



Modelling Plantar Pressure in a Smart Wearable Insole System Using Piezoresistive Sensors

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Abstract

Biomechanical analysis plays a crucial role in evaluating movement patterns and pressure distribution. It enables early detection of abnormal gait and posture that may lead to long-term musculoskeletal problems. By identifying pressure imbalances, biomechanical assessment supports injury prevention, rehabilitation monitoring, and personalised orthotic design. However, conventional tools are often bulky and expensive, limiting accessibility. This study introduces an insole system that integrates piezoresistive sensors with Radial Basis Function (RBF) interpolation to provide cost-effective, real-time visualisation of plantar pressure. Tests involving five subjects, conducted during standing, stair climbing, and walking, revealed distinct load patterns with a strong correlation to reference data ($R^2 = 0.925$). The static standing test demonstrated balanced pressure and an average MAPE of 24.9%, while the walking cycle exhibited consistent heel-to-toe transitions and proper weight transfer. Operating at a 10 Hz sampling rate, the wearable insole accurately quantified plantar pressure variations, demonstrating its potential for real-time gait assessment and rehabilitation monitoring.

Keywords: biomechanics; gait; interpolation; plantar; pressure mapping

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1. Introduction

Foot biomechanics plays a crucial role in human mobility and overall quality of life, including early diagnosis and therapeutic footwear for individuals with diabetic foot ulcers, making it an increasingly important area in modern healthcare [1], [2]. However, a concerning trend is the increasing prevalence of biomechanical foot disorders, particularly among younger populations. Modern lifestyles-characterised by prolonged sitting in non-ergonomic positions, unbalanced physical activity, and improper exercise techniques-have contributed to a significant rise in cases of foot pain and biomechanical abnormalities.

Conditions such as plantar fasciitis and Achilles tendon injuries are becoming more common, often associated with sedentary behaviour or poor training habits [3]. If left undetected or improperly treated, foot biomechanics problems can lead to long-term musculoskeletal complications.

Although significant advancements have been made in motion capture and force plate systems for foot biomechanics analysis, their adoption remains limited due to the high cost, bulky setup, and clinical-only applicability [4], [5]. Commercial systems, such as F-Scan® and Novel EMED pressure platforms, have been widely used for clinical and research applications but are still primarily restricted to laboratory environments. With the rise of wearable technologies and the increasing demand for real-time biomechanical monitoring, developing sensor-based innovative insole systems has become increasingly vital-not only for rehabilitation but also for early detection among at-risk populations, including diabetic patients and children in the early stages of walking development.

Recent research has explored plantar pressure analysis using various sensor technologies. Montagnani et al. (2025) demonstrated that statistical mapping of the Centre of Pressure (CoP) trajectories can reveal significant variations in initial contact points and lateral pressure

distribution, emphasising the need for comprehensive biomechanical modelling [6]. Simonsson et al. (2023) evaluated the reliability of the F-Scan® system in high-risk diabetic patients and found consistent peak pressure measurements across examiners despite differences in zone placement [7]. Meanwhile, studies employing piezoresistive Force Sensitive Resistors (FSRs) have shown that these sensors provide valid results for fundamental gait analysis, with good correlation with commercial references. Zhao et al. (2020) successfully utilised 16 piezoresistive sensors to record plantar pressure under both static (standing, sitting) and dynamic (walking, running, stair climbing, jumping) conditions [8].

Despite these advancements, several critical research gaps remain. First, there is a trade-off between the number of sensors and cost-effectiveness. Systems such as Zhao's employ many sensors, increasing hardware complexity and cost. Conversely, low-sensor-count systems capable of maintaining high accuracy through interpolation techniques remain underexplored. Reducing sensor count is significant because it can substantially lower system cost and complexity while preserving clinically relevant information. Second, there is limited work on low-power, real-time heatmap visualisation using minimal sensors. Such visualisation is essential because heatmaps provide clinicians with intuitive insights into pressure distribution and gait abnormalities.

Several studies have investigated interpolation-based plantar pressure mapping. Fatema et al. (2023) demonstrated that bicubic interpolation yields smoother and higher-quality pressure maps than nearest-neighbour and bilinear methods, achieving real-time performance with an average processing time of 38.38 μ s [9]. De Fazio et al. (2021) applied K-nearest neighbour (K-NN) interpolation using eight FSR sensors to detect plantar overload regions [10]. However, these conventional polynomial and neighbour-based methods remain limited in handling irregular and sparse data patterns and fail to exploit more advanced mathematical models.

To address these limitations, this study proposes a wearable plantar pressure visualisation system integrating eight piezoresistive sensors with multiquadric Radial Basis Function (RBF) interpolation. The RBF method offers mesh-free operation, global smoothness, and superior performance for sparse sensor data, enabling accurate yet cost-effective detection of motion abnormalities [11].

This work makes three primary contributions to the field of wearable biomechanical sensing. First, an integrated minimal-sensor RBF framework for reconstructing continuous plantar pressure maps in real time. This framework introduces the first integration of a single configuration comprising at least eight sensors, compared to other studies that used 22 [12], 32 [13], or

up to 104 and 173 piezoresistive sensors [14], [15]. Second, a low-cost real-time visualisation system, developed by creating a portable, cost-effective insole platform with real-time wireless data transmission and an intuitive pressure-mapping interface. Third, experimental validation and reliability analysis were conducted to demonstrate that the system's performance is validated through multi-activity experiments (standing, stair climbing, and walking), showing a strong correlation with reference measurements and high reliability.

Collectively, these contributions establish a practical-, accessible gait monitoring system that balances hardware simplicity and computational accuracy, paving the way for cost-effective clinical screening and rehabilitation monitoring applications.

2. Methods

This section describes the overall methodology for designing, implementing, and evaluating the proposed innovative insole system. It covers the participants, experiments, hardware configuration, data acquisition process, interpolation process, and performance evaluation metrics applied to assess system accuracy and reliability.

2.1 Subject Infographics

Our sample consisted of five subjects aged between 22 and 24 years. The subjects were recruited from the Faculty of Electrical Engineering at Telkom University for the normal and impaired groups. Participants did not receive financial compensation. The inclusion criterion was impairment in curve perception. We collected information on the age, height, and weight of all participants. Table 1 describes their physical characteristics. Both groups were matched for age, body mass index (BMI), and gender ratio. The sample was homogeneous with respect to age, BMI, and gender ratio.

Table 1. Physical characteristics of subjects.

