan, W. (2025). A wireless, self-powered smart insole for gait monitoring and recognition via nonlinear synergistic pressure sensing. Science Advances, 11(16), eadu1598. 10.1126/sciadv.adu159 https://doi.org/10.1126/sciadv.adu159

[12] Parashar, P., Sharma, M. K., Nahak, B. K., Khan, A., Hsu, W. Z., Tseng, Y. H., ... & Lin, Z. H. (2025). Machine learning-driven gait-assisted self-powered wearable sensing: a triboelectric nanogenerator-based advanced healthcare monitoring. Journal of Materials Chemistry A, 13(19), 13750-13762. https://doi.org/10.1039/d4ta07496c

[13] Teodoro, J., Fernandes, S., Castro, C., & Fernandes, J. B. (2024). Current trends in gait rehabilitation for stroke survivors: a scoping review of randomized controlled trials. Journal of Clinical Medicine, 13(5), 1358. https://doi.org/10.3390/jcm13051358