High-Resolution Plantar Pressure Insole System for Enhanced Lower Body Biomechanical Analysis

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2025 IEEE International Symposium on Circuits and Systems (ISCAS) | 979-8-3503-5683-0/25/$31.00 ©2025 IEEE | DOI: 10.1109/ISCAS56072.2025.11044303

***Abstract*—Gait analysis is a crucial method for evaluating and monitoring an individual's health. A critical aspect of this analysis is understanding how forces are distributed across the foot while walking. Existing plantar pressure insole systems often lack the resolution needed for detailed foot analysis. To address this, a real-time insole system is presented with 253 high-density resistive pressure sensors (4 sensors per cm²) for each foot with a wireless transfer rate of 60 Hz. In addition, our work combines the insole hardware with a custom convolutional neural network (CNNs) and long short-term memory (LSTM) model to predict six lower body joint landmark positions. The prediction achieves a coefficient of determination (R^2) of 0.83 and a mean squared error (MSE) ranging from 7.0e-4 to 9.6e-4. With an inference time of 0.6 ms, this system provided accurate, high-resolution plantar foot pressures and insights into 3D joint movements in the lower body. It is a promising tool for applications in rehabilitation and sports performance optimisation.**

Keywords—Body landmark prediction, Flexible sensor, Gait analysis, Smart insole.

I. Introduction

Gait, the posture and behaviour characteristic of the human body during walking, often reflects an individual's physical condition and musculoskeletal functions. Monitoring and analysis of gait based on wearable sensors has recently shown great potential in a wide range of healthcare applications [1], [2]. The distribution of plantar forces during various phases of the gait cycle can identify changes in body postures and motions. These subtle force variations are essential for predicting the detailed motion of lower body joints and are key to many health monitoring and biomechanical studies [3]. However, current gait analysis systems, particularly those using insole-based sensors, often rely on a limited number of large sensors [4]. These systems may underestimate peak pressure values and omit details in certain areas of the foot due to the limited spatial resolution of large sensors. Other researchers have argued that using a denser array of smaller sensors can accurately collect comprehensive data across the entire foot [5]. Capturing high-resolution pressure data in real-time not only offers more valuable insights into gait dynamics but also provides new possibilities for lower limb joint motion prediction, an area that has been relatively underdeveloped in the existing literature.

Previous research on gait analysis has focused on areas such as activity classification or posture recognition. For instance, D. Chen et al. [6] have used pressure sensors embedded in insoles to classify everyday activities such as walking, running, or standing. Another study has successfully achieved basic posture classification using a limited number of sensors [7]. However, in application scenarios such as

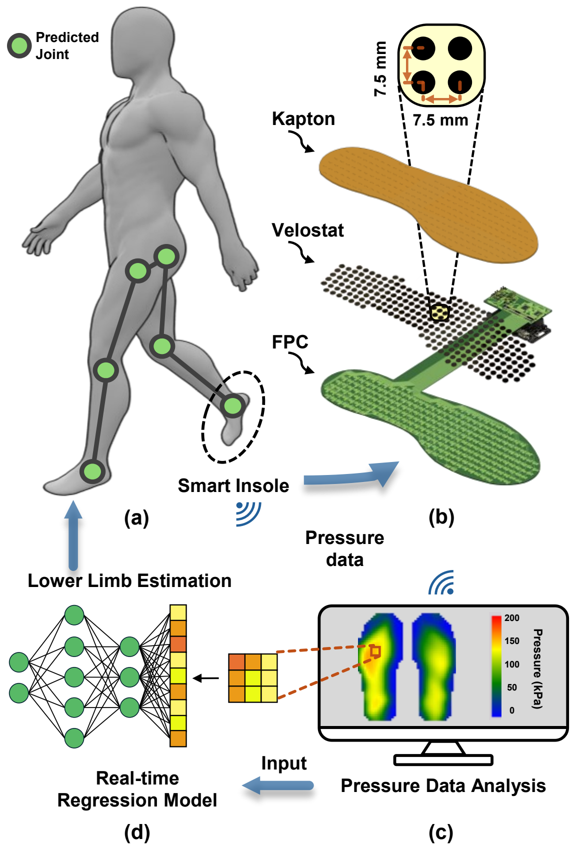

Fig. 1. (a) Predicted lower body joints. (b) Proposed insole system. (c) Display of pressure heatmap. (d) Customized neural network for lower body prediction.