Subject (S)	Gender	BMI (kg/cm ²)	Age (yr)	Shoe size (EU)	Arch
S1	Female	39/152	23	36	Normal
S2	Female	39/160	24	40	Normal
S3	Female	55/152	22	38	Normal
S4	Male	51/173	25	42	Supinated
S5	Male	68/183	22	43	Normal

The ground truth in Figure 1 presents a visual analysis of the heel strike (initial contact) phase during the gait cycle across several subjects. This figure serves as a reference for validating the arch classification and heel orientation data shown in Table 2. By comparing the measured intermalleolar line and heel curve angles with the visual reference, the system can verify the accuracy of supination or normal arch identification used later in the analysis [16]. The white line in Figure 1 identifies the angle and position of the heel during initial contact with the floor. The upper line is the intermalleolar line,

an imaginary line drawn between the medial malleolus (inner ankle) and the lateral malleolus (outer ankle). The heel curve is the curved shape at the back of the heel. This ground truth is used as a reference to verify the statements in Table 1 with the actual conditions after measurement.

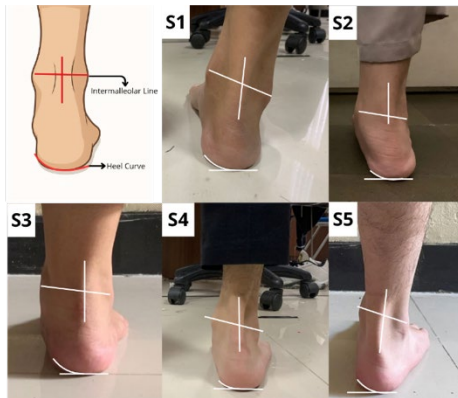


Figure 1. Participants' foot posture was assessed in this study as ground truth data.

Based on the results of measuring the intermalleolar line and heel curve values in five subjects shown in Table 2, the heel curve value for subject 4 was 12, the highest and most striking value, while the other subjects' values ranged from 5 to 7. This high heel curve value indicates abnormal curvature in the posterior heel area, typically due to heel inversion, a condition where the heel tilts toward the medial side. The combination of an intermalleolar line value that remains within the normal range but is accompanied by excessive heel curvature indicates a shift in heel structure without significant changes in ankle position, a characteristic of feet with supination posture. Meanwhile, other subjects showed a balance between intermalleolar line and heel curve values, reflecting balanced weight distribution and a neutral heel position.

Table 2. Comparison of Intermalleolar Line and Heel Curve Measurements Across Subjects for Foot Posture Classification

Subject	Intermalleolar Line	Heel Curve	Arch
S1	16°	7°	Normal
S2	16°	5°	Normal
S3	18°	6°	Normal
S4	15°	12°	Supinated
S5	23°	6°	Normal

2.2 Experimental procedures

All participants performed several activities. First, they stood in a normal standing position on an insole equipped with eight piezoresistive sensors, spread across a 27 cm area, with a pressure range of 0 to 3.3 volts and a data acquisition rate of 10 Hz. Second, they climbed a 15-step staircase, ascending and descending. Third, they walked normally for 60 seconds.

An insole with eight piezoresistive sensors simultaneously collected data from the centre of pressure (CoP). Measurements were taken during three trials, each lasting 60 seconds in each condition. Figure 2 illustrates the division of the plantar surface into eight

zones corresponding to the sensor positions embedded in the insole. Each label (T1–T4, M1–M2, LH, MH) represents a measurement region used for data acquisition and subsequent interpolation. These zones ensure consistent spatial mapping between raw voltage data and the interpolated pressure heatmaps.

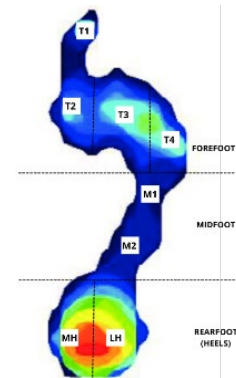


Figure 2. Plantar Surface Zone

2.3 System Architecture and Design

The proposed insole system is designed to provide real-time plantar pressure monitoring through a combination of low-cost piezoresistive sensors, a wireless microcontroller, and an interpolation-based visualisation platform, as shown in Figure 3. Each insole integrates eight DF9-16 piezoresistive sensors strategically positioned across the forefoot, midfoot, and rearfoot regions to capture critical load distribution patterns. These sensors convert mechanical pressure into resistance variations, which are then translated into voltage signals using a voltage-divider circuit with a fixed 10 kΩ pull-up resistor. The sensor array interfaces with an ESP32 microcontroller that performs real-time data sampling, chosen for its low power consumption and robust wireless connectivity, making it suitable for continuous wearable use.

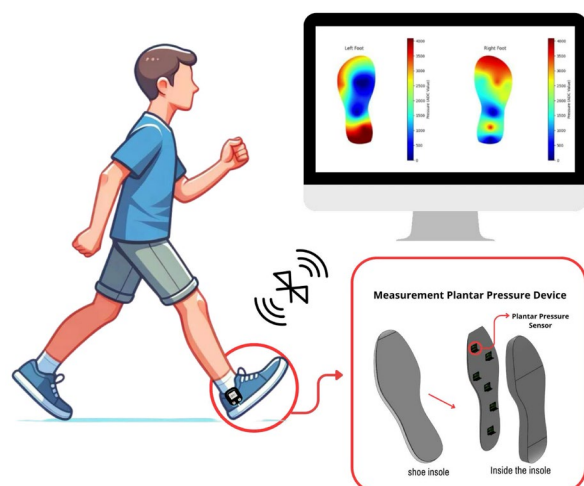


Figure 3. Wearable Monitoring System Design and the Insole Design.

Data transmission is handled via Bluetooth Low Energy (BLE), selected for its low power consumption and stable transmission, ensuring reliable communication

over extended periods of use [17]. The BLE protocol enables seamless wireless connectivity between the insole hardware and the visualisation platform without introducing significant power overhead, a critical requirement for wearable biomedical devices intended for prolonged monitoring sessions. All electronic components are assembled in a compact three-layer structure comprising the sensor array, the control unit, and a protective cover, as illustrated in Figure 3.

Meanwhile, the selection of the Li-Po battery as the primary power source is based on its high energy density and lightweight characteristics, which are suitable for wearable applications. The chosen battery capacity must account for the ESP32's power consumption in BLE transmission mode. Optimising power management in this wearable sensor can extend battery life by up to 42%. All electronic components are assembled compactly into a three-layer structure comprising the sensor array, the control unit, and a protective cover.

To enable efficient gait analysis, the architecture integrates wearable sensing technology, wireless data transmission, and visual analytics. As shown in Figure 3, the complete system comprises three main modules: wearable insole sensors embedded in shoes, a BLE-based wireless communication interface, and a data visualisation platform for real-time feedback.

