

Early Detection of Sciatica Using Ensemble Learning Algorithms

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Abstract. Sciatica is a musculoskeletal disorder caused by compression or irritation of the lumbar nerve roots. Gait and posture abnormalities that appear before clinical symptoms can be detected early by continuously monitoring biomechanical parameters such as pelvic movement and plantar pressure. This paper proposes an ensemble learning approach that uses a lumbar inertial measurement unit (IMU), which contains an accelerometer and a gyroscope, together with a multi-node plantar pressure insole. The sensor signals are fused, and engineered time-domain and statistical features are used by a random forest (RF) model to classify short windows as either normal or at risk. On a held-out test set of 250 windows, the model achieved an overall accuracy of 95%.

Keywords. Sciatica detection; wearable sensors; gait analysis; IMU; plantar pressure; random forest; sensor fusion

I. INTRODUCTION

Sciatica is a common condition in which pain radiates into the lower limbs as a result of compression or irritation of the lumbar nerve roots. In most patients, long-term biomechanical deviations such as pelvic misalignment, trunk compensation, and asymmetric gait precede the clinical episode. Traditional evaluation is episodic and clinic-based, and it relies on visual examination and patient-reported symptoms.

This work proposes an end-to-end wearable system with a belt-mounted inertial measurement unit (IMU) [1] and a shoe-mounted insole with force-sensitive resistors (FSRs) [2]. The sensor data are sent over Bluetooth to a mobile application, where a random forest (RF) [3] classifies time-domain and statistical features.

Current wearable gait systems usually measure either trunk movement or plantar pressure alone. In contrast, the proposed architecture covers multiple levels, from the lumbar region to the legs. The system is designed to detect sciatica-prone gait under real-world conditions and to provide an effective platform for continuous risk monitoring.

II. RELATED WORK

Motion and pressure sensors have been widely used for wearable gait analysis. IMU-based systems on the trunk, shank, and foot have been used to measure spatiotemporal gait parameters and stability and to identify pathological gait patterns in conditions such as lumbar disc herniation and Parkinson's disease [4]. Insoles instrumented with resistive pressure sensors have been developed to monitor plantar loading and detect abnormal pressure hotspots.

Several studies have combined IMUs with force or pressure sensors to build low-cost, portable gait measurement tools. These systems generally address generic abnormal-gait detection, energy-efficient gait recognition [5], or activity classification. Deep learning models such as convolutional neural networks (CNNs) [6], long short-term memory (LSTM) networks [7], and CNN-LSTM models [4] extract temporal patterns well but need large labeled datasets and substantial computing resources.

Unlike these studies, this work targets early detection of sciatica risk and fuses a lumbar belt with instrumented insoles for both feet. The system consists of a lumbar IMU and an FSR-based insole that transmit data wirelessly to a smartphone. The focus is on ensemble models, specifically RF [8], because of their accuracy, interpretability, and low-latency inference.

III. SYSTEM ARCHITECTURE

A. Belt-Mounted IMU

As Fig. 1 shows, a 6-axis inertial module (3-axis accelerometer and 3-axis gyroscope) is placed at the lumbar region with an adjustable belt. This position captures pelvic tilt, trunk rotation, angular jerk, and compensatory upper-body motion, which are commonly associated with sciatic nerve irritation. The belt IMU is connected directly to an ESP32 microcontroller that acts as the master node of the wireless network.

B. Shoe-Mounted Sensor Nodes

Each shoe has an independent ESP32 node with a 6-axis IMU and two FSR sensors (heel and forefoot) that measure

lower-limb kinematics and plantar pressure. The incoming data, sampled at 50 to 100 Hz, are time-stamped and sent to the master node on the belt over ESP-NOW, which allows low-latency gait monitoring.

C. Wireless Hub and Synchronization

The belt-mounted ESP32 receives the data from both shoe nodes and from its own sensor, and it synchronizes them by timestamp to keep trunk motion, foot kinematics, and plantar pressure temporally consistent.



Fig. 1. Wearable sensing system prototype, with the harness and IMU on the belt and a sensing unit (ESP32, IMU, and pressure insole) on each shoe.

D. Mobile Application and Cloud Flow

After fusion, the belt module sends the data to a smartphone over Bluetooth (Fig. 2). The application provides real-time visualization, on-device feature extraction, and RF inference, and it can upload data to the cloud for long-term monitoring.

