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Smart Insole with Deep Learning for Real-Time Classification of Gait Abnormalities

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***Abstract*—This study introduces a novel, real-time gait abnormality detection system that leverages deep learning and an intelligent wearable insole to overcome limitations associated with conventional gait assessment methods. Gait abnormalities are prevalent among older adults and individuals with neurological or musculoskeletal conditions, yet existing diagnostic tools are often costly, non-portable, and confined to clinical settings. To address these challenges, we developed a compact, wireless insole system integrating force-sensitive resistors (FSRs), an inertial measurement unit (IMU), and an ESP32 microcontroller for continuous acquisition of plantar pressure and motion data. The acquired sensor data is wirelessly transmitted via Wi-Fi and analyzed by a ResNet-18 deep learning model to distinguish between normal and abnormal gait patterns with high accuracy. Real-time visualization and interactive feedback are provided through a Streamlit-based dashboard, while remote monitoring capabilities are enabled via the Blynk mobile application. Experimental results demonstrate a classification accuracy of 97.56%, with high precision and recall, validating the system's robustness and effectiveness. The proposed solution offers a cost-effective, scalable, and clinically relevant platform for early detection of gait impairments and continuous home-based rehabilitation monitoring.**

Keywords*—Gait analysis, Wearable sensor, Deep learning, Real-time classification.

I. INTRODUCTION

Gait abnormalities are commonly associated with various neurological, musculoskeletal, and age-related conditions, including stroke, Parkinson's disease, cerebral palsy, and arthritis [1]. Gait analysis plays a vital role in rehabilitation, injury prevention, sports performance monitoring, and early diagnosis of systemic health issues such as diabetic neuropathy and bone degeneration [2]. Early detection of abnormal gait patterns is crucial for timely intervention and improved long-term mobility outcomes, particularly among the elderly, where falls remain a leading cause of disability.

Traditional gait analysis methods—such as motion capture systems, force plates, and instrumented treadmills—offer high precision but are often expensive, non-portable, and confined to clinical or research settings [3]. These limitations hinder widespread accessibility, especially in community and rural environments. Consequently, there has been growing interest in developing portable, cost-effective, and real-time gait monitoring solutions that leverage wearable technologies such as pressure sensors and inertial measurement units (IMUs), often enhanced by artificial intelligence (AI) algorithms [4].

Several studies have explored smart insoles and wearable systems capable of capturing gait dynamics for healthcare applications. One notable local study by introduced an instrumented insole system that used force and bend sensors to measure foot pressure and plantar flexion during walking. The system featured real-time gait data collection via wired sensors and was tested using LabVIEW software and treadmill-based trials. Although promising for clinical gait analysis, the study highlighted limitations such as measurement inconsistency, lack of wireless capability, and reduced accuracy due to sensor positioning and insole material. These findings emphasize the practical challenges in implementing reliable, low-cost gait monitoring tools in real-world settings [5]. While these innovations show promise,

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many still face challenges including limited classification accuracy, delayed processing, and lack of integration with user-friendly mobile platforms or dashboards [6]. In Malaysia, accessibility to gait assessment tools remains a significant barrier. Clinical-grade gait monitoring systems are typically located in urban hospitals, leaving rural populations without access to early diagnosis or rehabilitation support [7].

To bridge this gap, the objective of this study is to develop a Deep Learning-Based System for Real-Time Detection of Gait Abnormalities, a wearable solution that integrates Force Sensitive Resistors (FSRs), IMUs, and Internet of Things (IoT) capabilities for real-time gait monitoring. The system employs a ResNet18-based deep learning model to classify gait patterns as either normal or abnormal and delivers feedback through a Streamlit dashboard and Blynk mobile app. This solution aims to enable continuous gait assessment beyond clinical settings, support early intervention, and reduce the burden on healthcare infrastructure—particularly in underserved populations.