The technical specifications of the piezoresistive element adopted in this work are summarised in Table 3. The DF9-16@2kg unit was selected because its 0–2 kg force-sensing range matches the per-zone load expected when body weight is distributed across the eight measurement zones defined in Figure 2, allowing each sensor to operate within its linear region instead of saturating during heel strike and push-off. Its low actuation force of 20 g ensures that the light contact occurring in the midfoot (M1–M2), where pressure is minimal because of the medial longitudinal arch, is still registered rather than lost as a dead zone, which is essential for reconstructing a continuous pressure surface from only eight sampling points. The 16 mm overall size and 10 mm sensing area keep each sensing node small enough to be embedded within the 2 mm-thick insoles without introducing pressure artifacts beneath the foot, while still providing a contact area large enough to average out local load irregularities. The response time of less than 1 ms is two orders of magnitude shorter than the 100 ms intervals imposed by the 10 Hz sampling rate adopted in this study, confirming that the temporal resolution of the system is limited by the acquisition and BLE transmission scheme rather than by the sensor itself. Collectively, the specifications listed in Table 3 confirm the suitability of the DF9-16 sensor for low-cost, real-time plantar pressure monitoring, and they define the input range that the voltage-divider circuit and the subsequent RBF interpolation must accommodate.

Figures 4 and 5 depict the core hardware layout and layered construction. The insole module incorporates eight pressure sensors, a power and charging unit, the ESP32 microcontroller, and a protective top cover. The bottom layer houses the Li-Po power module and TP4056 charger, the middle layer contains the ESP32 controller, and the upper layer serves as a protective enclosure. The wiring configuration, shown in Figure 4, connects the sensor array to the ESP32 using JST connectors for easy assembly and maintenance. The design follows the optimal configuration reported by Chen et al. [18], in which a 10 k Ω pull-up resistor provides the best sensitivity-to-stability ratio for plantar-pressure sensing.

Table 3. DF9-16 Piezoresistive Sensor Specification

	Piezoresistive
Model no.	DF9-16@2kg
Force-sensing range	0 – 2 kg
Actuation force	20 g
Size	16 mm
Sensing area	10 mm
Response time	< 1 ms

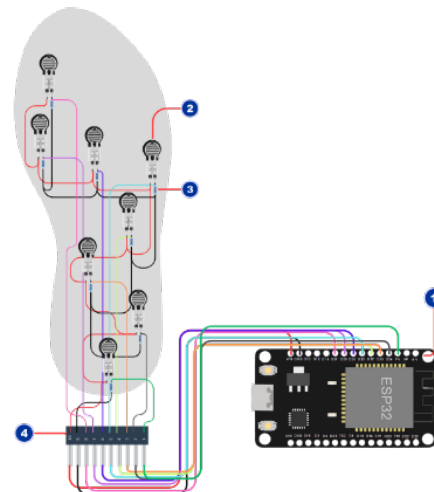


Figure 4. Hardware Design of Insole System consisting of (1) ESP32 microcontroller, (2) piezoresistive sensors, (3) a 10 k Ω pull-up resistor for each sensor, and (4) a JST connector.

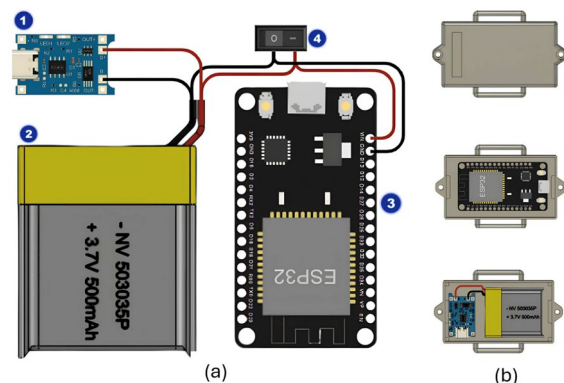


Figure 5. (a) Microcontroller circuit design with the Li-Po battery, power module, and TP4056 charger housed in (b) a protective enclosure.

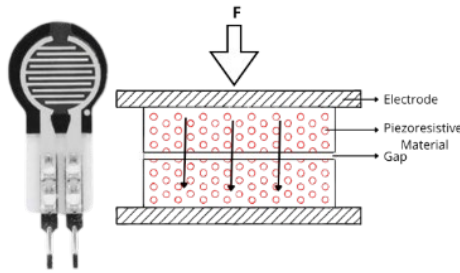


Figure 6. The DF9-16 2 kg Piezoresistive sensor detects the pressure applied to its sensing area.

The DF9-16 2 kg piezoresistive sensor, illustrated in Figure 6, operates similarly to a force-sensitive resistor (FSR). The applied pressure changes the resistance due to variations in the contact area between electrodes [19]. Structurally, the sensor consists of two electrodes that sandwich a piezoresistive layer, separated by a small gap. When force is applied, the gap narrows, increasing the contact area and reducing total resistance. The sensor's minimum activation force is 20 g, making it highly sensitive for low-pressure applications such as foot-plantar monitoring. With a 16 mm length, a 10 mm active diameter, and a <1 ms response time, it is well suited for compact wearable systems that require fast response and high sensitivity [20].

A simplified voltage-divider circuit used for resistance-to-voltage conversion is presented in Figure 7. The sensor acts as a variable resistor whose output voltage varies with applied pressure, as defined by Equation 1.

$$V = V_{cc} \left(\frac{R_{fixed}}{R_{fixed} + R_{sensor}} \right) \quad (1)$$

The output voltage, V , changes proportionally with the pressure magnitude, since pressure variation directly alters the value of R_{sensor} . When no force is applied, R_{sensor} remains high, and the resulting voltage is minimal. Conversely, as pressure increases, the resistance decreases, resulting in a rise in the voltage output. The fixed resistor R_{fixed} is set to 10 k Ω to balance sensitivity and measurement range for plantar pressure applications.

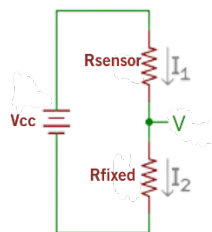


Figure 7. Voltage Divider Circuit.

This voltage-divider principle was implemented in the ESP32 firmware, enabling real-time conversion of sensor resistance changes into voltage values before wireless transmission. These voltage readings served as the raw data for the RBF-based interpolation process and correspond directly to the linear relationship between pressure and voltage shown in Figure 8 [21].

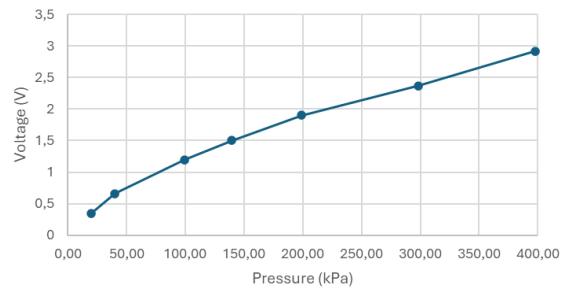


Figure 8. Correlation between Voltage and Pressure.

Before data acquisition, each DF9-16 sensor was calibrated to establish its stress-to-pressure characteristics using a known reference mass (0–2 kg). The corresponding output voltage was obtained from a voltage divider circuit (Equation 1) and recorded to yield a linear stress-to-pressure relationship, as shown in Figure 8 (Equations 2–3) or following the calibration procedure reported by Jung et al. [21]. This per-sensor calibration ensured consistent and proportional responses across all eight sensor channels before interpolation. To address long-term reliability under repeated use, a 2 mm-thick insole construction minimised mechanical deformation, thereby reducing hysteresis and creep, which are commonly observed in piezoresistive materials during cyclic loading. A smoothing factor of 0.1 in the multiquadratic RBF formulation further reduced residual signal shifts. However, specific cyclic durability tests under prolonged repetitive loading remain part of the planned future work.