E. Summary of Sensing Coverage

Fig. 2 shows a multimodal system with three sensing points on the trunk and legs: a lumbar IMU to detect posture and leg asymmetry, shoe IMUs to measure step timing and foot positioning, and FSR sensors to measure plantar-pressure patterns. This design allows gait abnormalities caused by sciatica to be identified in a timely way.

IV. METHODOLOGY

A. Preprocessing

The IMU and FSR signals were filtered with a fourth-order Butterworth low-pass filter with a cutoff frequency of approximately 20 Hz. Sliding windows of 1.0 s with 50% overlap were then extracted. The overall workflow from signal acquisition to feature vector generation is shown in Fig. 3.

B. Feature Engineering

All features were computed for every window and grouped into four categories. The IMU features are the mean, variance, root mean square (RMS) of acceleration, RMS of angular velocity, and peak angular jerk. For each 1 s window w containing N IMU samples $x[n]$, the mean, variance, and RMS values were calculated with (1) to (3):

$$\mu_w = \frac{1}{N} \sum_{n=1}^N x[n], \quad (1)$$

$$\sigma_w^2 = \frac{1}{N-1} \sum_{n=1}^N (x[n] - \mu_w)^2, \quad (2)$$

$$\text{RMS}_w = \sqrt{\frac{1}{N} \sum_{n=1}^N x[n]^2}. \quad (3)$$

The temporal features are cadence, step interval, and stance-to-swing ratio. The pressure features are the heel-to-toe ratio, the center-of-pressure (COP) shift magnitude, regional peak pressures, and the left-right load distribution. The heel-to-toe pressure ratio is computed from the heel $P_h[n]$ and forefoot $P_f[n]$ FSR signals as

$$R_{HT} = \frac{\sum_{n \in w} P_h[n]}{\sum_{n \in w} P_f[n] + \varepsilon}, \quad (4)$$

where ε is a small constant that avoids numerical instability. The symmetry features are the gait symmetry index and plantar-pressure asymmetry. Gait symmetry is quantified with a symmetry index computed from the left (X_L) and right (X_R) gait features. The final feature vector contains 46 elements (42 IMU and 4 pressure).

C. Classification Model

Tree-based ensemble models were chosen for their stability and interpretability. RF (1,000 trees) was used as the baseline because it tolerates noise and resistant to overfitting.

V. DATASETS AND RESULTS

A. Data Summary

The dataset consists of lumbar IMU, bilateral shoe IMU, and FSR plantar-pressure recordings from 179 participants. It covers a wide range of demographics and gait conditions, which strengthens the system and its generalization.

B. Dataset Description

The 179 participants were aged 16 to 69 years and included healthy people and people with lower-back gait deviations. The sample has equal representation of the sexes and diverse body mass index and gait velocity, and all gait sections were confirmed by a physiotherapist. The dataset specification is given in Table 1.

TABLE 1. EXPANDED DATASET SPECIFICATION

Item	Value
Total participants	179
Age range	16 to 69 years
Groups	Normal, abnormal
IMU channels	42
Pressure channels	4
Sampling rate	50 to 100 Hz
Total windows	1,000
Window size	0.5 s, 1.0 s, 2.0 s
Labeling	Physiotherapist-verified
Validation	5-fold CV and LOSO
Stratification	Age and gender only

C. Performance Metrics

Performance was computed on a held-out test set of 250 windows (118 normal and 132 sciatica) drawn from the 1,000 windows in the dataset. The metrics in Table 2 are reported on this held-out test set.