rehabilitation therapy and sports performance optimisation, more detailed posture estimation methods are required. Precise joint motion feedback can prevent the development of undesirable movement patterns, thus creating a need for further exploration in this area. Although camera-based motion capture systems have achieved thorough and accurate lower body posture prediction, they still face limitations in practical applications, including susceptibility to obstacles and high costs, which hinder their widespread use in real-life settings. There is still a significant research gap for accurate lower body joint estimation using high-resolution insoles, which could hold great potential in many applications, especially in sports and rehabilitation training.

In this paper, a designed and fabricated high-resolution insole system is described. A sensor density of 4 sensors per cm², totalling 253 sensors for a UK size 8 insole. The insole design leverages existing fabrication technologies, enabling cost-effective large-scale manufacturing. The sensing hardware is designed to balance size, power consumption, and data acquisition speed. It wirelessly transfers all sensor data to a PC, providing plantar pressure imaging at 60 Hz. Using

This work was supported by the Rosetrees Trust, under grant reference: UCL-IHE-HA\1.

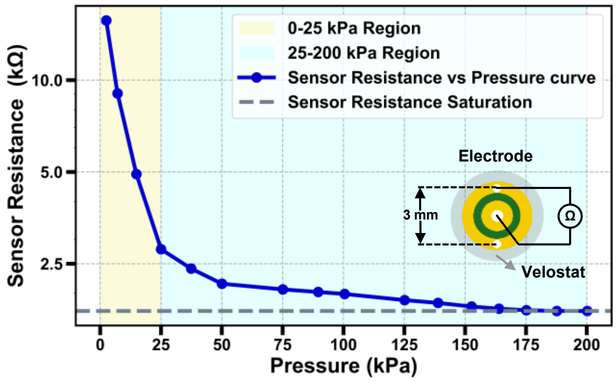

Fig. 2. Sensor resistance versus pressure curve.

custom convolutional neural networks (CNNs) and long short-term memory (LSTM) neural network, the system inputs these pressure images to predict six lower body posture landmarks as shown in Fig.1 (a) with an average R^2 of 0.83, offering a novel tool for body biomechanical analysis by transforming two-dimensional plantar pressure data into three-dimensional (3D) posture insights. The rest of this paper is organised as follows: Section II discusses the system architecture, including the insole design and the data acquisition system. Section III demonstrates the experimental design, data preprocessing process and deep learning algorithm. Section IV evaluates the experimental results. Conclusions are in Section V.

II. Overview and System Design

The work can be summarised as a pipeline composed of three key stages. 1) As shown in Fig. 1(b), a customised insole integrated with a small sensor readout board is fabricated. It collects plantar pressure data to generate foot pressure heat maps wirelessly. 2) A depth camera is used to capture the selected key body posture landmarks of the lower limbs, which serve as label data for the neural network. 3) Features from the plantar pressure heat maps are extracted and implemented as inputs, while the three-dimensional landmark coordinates of the lower limb joints serve as labels. These are then fed into a customised neural network model, which enables the prediction of three-dimensional coordinates of lower limb joints based on plantar pressure. The work pipelines are illustrated in Fig.1 (a) to (d), encompassing the entire process from insole fabrication, hardware design, data acquisition and feature extraction to model training and prediction.