To maintain reliable operation, an efficient power-management subsystem was implemented, as shown in Figure 5. It integrates the TP4056 charging circuit, Li-Po battery, ESP32 microcontroller, and a toggle switch for on/off control. The TP4056 provides over-charge protection, while the Li-Po battery was selected for its high energy density and lightweight characteristics. The design optimises power consumption during BLE transmission, potentially extending battery life by up to 42 %. The linear voltage–pressure relationship in Figure 8, described by Equations 2 and 3, further confirms that the piezoresistive sensors exhibit stable and proportional response characteristics, making them suitable for accurate real-time plantar pressure measurement.

$$P = \frac{F}{A} = \frac{m \times G}{A} \quad (2)$$

$$P = \frac{m \times 10 \text{ m/s}^2}{50,24 \times 10^{-6}} \quad (3)$$

2.4 Data Acquisition and Interpolation

The sensor signals are sampled at an average rate of 8–10 Hz and transmitted wirelessly via Bluetooth Low Energy (BLE) to the visualisation platform. The received data are processed using multiquadric Radial Basis Function (RBF) interpolation, which converts sparse sensor readings into continuous two-dimensional (2D) plantar pressure maps. This interpolation enhances

spatial representation and enables high-resolution visualisations while maintaining hardware simplicity. All plantar pressure visualisations were generated using the multiquadric RBF model, Equations 4 and 5 applied to raw voltage data from eight piezoresistive sensors. Through this process, discrete voltage readings are transformed into colour-mapped surfaces that represent estimated pressure distributions across the foot.

The overall data-processing workflow is illustrated in Figure 9, comprises four sequential stages. In the first stage, sensor data reception, the system receives raw analogue data from the piezoresistive sensors embedded in the insole, representing unprocessed voltage values corresponding to varying plantar pressure levels. The second stage, data processing, involves transforming the raw data collected via BLE, where each discrete sensor reading is mapped spatially and processed using interpolation algorithms to generate high-resolution pressure images by estimating intermediate values between sensors, producing smoother, more detailed maps [22]. In the third stage, result visualisation, the processed data are converted into an intuitive colour heatmap that displays real-time plantar pressure distribution, with colour intensity indicating pressure magnitude, enabling identification of high-pressure zones such as the heel, forefoot, and arch. Finally, in the analysis stage, the generated pressure patterns are examined to identify gait characteristics, balance, and load symmetry.



Figure 9. Function diagram of the proposed system.

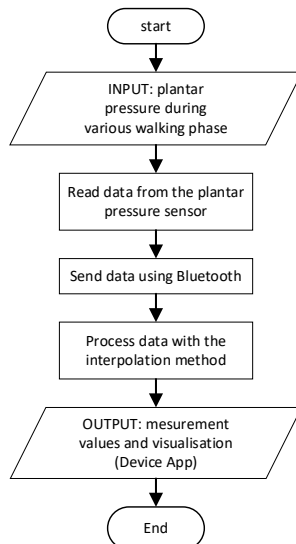


Figure 10. Flowchart of the proposed system.

The flow of data acquisition and processing is depicted in Figure 10. The system begins with the start stage, which initialises all components and prepares the sensor array for data capture. During the input stage, pressure data are collected in real time from the eight sensors in the insole. The readings are transmitted via BLE to the receiver, where data processing is performed. In the

Process Data stage, RBF interpolation algorithms enhance spatial resolution and generate smooth, continuous pressure distributions. The final output stage provides both numerical measurement values and graphical visualisations on the device application.

Spatial interpolation is used to estimate unknown values between discrete sensor readings, compensating for the limited number of physical sensors. Among various interpolation techniques, Radial Basis Function (RBF) interpolation, first introduced by Hardy (1968) [23] is particularly effective for scattered and non-uniform data such as plantar pressure measurements. The RBF interpolation relies solely on the Euclidean distance between data points, allowing for the smooth generation of a surface from irregularly spaced inputs.

The general form of the RBF interpolation is expressed as in Equation 4. Where $s(x)$ denotes the interpolated value at position x , λ_i represents the weighting coefficient for each basis function obtained by solving a system of linear equations, and ϕ is the radial basis function that defines the interpolation behaviour. The multiquadric RBF, defined in Equation 5, provides smooth yet locally adaptive interpolation, ideal for representing continuous plantar pressure gradients. The shape parameter ε controls the spread of each basis function; smaller values result in wider influence regions but may increase numerical instability. It is worth noting that the RBF method employed here refers strictly to multiquadric RBF, not to a neural network architecture; therefore, the concept of hidden-layer neurons is not applicable in this context.

$$s(x) = i = \sum_{i=1}^N \lambda_i \phi(\|x_j - x_i\|) \quad (4)$$

$$\phi(r) = \sqrt{r^2 + \varepsilon^2} \quad (5)$$

This interpolation algorithm was implemented in Python using the multiquadric RBF function to reconstruct continuous pressure surfaces from the eight discrete voltage inputs (x_1 – x_8). Each input vector contained normalised voltage readings, while the output produced colour gradients visualised in Figure 9. The resulting surface provides a smooth and realistic representation of plantar pressure despite sparse sensor placement.

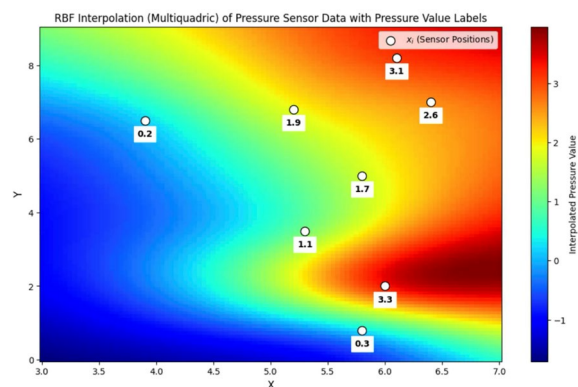


Figure 11. Result of the RBF interpolation method (multiquadric) of pressure sensors.

As shown in Figure 11, the RBF multiquadric interpolation effectively produces smooth transitions between high-pressure regions (in red, approximately 3.1–3.3 V) and low-pressure areas (in blue, approximately 0.2–0.3 V). The spatial arrangement of the eight sensors (x_1 – x_8) captures pressure variations across different anatomical zones of the foot, confirming the effectiveness of the interpolation approach in generating realistic plantar pressure distributions.

