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A Smart Insole-Based Explainable AI Framework for Non-Invasive Sciatica Diagnosis Using Optimally Selected Plantar Force Sensors

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A Smart Insole-Based Explainable AI Framework for Non-Invasive Sciatica Diagnosis Using Optimally Selected Plantar Force Sensors

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Abstract:

Sciatica is a neuropathic disorder that can cause significant alterations in lower-limb biomechanics, including gait asymmetry and abnormal plantar force distribution. This study proposes a wearable, explainable artificial intelligence (XAI)-based framework for automated sciatica diagnosis using optimally selected force-sensitive resistor (FSR) sensors integrated into a smart insole. A dataset of 37 subjects, comprising 20 patients with Sciatica and 17 healthy subjects, was acquired using 16 FSR sensors, with eight sensors positioned on each foot, along with concurrent electromyography (EMG) and inertial measurement unit (IMU) data. From the bilateral plantar force signals, 601 biomechanical features were extracted, incorporating statistical, temporal, magnitude, and inter-limb asymmetry characteristics. A K-fold combinatorial sensor-selection strategy identified the optimal sensor configuration, with K = 5 providing the most stable performance. The optimal configurations, L2, L5, L8 for the left foot and R2, R5, R8 for the right foot, reduced the number of sensors from 16 to 6, representing a 62.5% reduction in sensing hardware. The selected left-foot sensors achieved 96% accuracy, 96% precision, 93% recall, 94% F1-score, and 0.93 AUC, while the right-foot sensors achieved 87% accuracy, 83% precision, 76% recall, 79% F1-score, and 0.91 AUC. Using the six optimally selected sensors, the proposed one-dimensional convolutional neural network (1D-CNN) achieved 90.3% classification accuracy, 89.9% sensitivity, 90.3% specificity, and a ROC-AUC of 0.911. Furthermore, XAI-based plantar heatmaps confirmed the contribution of the selected biomechanical regions to the classification decision. Cross-validation against the concurrent EMG/IMU modality achieved 85.2% accuracy, with approximately 81.5% diagnostic agreement between the force-sensor and EMG/IMU models. The quantitative results demonstrate that a substantially reduced FSR sensor configuration can preserve diagnostically relevant biomechanical information while providing accurate, interpretable, and portable sciatica screening. The proposed framework offers potential for low-cost wearable gait assessment and automated clinical decision support.

I) Introduction:

Recent advancements in wearable sensing technology in orthopedics are transforming gait analysis from laboratory-based assessments to real-time monitoring in daily life (Mazzetta et al., 2018). Among these, plantar pressure-sensing insoles are an emerging technology, as the foot is the primary interface between the human body and the ground (Alegria et al., 2025; Santos et al., 2024; Wang et al., 2025). It provides coordinated neuromuscular interaction among the peripheral and central nervous systems, the musculoskeletal system, and the neuromuscular system. The rapid development of soft wearable devices led to AI-based insoles incorporating a force-sensitive resistor (FSR), a pressure sensor for continuous gait monitoring (Islam & Bai, 2017; Subramaniam et al., 2022a). Wearable system force plates insoles are lightweight, portable, and inexpensive, making them suitable for long-term monitoring in real-world environments (Subramaniam et al., 2022b). The flexible plantar is used for automatic gait variation detection for rehabilitation, as the pressure sensor has been analyzed from the three pressure sensors per foot [8]. However, it focused on the general gait assessment and the disease-specific diagnosis [9]. Plantar pressure analysis has been extensively investigated for the diagnosis and monitoring of diseases such as Parkinson [10, 11], stroke, musculoskeletal disorders (Günaydın & İkizoğlu, 2023; Ou et al., 2025; Yuan et al., 2025; Zhang et al., 2023), osteoarthritis [16–19], and sports injuries [20, 21]. The study was conducted to analyze gait during walking, squats, jumps, stair ambulation, and sit-to-stand by calculating vGRFs and the center of pressure [22].

The rapid advancement in AI is enhancing the diagnostic capability of plantar pressure analysis of patients. (Channa & Popescu, 2024). A machine learning framework for automated planar pressure analysis using U-Net anatomical segmentation [24]. The patients' diabetes was analyzed using foot-insole plantar pressure measurements and evaluated using statistical ML methods. [25]. EMG scalogram-based gait abnormality in the patient has been studied for neurological disorders using deep learning technologies (Negi

et al., 2024). The entire foot pressure distribution was analyzed using the LSTM-based deep learning model, resulting in reduced sensor pressure estimation from the nine FSR sensors; however, it did not investigate optimal sensor placement or disease-specific classification. (Mun & Choi, 2022).