A. Insole Design and Fabrication

As shown in Fig.1, the insole consists of a flexible printed circuit board (FPC) base and a Kapton top layer that sandwiches the circular piezoresistive material (Velostat). The only feasible design that can accommodate such a large sensor array is a row-column readout matrix. On the FPC base, each sensor requires two electrode contacts corresponding to the row and column readout lines. The electrode contacts are arranged in two concentric circles, as shown in Fig. 2. The pressure response characteristics of the designed circular Velostat sensors were tested with a pressure gauge, where different static pressures were applied using a clamp, and changes in resistance were measured. The resulting resistance-pressure curve is shown in Fig. 2. A significant drop in resistance is observed in the low-pressure region (0-25 kPa),

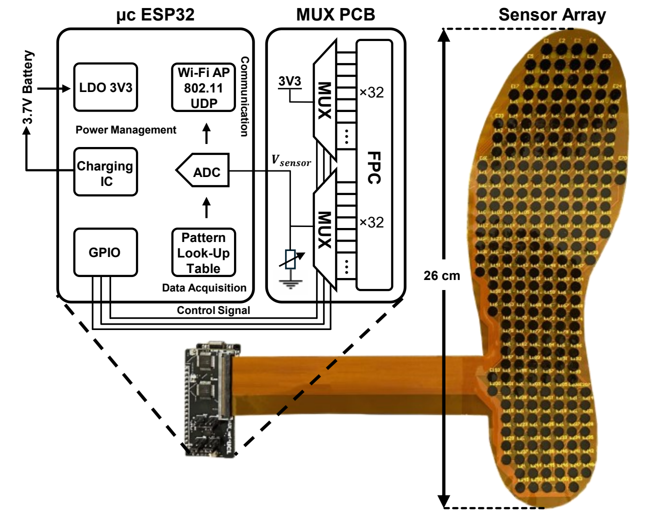

Fig. 3. Hardware architecture.

where resistance changes are not directly proportional to the applied pressure. From 25 to 200 kPa, a region of interest to the insole applications [8], the resistance of the sensor demonstrated a more linear and steadier decreasing trend.

The placement of the pressure sensor needs to cover all critical areas of the foot, such as the heel, the arch, and the edges, to monitor the pressure distribution across different foot regions. With a length of 26 cm and a width of 8 cm, the corresponding pitch of the sensor positions is determined to be 7.5 mm; in other words, there are approximately four sensors per cm^2, which is comparable to an industry-standard pressure sensing mat [9]. Using a two-layer FPC, all the tracks can be placed on the bottom layer to facilitate easy routing. Due to the unsymmetrical shape of the insole, routings are interconnected diagonally, forming a grid of 32 rows by 10 columns. This arrangement optimises the connection paths when reading the piezoresistive values.

The fabrication process is critical in determining its cost and scalability, which ultimately affects the insole's likelihood of reaching end-users. It consists of: 1) each electrode is laser-cut from a sheet of Velostat into individual circular sensors with a 3 mm radius. This radius is chosen to align the FPC electrodes better, allowing slight overlays to ensure good contact. These sensor cutouts are arranged in a pattern that matches the FPC electrode layout. Notably, the sensor is still attached to the original sheet with a 1 mm arc bridge. 2) the Velostat sheet is firmly adhered to Kapton tape. Then, the Kapton tape is peeled away from the sheet, and the 1 mm arcs break, leaving the individual sensors securely bonded to the tape. This tape, with the sensors arranged in the desired pattern, is subsequently adhered to the FPC. The Kapton tape adhesion ensures that sensors remain in place and do not detach or shift due to friction or movement during use. This fabrication process method is quick, reproducible, and scalable, and it can be automated on a large scale.