2.5 Data Analysis and Evaluation Metrics

To evaluate the performance of the RBF interpolation model and system reliability, statistical error metrics were used: Mean Squared Error (MSE), Mean Absolute Error (MAE), Root Mean Squared Error ($RMSE$), Mean Absolute Percentage Error ($MAPE$), and the coefficient of determination (R^2). These metrics quantify the deviation between the measured sensor values (y_i) and the interpolated or predicted values ($\hat{y}_i$) in Equations 6–10.

$$MSE = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2 \quad (6)$$

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \quad (7)$$

$$RMSE = \sqrt{MSE} \quad (8)$$

$$MAPE = \frac{100}{n} \sum_{i=1}^n \left| \frac{y_i - \hat{y}_i}{y_i} \right| \quad (9)$$

$$R^2 = 1 - \frac{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2}{\frac{1}{n} \sum_{i=1}^n (y_i - \bar{y})^2} \quad (10)$$

Lower MSE , MAE , $RMSE$, and $MAPE$ values indicate better accuracy, while R^2 values closer to 1 denote stronger agreement between predicted and observed pressures.

3. Results and Discussions

This section presents the experimental results obtained from various activity scenarios to evaluate the performance of the proposed *innovative* insole system. The experiments were conducted under three primary conditions—standing static, climbing stairs, and walking cycles—to assess the system's ability to capture dynamic plantar pressure variations across different gait phases. Additionally, a comparative analysis of activities was conducted to evaluate consistency, repeatability, and accuracy across different motion types. The results are analysed quantitatively using the evaluation metrics defined in Section 2.4, including MSE , MAE , $RMSE$, $MAPE$, and R^2 . Subsequently, the discussion section interprets these findings in the context of system performance, interpolation accuracy, and biomechanical significance, highlighting the implications of the observed pressure patterns for gait characterisation and potential clinical applications.

3.1 Experimental Test: Standing Static

The first experimental condition involved static standing, performed for 60 seconds with the subject maintaining a stationary posture. A foot posture assessment of five subjects revealed noticeable variations in anatomical parameters and patterns of plantar pressure distribution. The anatomical reference for static standing divides the plantar surface into three regions: the forefoot (T1–T4), midfoot (M1–M2), and rearfoot or heel (MH–LH), as illustrated in Figure 2. Under normal conditions, the foot forms a tripod base through three main contact points: two at the forefoot (the first and fifth metatarsal heads) and one at the heel. The midfoot region typically exhibits minimal contact due to the elevated medial longitudinal arch, which allows for a more stable gait. During static standing, this arch maintains optimal height, ensuring balanced weight distribution and neutral alignment with minimal inversion or eversion. Based on the intermalleolar line measurements in Table 2, Subject 5 displayed the largest angle (23°), challenging the assumption that a greater angle consistently indicates pronation. The wide range observed among subjects (6° – 23°) suggests significant individual variation within normal parameters. The 8° difference between Subject 5 (normal, 23°) and Subject 4 (supinated, 15°) suggests a possible classification anomaly that raises questions about the reliability of the intermalleolar parameter alone. However, heel curve measurements showed a consistent correlation with foot type: Subject 4, classified as supinated, exhibited a 12° increase in heel curvature, nearly double the normal range (5° – 7°).

Plantar pressure analysis under normal foot conditions (Figure 12) revealed peak pressure zones at the forefoot, typically under the first and fifth metatarsal heads, and at the rearfoot (heel). For Subject 5, higher stress concentration appeared in the forefoot region, with maximum pressure of approximately 300 kPa beneath the fifth metatarsal head. Subjects 1–3 exhibited normal, balanced forefoot-rearfoot loading consistent with the standard tripod pattern, whereas Subject 5 showed a lateral shift of the high-pressure zone—an indication of compensatory loading likely related to the larger intermalleolar angle.

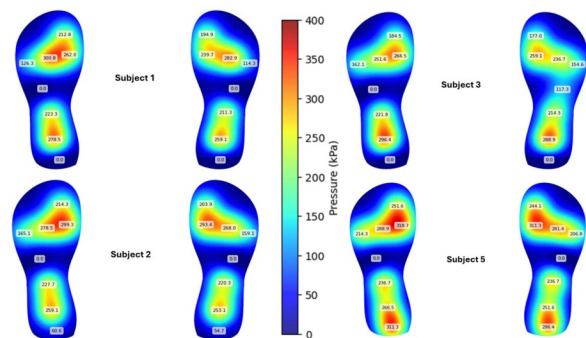


Figure 12. Interpolated plantar pressure distribution for each subject with a normal arch during static standing, obtained using RBF interpolation of eight sensor readings.

The general mechanical characteristics of normal feet during static standing are then summarised. Weight distribution follows a balanced tripod loading pattern, with approximately 60% of body weight borne by the rearfoot (MH–LH) and the remaining 40% by the forefoot (T1–T4). The midfoot exhibits minimal contact due to the maintained medial arch height, while forefoot pressure is concentrated around the first and fifth metatarsal heads (T1, T4).

In contrast, Subject 4, classified as supinated, demonstrated clear lateral weight-bearing dominance. As shown in Figure 13, pressure distribution was concentrated on the lateral forefoot (T4 zone) and lateral heel, with significantly reduced contact in the midfoot (M1–M2). This pattern aligns with typical supination mechanics, where inversion of the foot increases load on the lateral side. Despite having a moderate intermalleolar angle (15°), Subject 4's high heel curvature (12°) served as a stronger indicator of supination. The mechanical behaviour observed during 60 seconds of static standing for the supinated foot reveals a distinct loading profile. Dominant lateral weight-bearing was evident, with high pressure concentrated at T4 and LH. This pattern was accompanied by increased heel inversion, resulting in elevated lateral heel pressure and concentrated loading in the lateral plantar zone.

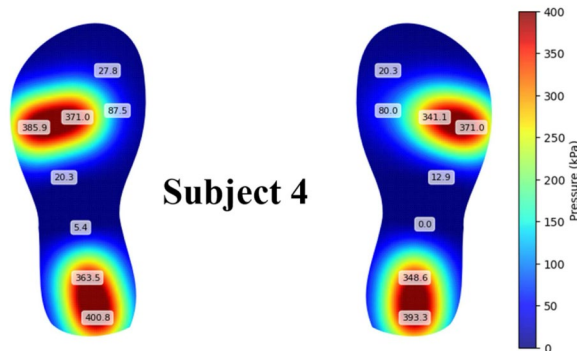


Figure 13. The RBF-interpolated pressure map of a subject with a supinated arch, highlighting lateral load dominance.

A total of 16 sensors were utilised during the static standing trials, recording data for each subject over a 60-second interval. During each sampling cycle, all sensors were acquired simultaneously, generating a complete set of pressure data across the plantar surface of the foot. The system's sampling rate (f_s) was set to 10 Hz, resulting in approximately 600 data points per trial [24]. This temporal resolution allowed the system to capture subtle changes in pressure distribution and shifts in the Centre of Pressure (CoP) with sufficient accuracy for biomechanical evaluation.