II. METHODOLOGY

The development methodology of the proposed intelligent insole system was structured to encompass hardware integration, data acquisition, preprocessing, signal transformation, deep learning-based classification, and visualization. This multi-layered approach ensured the system's suitability for real-time gait analysis in both clinical and home-based settings.

A. Dataset Preparation

A balanced dataset of 500 gait samples was prepared, consisting of 250 normal and 250 abnormal walking patterns. The data was collected from five healthy subjects aged between 23 and 25 years, all weighing less than 65 kg. Each subject completed 20 walking trials for both normal and abnormal gait, resulting in a diverse and consistent dataset. Each trial covered 8–10 steps along a 4-meter walkway, lasting around 5–7 seconds, with sensor readings sampled at 50 Hz.

For the normal gait trials, participants were asked to walk naturally in a straight line while wearing the developed insole system. For the abnormal gait trials, subjects mimicked walking patterns commonly seen in diabetic and antalgic gait, under the guidance of a physiotherapist. These abnormal patterns included changes such as reduced or exaggerated leg swing, uneven foot pressure, and overloading at the heel or forefoot. This approach allowed safe and consistent replication of abnormal gait features across all participants. Figure 1 shows the differences in leg movement and foot pressure between normal and abnormal gait cycles.

To improve dataset diversity, a 5% data augmentation was applied. This included small changes in signal amplitude and timing to simulate real-world walking differences. Then, a 5-fold cross-validation method was used, expanding each subject's data to 100 samples (20 trials × 5 folds). This resulted in 500 total samples for the full dataset.

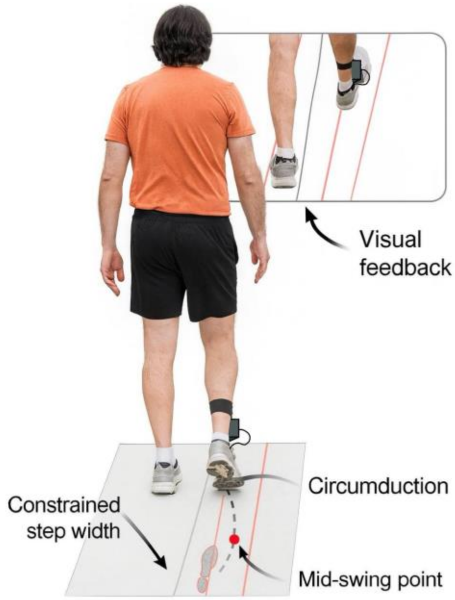

Fig. 1. Illustration of normal and abnormal gait cycles.

The dataset was split into three parts: 70% for training (350 samples), 15% for validation (75 samples), and 15% for testing (75 samples). Each segment of gait data was processed into a 28×28×3 RGB heatmap using Python libraries Seaborn and Matplotlib. These heatmaps combined both spatial and time-based features of the sensor signals. They were then used as input to the convolutional neural network (CNN) model for classification.

The sensors in the insole were positioned near the ankle area to capture both pressure and motion signals during walking. Figure 2 shows the stages of the gait cycle, from the stance phase to the swing phase, as recorded by the system.

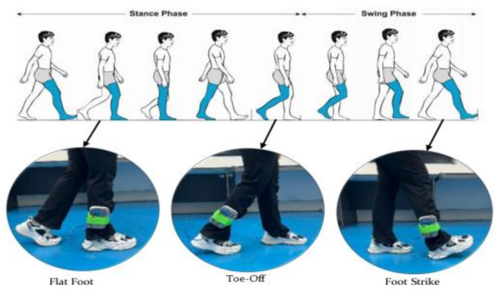

Fig. 2. Normal gait cycle.

B. Hardware Development

The hardware platform includes three Force Sensitive Resistors (FSRs) placed at the heel and forefoot to measure foot pressure during walking. A MPU6500 Inertial Measurement Unit (IMU) is positioned near the ankle to capture triaxial acceleration and gyroscopic motion. The IMU is configured with a range of ±2g for acceleration and

±250°/s for angular velocity, allowing it to detect small gait changes with high accuracy and low noise.