B. Sensor Readout Hardware Implementation

The readout hardware consists of a customised PCB stacked on an ESP32 Microcontroller (Espressif, China), as shown in Fig.3. Controlled by the ESP32, two 32-channel MUX (ADG732BSUZ) scan the rows and columns of the sensor array. A potentiometer is adjusted to accommodate high-pressure regions. The peak current flowing through the

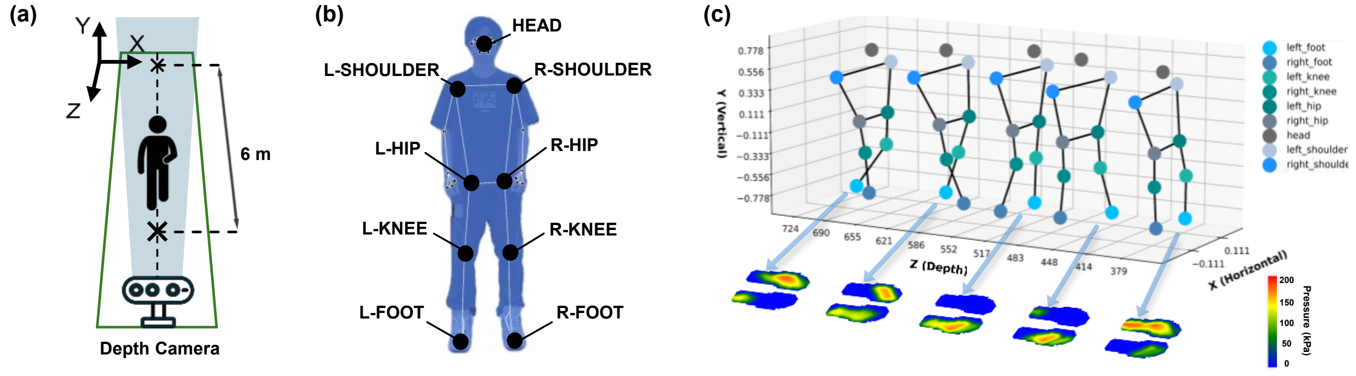

Fig. 4. (a) Experimental setup. (b) Joints captured using Mediapipe. (c) Visualization of corresponding foot pressure heatmap and body joints in a gait cycle.

sensor remains below 10 mA, which ensures that it is suitable for continuous pressure monitoring. Before reading the resistance changes across the pressure sensors by ESP32's analog-to-digital converter (ADC), a pattern lookup table determines whether the chosen position within the matrix contains an active sensor. This ensures efficient data acquisition speed since only 253 out of the 320 possible points are occupied by sensors.

C. Wireless Connectivities

The ESP32 is equipped with a Wi-Fi module that enables wireless connectivity, allowing multiple MCU devices to connect to a PC via access point (AP) mode. The system software is developed and configured using Espressif's ESP32 platform, allowing easy identification of the left and right foot insoles. To achieve a high transmission rate, data packets are encoded in a compact format, including sensor IDs and pressure values for each frame. The user data program (UDP) protocol, a connectionless communication protocol in the transport layer, is applied to send data packets, achieving a short delay time for real-time data transmission.

After receiving the binary data packets, the PC decodes the sensor IDs and pressure values using a Python script. The decoded data is then used to generate heatmaps for both feet, visualising pressure distribution dynamically at 60 frames per second (FPS). Table I compares this system with other works and commercial products, demonstrating both high sensor density and fast FPS as a wearable plantar pressure system.

TABLE I. PLANTAR PRESSURE SYSTEM COMPARISON

Study/ Work	Number of Sensors	FPS (Hz)	Sensor Type	Wearable Insole (Y/N)	Pressure Range (kPa)
This work	**253**	**60**	**Resistive**	**Y**	**0 - 200**
[10]	16	100	Capacitive	Y	0 - 50
[11]	24	NA	Capacitive	Y	0 - 200
[12]	99	400	Capacitive	Y	15 - 600
[9]	6080	100	Capacitive	N	10 - 1270
[13]	2500	60	Resistive	N	1.2 - 63