To assess interpolation accuracy, the evaluation metrics defined in Equations 6-10, were applied to compare interpolated pressure values with the reference sensor data. The results, summarised in Table 4, indicate that the proposed RBF interpolation model achieved consistent and reliable performance, with R^2 values exceeding 0.92 across all subjects. Subject S5

consistently performed best across both trials, with the lowest MSE and MAE and the highest R^2 . This superior performance is attributed to the close fit between the subject's foot contour and the insole surface. Conversely, Subject S4 showed the highest error values, although the R^2 remained acceptable (>0.89). Subject S1 exhibited a higher MAPE (40.6%), likely due to a partial mismatch between the foot and insole surface, resulting in less stable readings in specific zones. This size-related discrepancy is supported by a clear trend: shoe size inversely correlates with interpolation error. Subject S1, with the smallest foot (EU 36, about 23 cm) and the largest mismatch to the fixed 27 cm insole, had the highest MAPE of 40.6%. In contrast, Subjects S4 and S5, with foot sizes (EU 42 and EU 43, about 27–28 cm) closely matching the insole, recorded the lowest MAPE. This inverse relationship suggests that spatial misalignment between the plantar contact area and sensor array primarily causes interpolation errors, rather than limitations of the RBF interpolation model.

Table 4. RBF Interpolation Evaluation Standing Static

Location	MSE	MAE	RMSE	MAPE	R^2
S1_T1	0,058	0,195	0,240	40,593	0,923
S1_T2	0,067	0,209	0,260	44,904	0,917
S2_T1	0,032	0,148	0,179	15,648	0,931
S2_T2	0,085	0,219	0,291	26,993	0,895
S3_T1	0,057	0,191	0,238	26,095	0,913
S3_T2	0,060	0,189	0,245	24,867	0,907
S4_T1	0,055	0,214	0,235	19,385	0,959
S4_T2	0,057	0,217	0,240	23,756	0,959
S5_T1	0,048	0,176	0,219	14,866	0,897
S5_T2	0,039	0,141	0,197	18,367	0,925
average	0,056	0,190	0,234	25,547	0,923

3.2 Experimental Test: Climb Stairs

Stair climbing is a complex movement involving three primary phases: initial contact, when the foot first contacts the stair surface; mid-stance, when the foot supports the body's weight; and push-off, when the foot propels the body upward. The main distinction between ascending and descending lies in the controlled lowering phase during descent, where the extensor muscles actively decelerate the body. In this experiment, participants performed stair climbing for 60 seconds, allowing continuous monitoring of plantar pressure variation throughout the gait cycle.

The plantar pressure distribution visualised in Figure 14 demonstrates that during the initial contact and loading response phases, the highest-pressure concentrations (indicated in red on the heat map) occur in the rearfoot region, particularly in the medial heel (MH) and lateral heel (LH) zones defined in Figure 2. These regions act as the first points of ground contact, bearing the majority of the body's load at the start of each step.

During the mid-stance phase, pressure shifts toward the midfoot (M1–M2) zone, with moderate activation levels indicated by green to light blue colours. The midfoot primarily functions as a stabilising structure during stair climbing, maintaining balance and facilitating energy transfer rather than acting as a rigid lever as in level-ground walking. The longitudinal arch

plays an essential role in efficiently transferring force from the rearfoot to the forefoot during the transition to the push-off phase.

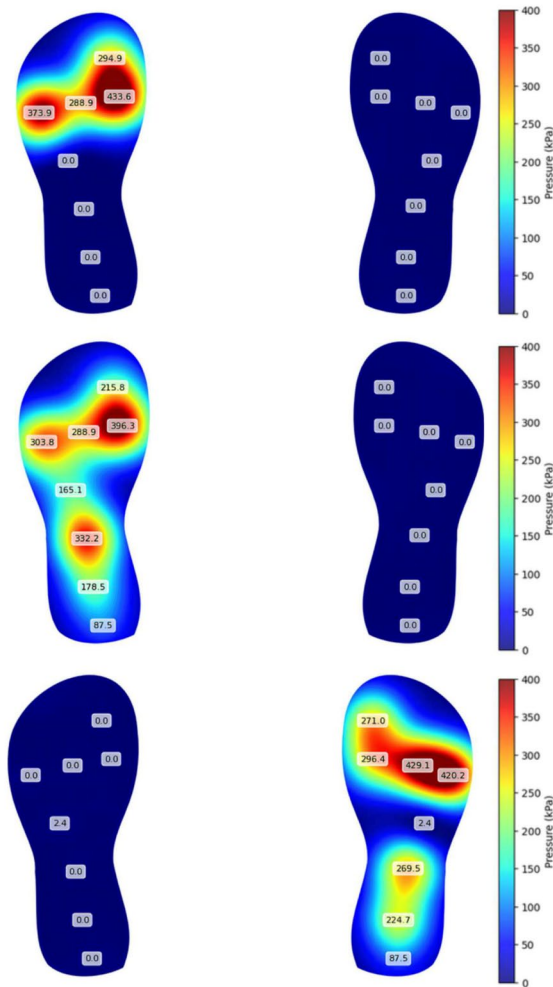


Figure 14. Interpolated pressure maps during stair climbing show a concentration of force in the heel and forefoot areas.

The biomechanics of the foot during stair climbing can be summarised across three functional zones. The heel acts as the primary shock absorber, dissipating impact forces at initial contact with the stair surface. The midfoot functions as a dynamic bridge, channelling kinetic energy from heel strike to toe-off during the stair-climbing cycle. Meanwhile, the forefoot becomes the propulsion zone during the push-off phase, generating upward momentum to elevate the body to the next step.

The observed loading sequence exhibits a consistent dynamic pattern, with each foot alternating between maximum pressure during contact and minimal pressure during swing. High-pressure regions are primarily concentrated in the heel strike and push-off phases. At the same time, intermediate loading spreads smoothly across the plantar surface, reflecting an efficient energy transfer mechanism throughout the climbing motion.

3.3 Experimental Test: Walking Cycle

The final experiment involved a 1-minute walking test designed to evaluate the system's real-time performance in detecting and visualising plantar pressure during a complete gait cycle. Throughout the walking cycle, the system continuously generated heatmap visualisations corresponding to the initial contact, stance, and swing phases. This test aimed to validate the proposed system's ability to accurately capture changes in foot arch and pressure distribution during dynamic motion.

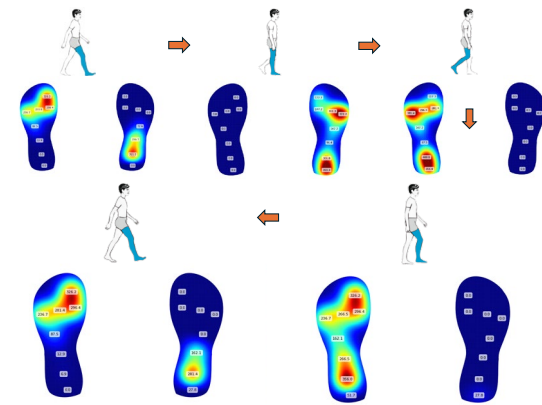


Figure 15. Interpolated pressure maps during a specific gait cycle of Subject 1 (Normal foot posture).