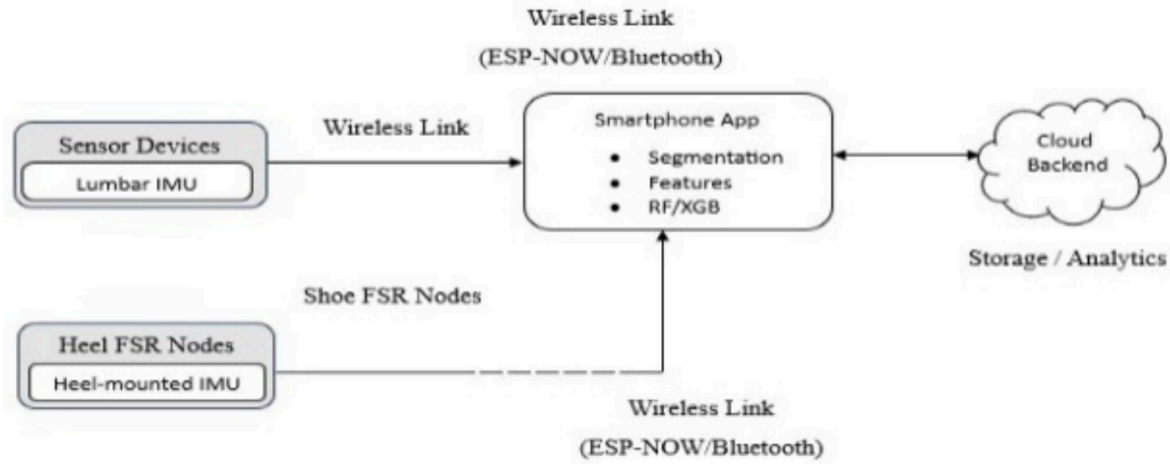


Fig. 2. System architecture showing the lumbar and heel IMUs, the shoe FSR nodes, the wireless link to the smartphone, and the cloud back end.

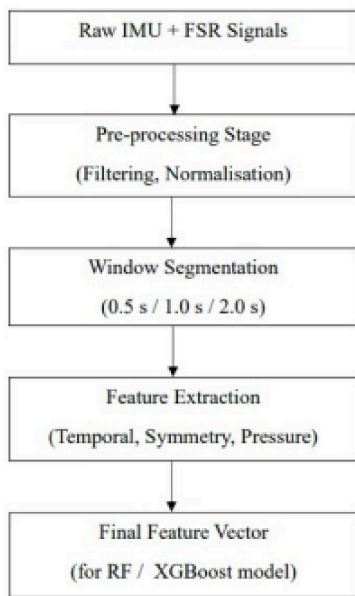


Fig. 3. Overall system workflow from signal acquisition to feature vector generation.

D. Validation Protocol

The model was validated by two methods: 5-fold cross-validation (CV) to check the stability of the model, and leave-one-subject-out (LOSO) validation to check subject-independent performance. The evaluation metrics were accuracy, precision, recall, F1 score, area under the receiver operating characteristic curve (ROC-AUC), sensitivity, and specificity. Statistical significance was evaluated with paired tests such as the t-test or the Wilcoxon test.

E. Results

Evaluation on the dataset of 179 participants yielded the performance metrics shown in Table 2 on the held-out test set of 250 windows.

TABLE 2. MODEL COMPARISON

Model	Accuracy	F1 score	Precision	Recall	ROC-AUC
Decision tree	0.77	0.76	0.78	0.76	0.76
Random forest	0.95	0.95	0.95	0.95	0.95
SVM	0.88	0.87	0.89	0.87	0.87
KNN	0.92	0.92	0.92	0.92	0.92

F. Confusion Matrix

The confusion matrices of the four classifiers are shown in Fig. 4. A significance test on the predicted probabilities indicated a meaningful separation between the normal and risk gait classes.

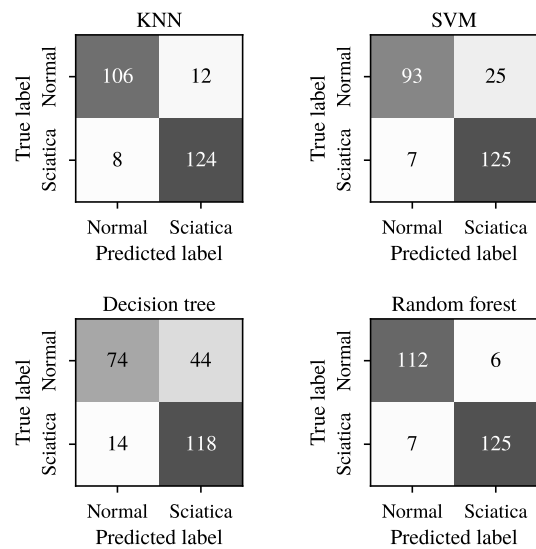


Fig. 4. Confusion matrices of the KNN, SVM, decision tree, and random forest classifiers for the normal and risk (sciatica) gait classes.

G. Additional Analyses

Window-size sensitivity: A 1.0 s window gave the best trade-off between responsiveness and stability; a 0.5 s window added noise, and a 2.0 s window smoothed out short gait variations.

Feature importance: SHapley Additive exPlanations (SHAP)-based analysis showed that the heel-to-toe ratio, COP shift magnitude, left-right loading asymmetry, and trunk rotation variance were the most important features. The feature importance ranking of the RF classifier is shown in Fig. 5.