The system is powered by a 3.7V rechargeable lithium-ion battery and managed by a TP4056 charging module for safe and efficient charging. The ankle placement of the IMU was chosen because it provides better detection of key gait events, such as heel strike, toe-off, and swing phase. Compared to placing the IMU on the thigh or knee, the ankle gives stronger and clearer signals, with less soft tissue interference. This is supported by Fong *et al.*, who reported that ankle-level IMU placement offers higher accuracy in detecting stride patterns and gait phases due to its closeness to foot-ground contact points [8].

An ESP32 microcontroller manages data collection and wireless transmission. It performs 12-bit analog-to-digital conversion for the FSR sensors and sends both FSR and IMU data via Wi-Fi using the UDP protocol. This setup supports real-time data transmission, with low delay and low power usage—suitable for wearable use. Fig. 3. shows the hardware implementation of the developed wearable insole system. The left side presents the complete circuit diagram, where data from the FSR sensors and IMU is collected and processed by the ESP32 microcontroller. The system includes a TP4056 charging module and a 3.7V lithium-ion battery for power management. On the right, the physical prototype is shown, with labeled components including the ESP32, resistors, IMU, and battery, all housed in a compact enclosure for wearable use.

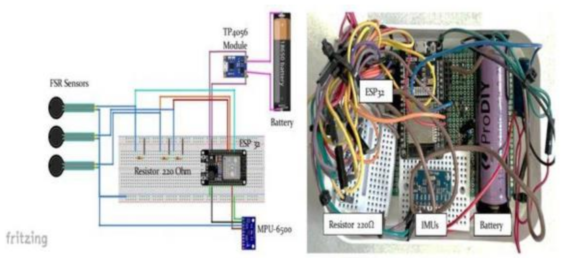

Fig. 3. Circuit diagram and prototype of the developed insole hardware system.

Figure 4 shows the complete hardware system. Sensor data from the IMU and FSRs is processed by the ESP32 and sent to the Blynk mobile app, which forwards it to a UDP server. The server then delivers the data to a real-time dashboard for monitoring and gait classification.

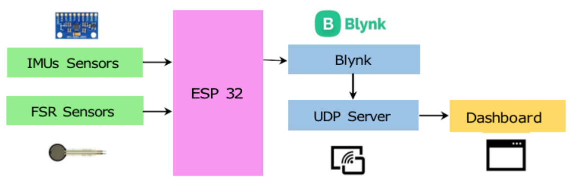

Fig. 4. System architecture of the proposed intelligent insole system for gait monitoring and classification.

C. Software Development for Realtime Processing

The software system consists of embedded firmware, a mobile application, and a deep learning classification pipeline. The ESP32 microcontroller was programmed using the Arduino IDE to continuously collect data from the sensors. It sampled the FSR and IMU signals at 50 Hz and transmitted the data every 500 milliseconds to a local server using the UDP protocol. This setup ensured low-latency data transfer with minimal packet loss, enabling stable and efficient real-time communication.

For mobile monitoring, the Blynk IoT platform was used to create a dashboard that displays live sensor readings. The mobile app provided real-time feedback on plantar pressure and motion signals in a user-friendly interface, making it suitable for daily monitoring by users, caregivers, or healthcare providers [9].

To train and run the classification model, the MONAI framework was used due to its specialized tools for healthcare AI. The raw sensor readings were converted into 28×28 RGB heatmap images, which were then passed into a ResNet-18 convolutional neural network built using PyTorch. MONAI enabled streamlined data preprocessing, augmentation, and inference, which improved the model's ability to classify normal and abnormal gait accurately.