Existing studies primarily focus on the dynamic plantar pressure measurement, peak pressure, pressure-time integral, pressure distribution, contact area, center-of-pressure (COP) trajectory, stance duration, swing duration, cadence, stride length, gait symmetry, and regional loading distribution. These parameters have demonstrated strong correlations with disease severity and functional impairment, making plantar pressure an important biomarker for computer-aided clinical diagnosis. Moreover, a commercial plantar pressure sensor array contains multiple sensing elements to maximize spatial resolution. This substantially increases hardware costs and computational complexity. Consequently, sensor optimization has become an important research topic in wearable healthcare.

Sciatica is a neuropathic condition of the sciatic nerve, which runs from the lower back through the posterior thigh and leg. Sciatica disrupts lower-limb neuromotor control by radiating pain, tingling, and numbness along the sciatic nerve pathway. Consequently, the patients develop gait disturbances, asymmetrical weight distribution, altered heel-strike impact, and modified toe-off propulsion forces. The early diagnosis of sciatica abnormalities is critical for preventing long-term muscular degradation and rehabilitation. Currently, the traditional methods for diagnosing Sciatica include neuroimaging [28–30] and EMG coupled with an IMU sensor (Floessel et al., 2026; Peralta et al., 2025; Samiee & Zarrindast, 2017). This traditional method has significant clinical limitations, including the high cost of MRI and its inability to capture dynamic and weight-bearing gait abnormalities. The literature lacks wearable insoles and an automated diagnostic tool for measuring sciatica pain. Conversely, the EMG and IMU wearable ML framework system provided excellent functionality for diagnosing biomechanical disorders (Estévez et al., 2024; Purohit & LaCourse, 2026; Ruhrberg Estévez et al., 2025; Santos et al., 2026). The placement of EMG wearable sensors requires a complex hardware setup and can cause discomfort for patients [38]. The existing pressure-based plantar diagnostic system relies on high-density sensor arrays or a full-foot pressure insole [15]. These systems generate redundant data.

In this work, we proposed an explainable AI (XAI)- based machine learning framework for sciatica diagnosis using Force Sensing Resistor (FSR) Sensor data acquired from a wearable smart insole. Unlike a conventional pressure insole, the FSR sensor was incorporated over the plantar region to replace the pressure sensor in the insole, and it is biomechanically influenced by sciatic nerve dysfunction. Rather than relying on the high-density array for the sciatica diagnosis, a machine learning model has been developed to isolate the most discriminative physiological markers of the sciatic nerve. The major contributions of this work are as follows:

1. The primary objective of the work is to identify the optimal sensor combinations using a K-Fold cross-validation strategy.
2. We developed a 1-D CNN classification model to diagnose Sciatica and healthy patients using optimally selected sensor force data. Explainable AI has been implemented to ensure transparency in diagnosis.

In this work, Section 2 describes the dataset and methodology; Section 3 presents the results and discussion; and Section 4 provides the conclusion.

II) Methods:

The Overall procedure of the proposed work is explained in Figure 1. The data acquired using the developed insole is explained in the dataset section. The force sensor data were processed using a K-Fold cross-validation-based sensor selection framework to select the optimal sensor combination model. The selected sensor combinations were then used to train the disorder classification model. The details of each stage are presented in the following sections.

a) Dataset:

The Force data were collected from the insole developed in the previous work [39]. The insole has eight sensors for each foot. The overall dataset comprises 37 subjects, categorized into two classes: Sciatica and Healthy, with 20 in the Sciatica class and 17 in the Healthy class. For each subject, concurrent biomechanical EMG and IMU kinematics data were also collected. The experiment was conducted after the Ethical

clearance from K.A.P. Viswanatham Government Medical College, Tiruchirappalli. IEC Approval No: KEC/10/01/2026 and Date of Approval: 21.01.2026. To prevent data leakage and ensure subject-level independence, data splitting was handled at the patient level rather than at the sample level.