H. Model Comparison

Table 2 compares the decision tree, RF, support vector machine (SVM), and k-nearest neighbors (KNN) classifiers. Fig. 6 compares artificial neural network (ANN), SVM, KNN, and RF models across five metrics, and Fig. 7 shows the precision-recall and ROC curves of the classifiers.

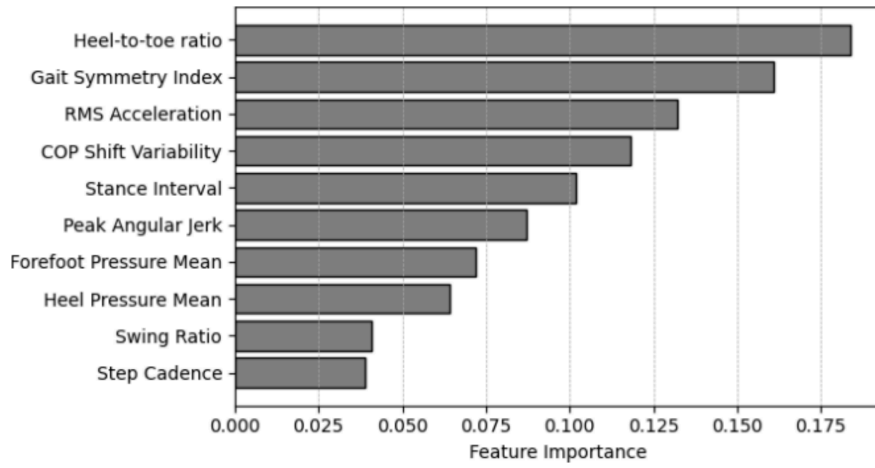


Fig. 5. Feature importance ranking for the random forest classifier, highlighting the dominant temporal and plantar-pressure predictors.

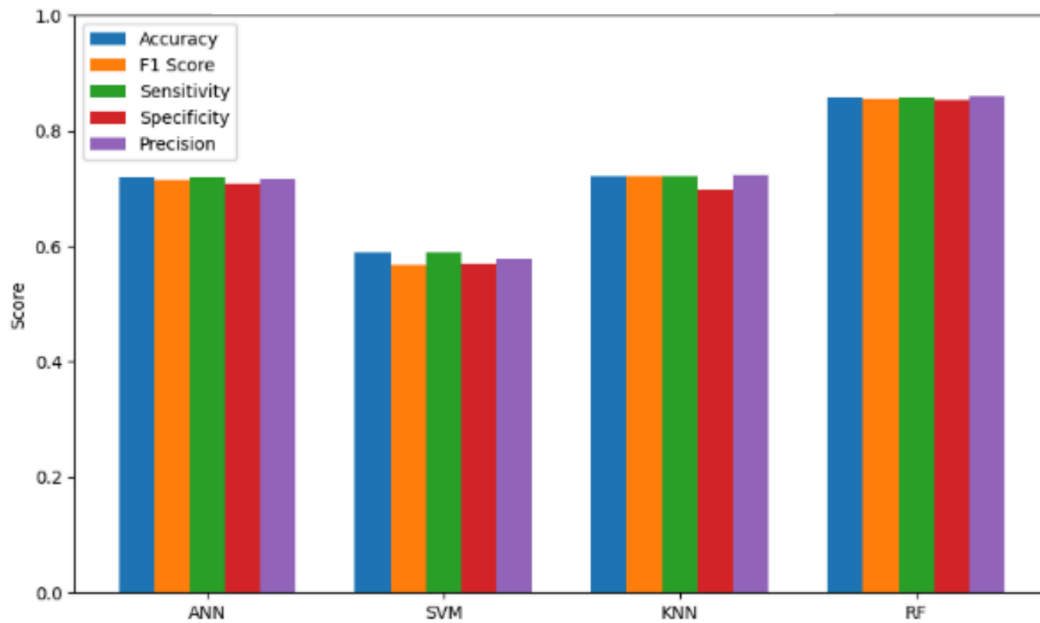


Fig. 6. Comparison of the ANN, SVM, KNN, and RF models in accuracy, F1 score, sensitivity, specificity, and precision.

The current evaluation is based on a relatively small preliminary dataset, which may limit generalization. Expanding the dataset, reporting the parameter settings more clearly, and including comparisons with alternative models would further strengthen the study technically.

VI. CONCLUSION

The belt-to-shoe sensing architecture based on multimodal gait features showed the feasibility of continuous sensing of sciatica risk. The system was 95% accurate on a held-out test set of 250 windows, and features such as the heel-to-toe ratio, gait symmetry, and COP shift helped to capture compensatory deviations. The assessment used a relatively small amount of data, which restricts generalization. The study used physiotherapist-verified labels.