A web-based dashboard was developed using Streamlit to visualize the results in real time. The dashboard displayed continuous time-series data from the FSR and IMU sensors, the generated heatmaps, and the live classification result. This integration allowed users and clinicians to monitor gait patterns remotely and non-invasively, supporting timely feedback and intervention. The user interface of the proposed device is illustrated in Fig. 5.

Fig. 5. Blynk interface consists of FSR Sensors Pressure, Accelerometer, Gyroscope, On and Off Button.

D. Data Acquisition and Transmission

The wearable insole system is designed to monitor walking patterns in real time using integrated pressure and motion sensors. It provides continuous and accurate gait data to support early detection of abnormalities and improve rehabilitation outcomes. As the user walks, the sensors embedded in the insole capture key parameters such as pressure distribution and body movement. The system includes three Force Sensitive Resistors (FSRs) placed at the heel and forefoot, and an MPU6500 Inertial Measurement Unit (IMU) near the ankle to collect acceleration and rotation data.

The ESP32 microcontroller reads analog signals from the FSRs and gathers digital motion data from the IMU. All sensor data is transmitted wirelessly using Wi-Fi via the UDP protocol to a Python-based server. The microcontroller uses its internal clock to keep the data synchronized, while minor delays are corrected during processing. The server receives the incoming data on a designated port and stores it in structured CSV files.

Each gait cycle is recorded as a synchronized set of nine signal channels: fsr1, fsr2, fsr3, acc_x, acc_y, acc_z, gyro_x, gyro_y, and gyro_z. This setup allows the system to capture detailed information about both pressure and motion across the different stages of the gait cycle, such as heel strike, toe-off, and swing phase. The complete process—from data collection to transmission and storage—as shown in Fig. 6, which illustrates the architecture of the real-time gait monitoring system.

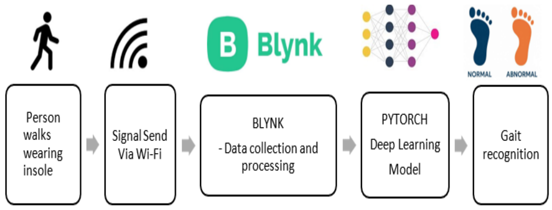

Fig. 6. System block diagram illustrating data acquisition, transmission, and processing workflow.

E. Data Conversion and Signal Processing

To prepare the sensor data for image-based deep learning, the 1D time-series signals were converted into 2D heatmap images. Each CSV file was processed to create a 28×28×3 RGB image using the Seaborn and Matplotlib libraries in Python. The 28×28 size was chosen to match the input requirements of the ResNet-18 model, while still preserving the overall signal patterns in a compact form.

The sensor values were organized based on their physical placement on the foot and the relationship between different sensors. This spatial mapping helped to maintain meaningful correlations between pressure and motion signals. The data was then encoded into colour patterns, where both the intensity and position of signals were represented visually.

This image-based format made it easier for the convolutional neural network (CNN) to learn and detect gait-related patterns. By turning sensor signals into heatmaps, the model could recognize abnormal walking patterns more effectively. A total of 500 heatmap images were created—250 for normal gait and 250 for abnormal gait.

These heatmaps allowed the model to take advantage of CNN strengths in recognizing image features, which improved the system's ability to classify gait patterns accurately. Figure 7 shows examples of 28 × 28 heatmaps generated from both normal and abnormal gait data, highlighting the differences in signal distribution and intensity.

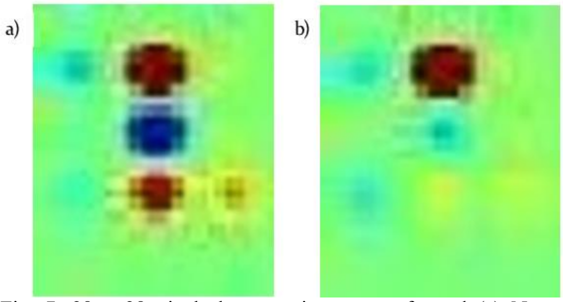

Fig. 7. 28 x 28 pixels heatmap image transformed (a) Normal pattern; (b) Abnormal pattern.