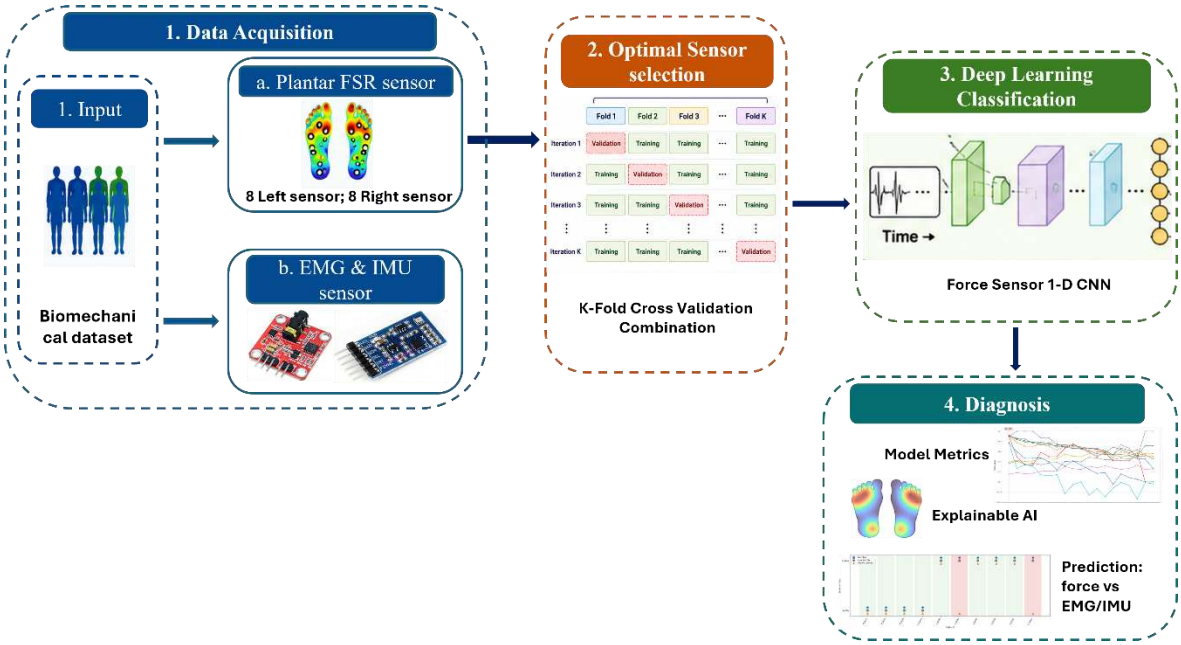


Figure 1 Block Diagram of Sciatica Diagnosis: Deep Explainable AI Framework

b) Sensor Selection:

(i) Feature Engineering:

The development of a sensor-integrated insole has been published [39]. The eight force pressure sensors are arranged in each insole. The sciatica pain is induced by a highly localized biomechanical position rather than by generalized pressure changes. As the major nerve of the lower extremity, it directly innervates the plantar surface and controls the stability of the foot. They never pass through the position of the insole sensor. Hence, in this work, we developed a machine learning algorithm to find the optimal sensor position relative to the sciatica nerve. To systematically identify the most discriminative pressure regions, our algorithm was successfully implemented on the eight left and eight right insole sensors. Rather than arbitrarily selecting the sensor based on anatomical assumptions, our approach evaluated the 16 insole sensors through comprehensive feature engineering.

The raw high-dimensional pressure time-series data have been extracted into high-dimensional features using a feature engineering pipeline. The raw input is the continuous time series force data from the insole sensors. The raw signals were preprocessed by neutralizing all time-series points, and missing data points were resolved using backward and forward techniques with zero-padded arrays. To capture the complete biomechanics, 13 distinct characteristics were computed for individual sensors, including central tendency, dispersion, and distribution, signal magnitude, and temporal metrics, for a total of 208 baseline features.

Sciatica was primarily characterized by unilateral pain that results in compensatory asymmetrical weight-bearing. Secondly, the dataset was first computed by including features of bilateral asymmetry. The sensor pairs from the left and right feet were mathematically combined to extract distinct features. Pairing the corresponding sensors was both computationally and biologically necessary due to the heterogeneous nature of the clinical cohort, which includes a mixture of left- and right-sided sciatica patients. Evaluating individual sensors in isolation would confuse the classification model, since the overloading shifts between the left and right limbs depending on the patient's affected side. In bilateral asymmetrical features, we computed three distinct continuous differential signals over the period: 1) direct difference; 2) computing the paired absolute difference (|Right - Left|) yields side-agnostic biomarkers;3) relative difference to normalize the asymmetry against the total force of the patient. These parameters ensured that severe gait asymmetry driven by left- or right-sided pain cleanly separated the pathological difference from the highly symmetrical

baseline of healthy controls. Again, the 13 distinct characteristics from the bilateral features were extracted, a total of 312 features. Finally, to capture the macro-level biomechanics of the gait, the spatial means across the entire foot were calculated separately. Extracting our 13 statistical metrics from these macro-level arrays yielded the final global features. Ultimately, the multi-layered extraction process transformed the raw 16-channel force time series into 601 features per patient, providing the necessary biomechanical granularity for the sensor selection and classification.