III. THREE DIMENSION POSTURE PREDICTION

A. Experiment Setup

Fig. 4 (a) illustrates the experimental setup used for data collection during a 6-meter walk. Two-foot pressure and body posture data were recorded using the smart insole and Intel RealSense Depth Camera D435i (Intel, USA), respectively. Although the smart insole's wireless data transfer rate can achieve 60 FPS, the depth camera's RGB frame rate is 30 FPS. The overall system is downsampled to match the camera. To capture the 3D coordinates of body joint landmarks, Mediapipe was used to predict the horizontal and vertical space information of the joints (i.e., the 2D x and y coordinates) from the RGB frame. The depth frame from the depth camera was aligned with the RGB frame to provide the complete 3D coordinates of the body joints. Subsequently, 9 key joint landmarks from the 33 predicted pose landmarks were extracted as shown in Fig. 4 (b).

Five participants were recruited for this experiment, each with a U.K. shoe size of 8 ± 1, height of 175 ± 5 cm, and weight of 75 ± 15 kg. They walked back and forth in a straight line along the six-meter walkway, with each contributing 5,000 frames of data to the dataset for subsequent training. [This study was approved by the Ethics Committee of University College London, ID: 27647/001].

B. Data Preprocessing

Several preprocessing steps are applied to the raw foot pressure and 3D coordinates of the nine joints to prepare the collected data for analysis and training, as shown in Fig. 4 (c).

For label preprocessing, Z-score, which indicates how far a particular data point is from the mean of the data, is calculated for each joint using equation (1):

$$z = \frac{x - \mu}{\sigma} \quad (1)$$

where μ is the mean and σ is the standard deviation. Potential outliers caused by the inaccuracy of Mediapipe are then removed. Instead of using the absolute coordinates as labels, six relative coordinates (left hip, right hip, left knee, right knee, left foot, and right foot) are calculated and used to eliminate variations due to differing starting positions. A reference point, which consists of the x and y coordinates of the mid-hip and the z coordinates of the mid-foot, is calculated to extract this relative information for maximum stability.

For input (the pressure image) preprocessing, a Gaussian filter is applied to smooth the raw pressure data, reducing noise while retaining important signal features. In addition, all input data were normalised to ensure that the different individual's features lie on the same scale, improving the performance and stability of the machine learning models.

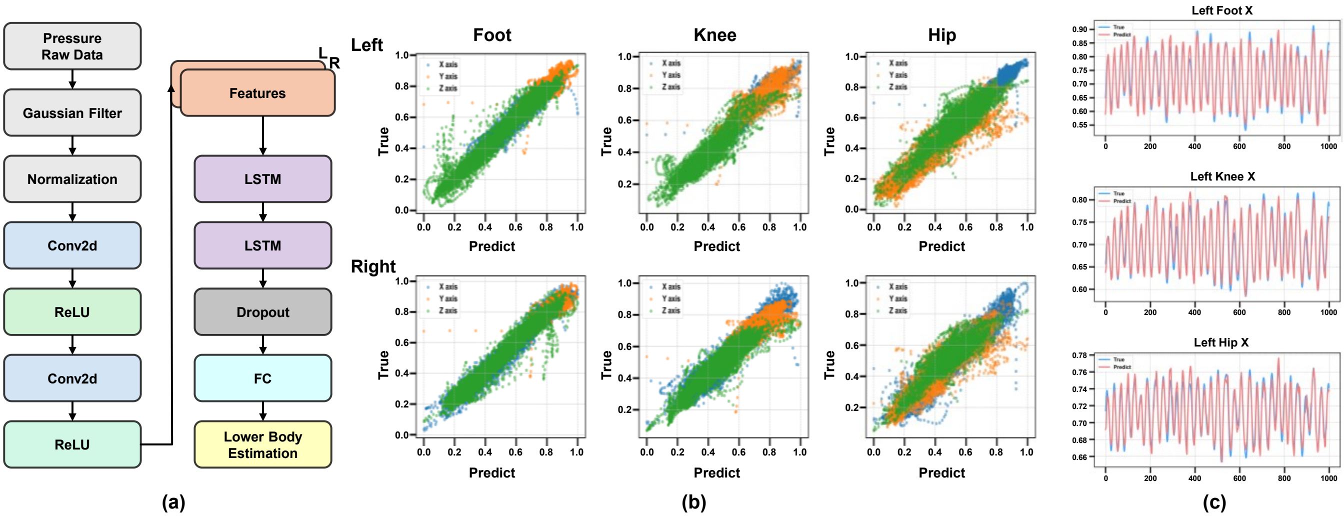

Fig. 5. (a) CNN-LSTM model architecture. (b) Scatter plots of the regression results for six joints. (c) Labels versus predicted outputs for x axis of left foot, knee and hip.