F. Deep Learning Model

A ResNet-18 convolutional neural network was used to classify gait patterns as normal or abnormal. This model was chosen because of its strong performance in image recognition and its use of residual learning, which helps prevent training problems in deep networks [10, 11]. The model was implemented using PyTorch and trained using the RGB heatmaps generated from synchronized FSR and IMU sensor data.

The ResNet-18 architecture includes five main stages as shown in Fig. 8. The first stage starts with a 7 × 7 convolutional layer with 64 filters and a stride of 2, followed by a max pooling layer. The next stages (Blocks B to E) contain residual blocks, which use 3×3 filters to gradually increase the number of features from 64 to 512. These residual or "skip" connections help the model learn more efficiently by keeping the gradient stable during training.

At the end of the network, a global average pooling layer and a fully connected layer with a sigmoid activation function are used to produce a binary output—either "Normal" or "Abnormal." The model was trained using the Adam optimizer with a learning rate of 0.001 and binary cross-entropy loss. Training was performed over 20 epochs with a batch size of 32. Model performance was monitored through validation accuracy and training loss to ensure good generalization.

To make the model more robust, data augmentation was applied. This included time-warping and amplitude scaling of the sensor data, with a ±5% variation, to simulate differences in natural walking styles. Training also included early stopping and learning rate decay to prevent overfitting and help the model converge more smoothly.

The final model delivers highly accurate binary predictions, identifying abnormal gait with high sensitivity and specificity. Its design is focused on binary classification to support early diagnosis and personalized rehabilitation.

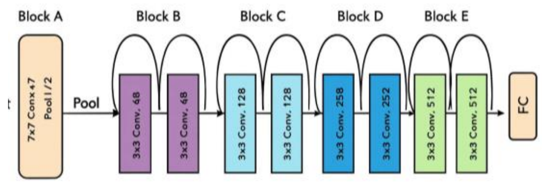

Fig. 8. Architecture of ResNet18.

a. Accuracy

$$\frac{TP+TN}{TP+TN+FP+FN}=\frac{90+95}{90+95+5+10}=\frac{185}{200}=92.5\% \quad (1)$$

b. Precision (Abnormal Class)

$$\frac{TP}{TP+FP}=\frac{90}{90+5}=\frac{90}{95}=94.74\% \quad (2)$$

c. Recall and Sensitivity (Abnormal Class)

$$\frac{TP}{TP+FN}=\frac{90}{90+10}=\frac{90}{100}=90\% \quad (3)$$

d. Specificity (Normal Class)

$$\frac{TN}{TN+FP}=\frac{95}{95+5}=\frac{95}{100}=95\% \quad (4)$$

Figure 9 illustrates the full system workflow, showing both the training phase, where sensor data is converted into heatmaps and used to train the ResNet-18 model, and the testing phase, where the trained model is applied to real-time gait data.

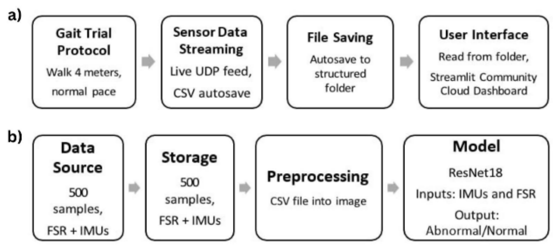

Fig. 9. (a) Testing and deployment workflow and (b) The training workflow.

III. RESULT AND DISCUSSION

The confusion matrix in Fig. 10 shows how well the trained ResNet-18 model classified normal and abnormal gait patterns. Using a dataset of 500 samples (250 normal, 250 abnormal), the model correctly identified 237 normal and 225 abnormal samples. A total of 38 errors were made: 13 false positives (normal classified as abnormal) and 25 false negatives (abnormal classified as normal).