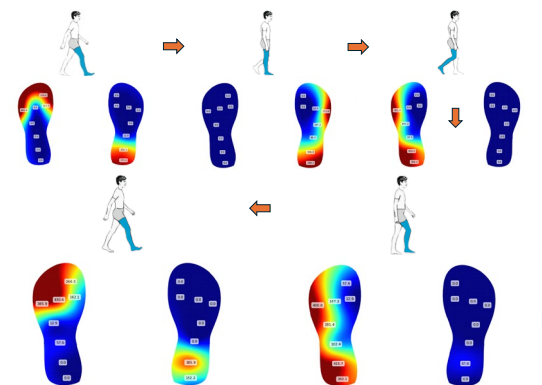


Figure 16. Interpolated pressure maps during a specific gait cycle of Subject 4 (Supinated foot posture).

Figures 15 and 16 demonstrate a normal and balanced walking pattern. During heel strike, high pressure was observed in the rearfoot region, indicated by red colouration on the heatmap. As the subject transitioned to the mid-stance phase, the pressure distribution became more uniform across the plantar surface, as indicated by a mix of green and yellow tones. During the push-off phase, pressure shifted toward the forefoot and toes, confirming the expected anterior weight transfer before foot lift-off. The alternating pressure patterns between the left and right feet show that while one foot bears the full load, the other remains in the swing phase with minimal or no contact pressure, indicating coordinated and symmetrical gait mechanics.

Quantitatively, Figure 17 presents voltage-based pressure measurements from five subjects. Subject 1 exhibited an average forefoot pressure of 0.74 V, midfoot 0.97 V, and rearfoot 1.04 V, representing a

balanced gait pattern. Subjects 2 and 3 displayed similar profiles, with Subject 2 recording 0.82 V (forefoot), 0.94 V (midfoot), and 1.02 V (rearfoot), and Subject 3 recording 0.80 V (forefoot), 0.96 V (midfoot), and 1.04 V (rearfoot).

In contrast, Subject 4 exhibited a pronounced heel-loading pattern, characterised by the lowest forefoot pressure (0.56 V) and the highest rearfoot pressure (1.10 V), suggesting a heel-dominant gait. Conversely, Subject 5 showed an opposite trend, with the highest forefoot pressure (1.25 V) and lowest rearfoot pressure (0.82 V), indicating a forefoot-dominant walking pattern and potential variation in step propulsion mechanics.

Overall, the dynamic changes in plantar pressure observed across subjects confirm the system's ability to detect gait-phase transitions and inter-subject variations in walking style, validating its potential for real-time gait analysis and rehabilitation monitoring.

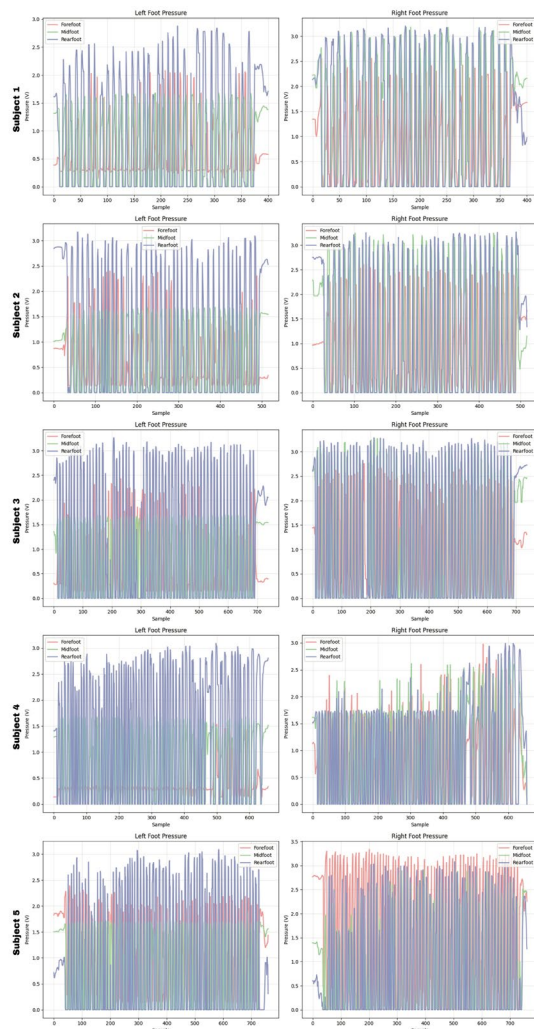


Figure 17. Foot Pressure During Walking Cycle.

3.4 Comparative Analysis Between Activities

Figure 18 presents the average sensor readings obtained from multiple activity conditions, including static

standing, stair climbing, and stair descending. The results reveal clear asymmetries in plantar pressure distribution between the left and right feet, highlighting differences in balance and loading patterns across activities.

During static standing, several sensors demonstrated notable imbalances. Sensor 1 (S1) recorded substantially higher pressure on the left (3.8) than on the right (0.4), whereas Sensors 2–4 (S2–S4) showed the opposite trend, with greater pressure on the right. Similarly, Sensor 5 (S5) indicated higher left-side pressure (2.7) compared to the right (0.3). In contrast, Sensor 8 (S8) showed a nearly symmetrical response, with both sides recording 2.8, indicating a balanced stance pattern. When descending stairs, the pressure shifted predominantly to the right side, particularly at Sensor 6 (S6), which registered 2.4 on the right and almost no pressure on the left. Meanwhile, Sensor 5 (S5) maintained a left-dominant pattern (2.1 vs 0.3), suggesting slight asymmetry in stabilisation during descent.

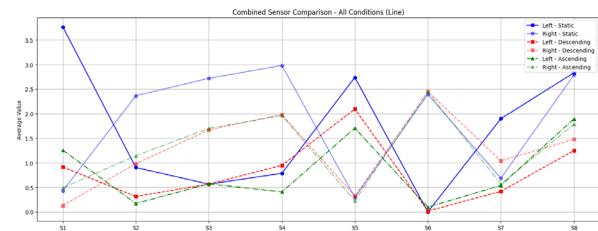


Figure 18. Average sensor values recorded by each insole sensor.

In the stair-climbing condition, the pressure distribution followed a more consistent bilateral pattern. Sensor 1 (S1) showed higher left pressure (1.3) than the right (0.5), whereas Sensors 2–4 (S2–S4) showed higher readings on the right. Sensor 8 (S8) again displayed near symmetry, with only a slight variation between the left (1.9) and right (1.8) sides. Overall, the comparative analysis across activities demonstrates that static standing tends to exhibit greater left–right asymmetry due to individual posture tendencies, while stair-climbing and descending produce more dynamic but functionally consistent pressure transitions. These findings suggest that the system effectively captures inter-limb load distribution and can detect subtle variations in postural balance and gait dynamics across different physical activities.