AUTHOR CONTRIBUTIONS

All authors contributed to the conception and preparation of this work and approved the final version of the manuscript.

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DECLARATION OF GENERATIVE AI USE

The authors declare that no generative artificial intelligence tools were used in the preparation of this manuscript. The authors take full responsibility for the content of the publication.

DATA AVAILABILITY

The data supporting the findings of this study are available from the corresponding author upon reasonable request.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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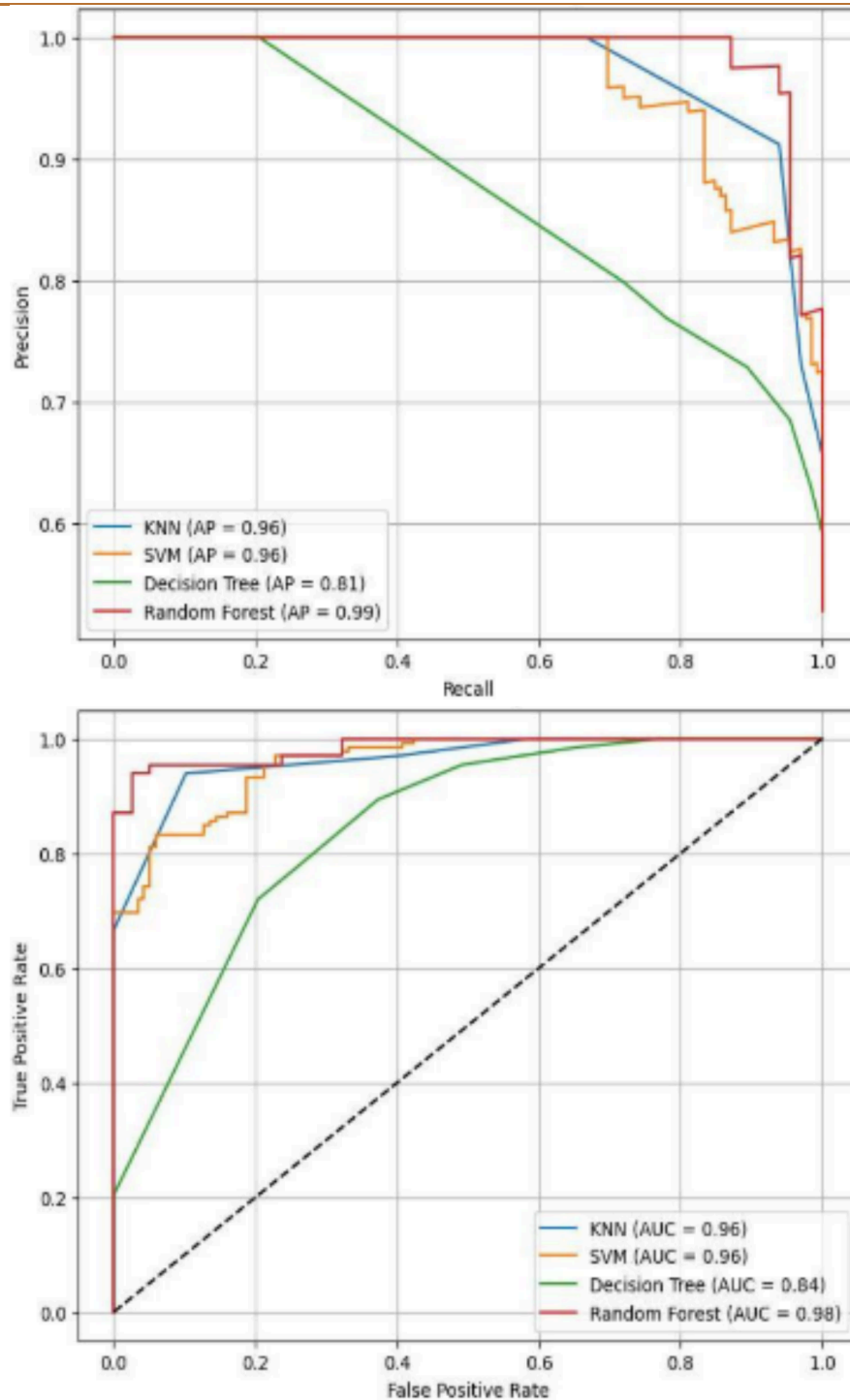


Fig. 7. Precision-recall and ROC curves of the compared models.

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