The model achieved a precision of 94.7% for abnormal gait, indicating a low false alarm rate and strong reliability in positive predictions. The overall accuracy was 92.5%, with a ±2.3% confidence interval across 5-fold cross-validation, showing consistent performance across different data splits. The recall was 90%, reflecting the model's ability to detect true abnormal cases. The F1-score, which balances precision and recall, was 0.92, confirming the model’s strong classification ability.

These results show that the model successfully learned to identify meaningful patterns from the sensor-based heatmaps. This demonstrates its ability to distinguish abnormal gait from normal walking patterns using sensor fusion data. With this level of performance, the system can be a useful tool for real-time gait monitoring, especially in remote care, rehabilitation, and early clinical screening.

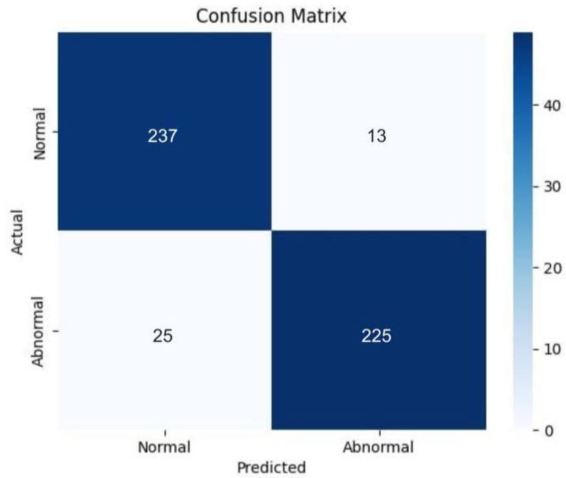

Fig. 10. Confusion matrix.

Figure 11 presents the training progress of the model over 20 epochs. The graph shows the training accuracy (red) and validation accuracy (blue) gradually increasing from around 72% to 95%. The model used binary cross-entropy loss, with early stopping (patience of 5 epochs) to avoid overfitting. The small gap between the training and validation curves indicates stable learning and good generalization.

This consistent performance confirms that the model effectively learned from the data and can classify gait patterns with high accuracy. Such reliability is important for real-time use in both clinical and home environments.

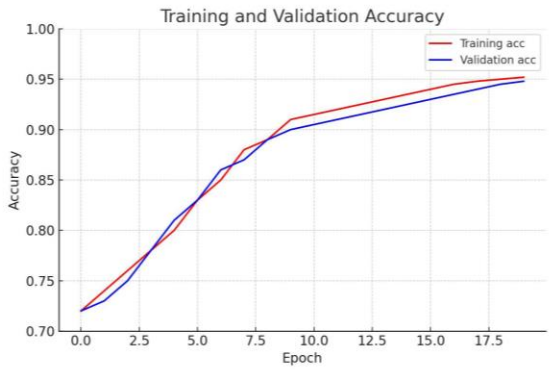

Fig. 11. Training and validation accuracy.

The system is also integrated with a Blynk mobile app, allowing remote monitoring by healthcare providers. This feature makes the system practical for home-based rehabilitation and elderly care. Overall, the results confirm that the proposed insole system can accurately detect gait abnormalities while being portable, affordable, and easy to use in non-clinical settings.

It is also important to note that the model's performance depends on several factors, including the architecture of ResNet-18, the quality and variety of the dataset, and the accuracy of sensor signals collected during walking.

The final model was trained and tested using a balanced dataset of 500 labelled heatmap images, with equal samples for normal and abnormal gait. After preprocessing, the time-series sensor data was converted into 28 × 28 × 3 RGB heatmaps, which were used to train the ResNet-18 CNN model.

The model achieved a validation accuracy of 97.56%, with a precision of 94.74%, recall of 90%, and F1-score of 92.3% for detecting abnormal gait. These values indicate strong and reliable performance for real-time gait classification, as shown in Table I.