3.5 Discussions

The comparative evaluation confirms that the RBF interpolation method provides higher fidelity in reconstructing plantar pressure maps compared to conventional regression-based models. This improvement stems from RBF's ability to capture localised and nonlinear variations in plantar pressure that linear estimators typically overlook. By modelling spatial correlations in sensor data, the RBF approach yields smoother, more anatomically coherent pressure distributions.

The model evaluation results indicate an average coefficient of determination (R^2) of approximately 0.92, with the highest value achieved in scenario S1_T1 ($R^2 = 0.951$) and the lowest in S5_T1 ($R^2 = 0.893$). These results demonstrate high consistency and reliability across all test conditions. Beyond interpolation accuracy, the system's physical design also contributes to measurement stability. Sensor hysteresis and creep, which are commonly reported limitations of piezoresistive materials, were mitigated by a compact 2 mm insole construction, which minimises mechanical deformation between the sensor surface and the plantar region during both static and dynamic activities. The smoothing factor of 0.1, incorporated into the multiquadric RBF formulation, also serves as an implicit regularisation term, attenuating transient signal fluctuations associated with creep behaviour.

Regarding inter-subject variability in body weight, the voltage-based pressure readings demonstrated proportionally consistent responses across subjects with varying weight profiles, as reflected in the stable R^2 values observed across all five participants. Moreover, the achieved accuracy exceeds that reported in prior studies. For example, Kobayashi et al. [24] investigated posture and joint-angle estimation based on plantar pressure, achieving an R^2 of approximately 0.9 using a multivariate linear regression model [25]. Although their focus included joint-angle estimation, the comparable R^2 values validate the robustness of the approach used in this work.

Compared with earlier research employing linear or multivariate regression techniques [26], which typically reported R^2 values of 0.72–0.90, the proposed RBF-based model demonstrates superior accuracy and stability ($R^2 = 0.92$ –0.95). This performance gain stems from RBF's inherent ability to model nonlinear dependencies and spatial relationships among sensor nodes, enabling finer adaptation to irregularities in pressure patterns. In contrast, linear regression models assume global linearity and are unable to model localised distortions effectively.

The consistent R^2 performance across multiple experimental conditions, static standing, stair climbing, stair descending, and walking, further confirms the robustness and generalizability of the proposed system. These findings demonstrate that integrating RBF interpolation enhances the precision of plantar pressure reconstruction, providing a reliable computational framework for gait monitoring and potential clinical assessment applications.

Beyond the healthy cohort examined in this study, the sensitivity of the proposed system to abnormal plantar loading is clinically relevant, since comparable loading abnormalities are reported in populations such as elderly patients and individuals with diabetic foot ulcers [1], [2]. Simonsson et al. [7] previously reported reliable peak pressure measurements in high-risk diabetic patients using commercial insole systems,

supporting the clinical viability of piezoresistive-based platforms such as the one proposed here. This clinical relevance also motivates the automated classification stage envisaged for further development. Naive Bayes has demonstrated stable performance in sensor-based medical classification tasks, achieving 94% overall accuracy, 100% precision, and 100% recall in classifying degrees of hearing loss from audiometric threshold data [27] which indicates its suitability for structured biomedical signal classification, including plantar pressure-based gait analysis. In addition, a comparative study of K-Nearest Neighbours (KNN) and Support Vector Machines (SVMs) for health-related predictions reported that KNN achieved 98.2% accuracy compared with 94.3% for SVMs in obesity classification using patient physiological data [28]. Together, these findings provide a methodological basis for the automated classification of gait disorders using the labelled feature set obtained with the proposed insole system.

4. Conclusions

This study developed a wearable insole system equipped with 16 piezoresistive sensors, eight on each insole, to monitor plantar pressure in real time. Experimental evaluations across four activity conditions (static standing, ascending stairs, descending stairs, and walking cycles) demonstrated the system's ability to accurately analyse pressure distribution patterns. In the static standing condition, noticeable asymmetries were observed, particularly in Subject 4, who exhibited supination characteristics with the highest heel curvature (12°), whereas the other subjects ranged from 5° to 7° . The system operated with a sampling rate of 10 Hz, providing sufficient temporal resolution for continuous plantar pressure tracking. During gait analysis, a consistent pattern was observed in which pressure transitioned from heel strike (high heel pressure) to push-off (increased forefoot pressure), highlighting distinct variations between normal and supinated subjects.

The proposed insole system effectively detected and distinguished plantar pressure characteristics across different activities. Its performance exhibited strong consistency, with R^2 values ranging from 0.896 to 0.925, indicating high measurement reliability. The identified differences in pressure distribution, particularly among subjects with supinated feet, demonstrate the system's potential as a screening tool for assessing foot posture. Moreover, the real-time measurement capability suggests potential clinical applications as an objective diagnostic aid for podiatrists, supporting personalised orthotic design and rehabilitation monitoring.

This study has limitations, including a small sample size ($n = 5$) and a fixed insole length (27 cm), which may limit the generalizability of the findings. The homogeneity of the healthy young adult sample further constrains generalizability. Despite these constraints,

the system demonstrated the ability to detect pathological pressure patterns, shown by the accurate identification of supination characteristics in Subject 4. Specifically, the RBF interpolation model effectively captured lateral load dominance and elevated heel curvature (12°). Thus, the system's sensitivity to abnormal plantar loading patterns was evident. The clinical relevance of this sensitivity, together with the supporting evidence from earlier studies, is discussed in Section 3.5. To build on these findings, future research should expand participant recruitment to include clinical populations and further validate the system's diagnostic applicability.

Future research will integrate artificial intelligence and machine learning algorithms to enable automatic gait classification and anomaly detection. Classifiers such as Naive Bayes, K-Nearest Neighbours (KNN), and Support Vector Machines (SVMs) are strong candidates for this purpose; the reported evidence supporting their use for structured biomedical signal classification is presented in Section 3.5. Together, these considerations provide a strong methodological basis for the future automated classification of gait disorders using the proposed insole system.

To clarify the relationship between the existing dataset and the proposed machine learning implementation, the features obtained in this study, namely the stress/pressure values per region for the forefoot (T1–T4), midfoot (M1–M2), and rearfoot (MH–LH), along with the gait phase patterns (heel strike, mid-stride, and push-off) and the foot posture label (normal versus supination), constitute a labelled feature set that can be directly fed into the aforementioned classifiers. In this way, the current measurements have provided the input features and ground truth labels necessary to train and validate the proposed Naive Bayes, KNN, and SVM models for automated gait and foot posture classification, thus creating a clear and reproducible path from the collected data to the planned automated analysis.

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