C. Deep Learning Model

To achieve the lower body prediction, a CNN-LSTM model shown in Fig. 5 (a) was developed and applied to train the pre-processed data. The dataset was split into training (80%) and testing (20%) sets. By sending two pressure matrices (Left and Right foot) to 2D convolutional layers followed by a MaxPooling layer (2×2), their spatial features and dimensionality are both extracted and reduced. They are then combined at the input of an LSTM model with a hidden size of 128 and a timestep of 50. A dropout layer of 0.3 is added to the output of the LSEM model, preventing overfitting. Finally, it is connected to a fully connected layer to output the predicted six joints.

IV. Results and Discussion

The regression model was trained and evaluated using 5-fold cross-validation on the pressure data. Its average inference time is 0.6 ms on Nvidia Geforce 4060. The results in Fig. 5 (b) and (c) are from the best-performing fold, showcasing the model's top potential.

The model's performance is evaluated through both scatter plots and time series comparisons between the predicted and true joint landmark positions as shown in Fig. 5 (b) and (c). The scatter plots show the predicted versus true values for the joints across three axes (X, Y, Z). Most of the points are distributed close to the diagonal, indicating a strong correlation between the predicted and true values. This suggests that the model generally performs well in estimating joint positions. However, there are slight deviations, particularly at the extremes of the value range, where some points are more scattered. This indicates that the model's accuracy may decrease when predicting extreme positions.

The time series plots further demonstrate the model's ability to capture the temporal dynamics of joint movements. The predicted values closely follow the true values, confirming that the model can effectively capture the overall trend in joint position changes over time. Some minor discrepancies are observed at certain time points, but these do not significantly affect the overall trend prediction.

It is worth noting that the performance across all folds was quite consistent, with only minor variations. The average performance across the different folds showed similar trends, indicating that the model is stable and generalises well across different data splits.

The correlation coefficient (R^2), mean absolute error (MAE), and mean squared error (MSE) of the regression model are detailed in Table II. When compared to previous lower body estimation results from a system that integrated an IMU and eight pressure sensors, as described in [14], the performance is slightly lower. However, the results demonstrate the strong potential of using only pressure sensors to achieve accurate lower body estimations. This approach allows for a more lightweight regression model, reducing system complexity while maintaining promising accuracy.

Table II Landmark Prediction Results from the CNN-LSTM Model

	R^2	MAE	MSE
L-Foot	0.885	0.0205	9.6e-4
R-Foot	0.902	0.0197	8.6e-4
L-Knee	0.815	0.0195	9.0e-4
R-Knee	0.852	0.0176	7.0e-4
L-Hip	0.767	0.0178	7.4e-4
R-Hip	0.779	0.0163	7.0e-4

V. Conclusion

This paper presents a real-time, high-resolution insole system combined with a deep learning model to predict lower body movements during walking using data collected from the system. By using custom hardware architecture, the established system can provide detailed plantar information at a decent transmission rate. After feeding these pressure data into the CNN-LSTM model, the 3D coordinates of six lower body joints can be estimated with an average R^2 of 0.83. The model achieves an MSE ranging between 7.0e-4 and 9.6e-4, reflecting its high accuracy. The results indicate that using only pressure sensor data from the designed insole system, the accuracy of the model is high for the prediction of lower body joints, which shows potential in areas like rehabilitation and sports performance optimisation.

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