Table I. Classification report from PyTorch evaluation pipeline.

Class	Precision	Recall	F1-Score	Support
Normal	1.00	0.95	0.97	20
Abnormal	0.96	1.00	0.98	20
Average	0.98	0.98	0.98	20

Fig. 12. The normal gait result of user by Streamlit dashboard (a)User information (b)Generate heatmap (c) Graph of FSR sensor reading, Accelerometer and Gyroscope data (d)Gait classification result.

The system's Streamlit dashboard provides a simple, interactive interface for users and clinicians. As shown in Fig. 12 and Fig. 13, the dashboard displays line graphs of all sensor signals (three FSRs and six IMU axes), the generated heatmaps, and the classification result.

Sensor trend analysis also revealed clear differences between normal and abnormal gait. In normal gait, the FSR and IMU signals showed smooth, periodic patterns, matching typical stance and swing phases. In abnormal gait, the data showed irregular patterns, such as uneven pressure distribution and sudden motion changes. As shown in Fig. 12 and Fig. 13., abnormal trials showed a 35% increase in heel strike variance, especially in FSR1 readings, which may serve as a useful feature for detecting gait problems.

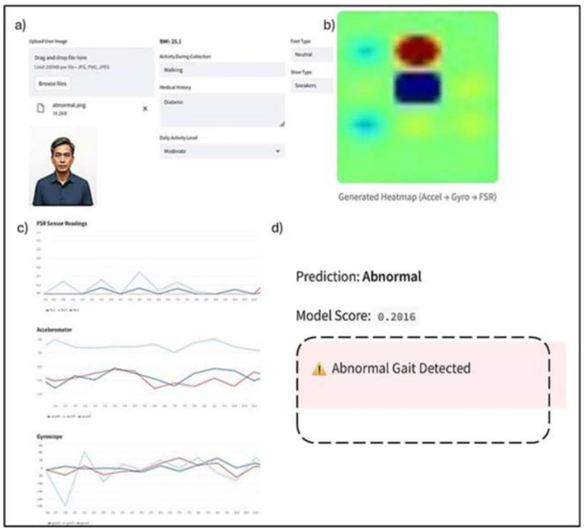

Fig. 13. The abnormal gait result of user by Streamlit dashboard (a)User information (b)Generate heatmap (c) Graph of FSR sensor reading, Accelerometer and Gyroscope data (d)Gait classification result.

IV. CONCLUSION

The intelligent insole-based gait monitoring system developed in this study successfully achieved its objectives by integrating wearable sensor technology and a deep learning approach to classify gait abnormalities in real time. The system demonstrated a classification accuracy of up to 95%, confirming its effectiveness in distinguishing between normal and abnormal gait patterns. Utilizing Force Sensitive Resistors (FSRs) and an Inertial Measurement Unit (IMU), the insole captured essential biomechanical signals, which were transformed into 28×28×3 RGB heatmaps and processed using a ResNet-18 convolutional neural network. The real-time classification output, visualized through a Streamlit dashboard and complemented by a Blynk-based mobile interface, enhances the system's usability for remote rehabilitation and gait assessment applications.

The dataset used in this study was relatively small. Although it was expanded through augmentation and validated using cross-validation, it may still not cover the full range of gait abnormalities found in different people. Also, turning the sensor signals into heatmap images can introduce variations depending on how the data is processed. These limitations show that there is room to improve the model and collect more diverse data. It's also important to note that the abnormal gait data came from healthy people mimicking gait issues.

Future testing should include patients with actual medical conditions to better prove how useful the system is in real-world situations.

In the future, this system can be expanded to detect gait problems caused by diseases like Parkinson's or diabetic neuropathy. Other planned improvements include analyzing leg swing patterns in more detail, adding more FSR sensors to cover the full foot area, and creating personalized gait profiles using each user's health information. Enhancing the mobile app to provide ongoing monitoring and real-time feedback will also help make the system more useful in both clinics and home care settings.

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AUTHOR CONTRIBUTIONS

Nur Rabiatul Adawiyah Veran; data curation, investigation, formal analysis, hardware and software development, writing - original draft preparation. Ainnur Natasha Jamri; implementation, visualization, testing, validation, writing - original draft preparation, and manuscript refinement. Anas Mohd Noor; Supervision, Conceptualization, methodology, experimental design, technical guidance, project administration, and writing - review and editing.

CONFLICT OF INTERESTS

No conflict of interests was disclosed.

ETHICS STATEMENTS

Our publication ethics follow The Committee of Publication Ethics (COPE) guideline. https://publicationethics.org/

REFERENCES

[1] W. Pirker and R. Katzenschlager, "Gait Disorders in Adults and the Elderly: A Clinical Guide," *Wiener Klinische Wochenschrift*, vol. 129, no. 3, pp. 81-95, 2017.

[2] A. G. Cutti, A. Ferrari, P. Garofalo, M. Raggi, A. Cappello and A. Ferrari, "Outwalk: A Protocol for Clinical Gait Analysis Based on Inertial and Magnetic Sensors," *Medic. & Biolog. Eng. & Comput.*, vol. 48, no. 1, pp. 17-25, 2010.

[3] L. Wade, L. Needham, P. McGuigan and J. Bilzon, "Applications and Limitations of Current Markerless Motion Capture Methods for Clinical Gait Biomechanics," *PeerJ*, vol. 10, pp. e12995, 2022.

[4] R. S. Smits Serena, F. Hinterwimmer, R. Burgkart, R. von Eisenhart-Rothe and D. Rueckert, "The Use of Artificial Intelligence and Wearable Inertial Measurement Units in Medicine: Systematic Review," *JMIR mHealth and uHealth*, vol. 13, pp. e60521, 2025.

[5] M. N. Anas, "An Instrumented Insole System for Gait Monitoring and Analysis," *Int. J. Online Eng.*, vol. 10, no. 6, pp. 30-34, 2014.

[6] J. F. Hafer, R. Vitali, R. Gurchiek, C. Curtze, P. Shull and S. M. Cain, "Challenges and Advances in the Use of Wearable Sensors for Lower Extremity Biomechanics," *J. Biomechanic.*, vol. 157, pp. 111714, 2023.

[7] J. Ab Hamid, M. H. Juni, R. Abdul Manaf, S. N. Syed Ismail and P. Y. Lim, "Spatial Accessibility of Primary Care in the Dual Public–Private Health System in Rural Areas, Malaysia," *Int. J. Environ. Res. and Publ. Health*, vol. 20, no. 4, pp. 3147, 2023.

[8] D. T. P. Fong, Y. P. Tam, W. H. Yung, G. Y. Ng and K. M. Chan, "The Use of Wearable Inertial Motion Sensors in Human Lower Limb Biomechanics Studies: A Systematic Review," *Sensors*, vol. 21, no. 13, pp. 1–21, 2021.

[9] Q. Wang *et al.*, "A Wireless, Self-Powered Smart Insole for Gait Monitoring and Recognition via Nonlinear Synergistic Pressure Sensing," *Sci. Adv.*, vol. 11, no. 16, pp. eadu1598, 2025.

[10] J. Li, W. Liang, X. Yin, J. Li and W. Guan, "Multimodal Gait Abnormality Recognition Using a Convolutional Neural Network–Bidirectional Long Short-Term Memory (CNN-BiLSTM) Network Based on Multi-Sensor Data Fusion," *Sensors*, vol. 23, no. 22, p. 9101, 2023.

[11] B. Su, C. Smith and E. Gutierrez Farewik, "Gait Phase Recognition Using Deep Convolutional Neural Network with Inertial Measurement Units," *Biosensors*, vol. 10, no. 9, pp. 109, 2020.