(ii) Sensor selection:

The primary objective of the study was to identify the optimal sensor positions for accurately capturing the force variations associated with gait deviations induced by sciatic nerve disorders. To ensure the selected sensors are both biologically interpretable and computationally robust, we implemented and compared two distinct sensor selection strategies: K-fold cross-validation combinatorial search and the Statistical Feature Ranking approach.

Initially, the k-fold cross-validation was implemented to find the optimal sensor position. In this method, the eight sensors of each insole were mathematically combined into three sensor combinations. For each combination, raw signals were extracted using the feature engineering described in the previous section. A preliminary AutoML was performed to select the best ML model for the K-fold cross-validation loop. Then, K-fold cross-validation was performed with the best ML model to find the optimal sensors. For each of the 601 features, the algorithm extracts values for the Healthy and Sciatica patients.

The combination of raw sensor and evaluation using the k-fold method has limitations for small clinical cohorts. It evaluated thousands of combinations and evaluated the same combination across folds, introducing overfitting and data dredging. To address these limitations, we cross-validated using statistical rankings of features from the feature engineering step. In this method, features were evaluated independently using the t-test, a Mann-Whitney U test, and a standardized effect size. These were derived from the random forest classifier. The feature score exhibited both high statistical divergences. Finally, the top-ranking features were translated into a selection of physical hardware. We compared the empirical results of both combinatorial search and statistical feature-ranking methods, which converged on the same physical sensors.

(iii) Sciatica Classification:

Following the selection of the optimal sensor in the previous section, we developed a comprehensive ML pipeline in this work to classify patients with Sciatica and those with healthy conditions. To prevent overfitting, the top 15 features were used to determine the optimal sensor positions for the final classification model. The class balance of the data was maintained during K-Fold Cross-validation. The finalized model, trained on optimal sensor data from an unseen patient, outputs a binary classification.

(III) Results and Discussion:

i) Results:

The preprocessing of the continuous pressure time-series data resulted in the extraction of 601 asymmetry features from the 8 sensor channels of each leg. The primary objective of the initial selection of the optimal three sensors was to improve the accuracy of classifying sciatica patients using the force sensors. The primary objective of selecting optimal sensors was achieved using the K-Fold three-sensor combination method, and the selected sensor positions combination was validated through a statistical feature-ranking method. In the K-Fold three-sensor combination method, the sensor positions for each leg were combined in $16C_3$ ways to obtain the unilateral asymmetry combinations. For each combination, repeated stratified K-Fold cross-validation was performed to ensure robust model training. We evaluated the raw, unselected feature space utilizing optimal classifiers. The optimal classifiers for each foot were selected through rigorous comparative analysis of five machine learning algorithms. Models were ranked based on metrics. The comparison of all metrics is shown in Figure S1 in the supplementary section. Logistic Regression was selected for the left foot sensors, and Support Vector Machine (SVM) for the right foot sensors. The AUCs were 0.967 with logistic Regression and 0.811 with the SVM classifier. The optimal sensor was selected by performing K-fold cross-validation with K=2 to K=8 to avoid overfitting and ensure mathematical stability. The validation demonstrated clear stability convergence at K=5, as shown in Figure 2. The 27-patient dataset, comprising 15 sciatica patients and 15 healthy patients was used for K-fold cross-validation. The 20 subjects were used for the training and 7 subjects were used for validation. The dataset was split using the stratification

method, which ensured class balance. The 20 patients were split into 5 equally sized folds (4 patients per fold).

Furthermore, the variance from random sampling was eliminated by repeating the 5-fold split 5 times, each with a different random seed. The final diagnostic metrics were obtained by averaging the estimated generalizable performance across the 25 cycles. At optimal K=5, the 3-sensor combinations L2, L5, L8 (left foot) achieved an accuracy of 0.96, Precision of 0.96, Recall of 0.93, F1 score of 0.94 and an AUC of 0.93 and R2, R5, R8 (right foot) achieved an accuracy of 0.87, Precision of 0.83, Recall of 0.76, F1 score of 0.79, and an AUC of 0.91. These sensor combinations consistently outperformed all other 3-sensor configurations, which align with the anatomical Sciatica Nevers constraints. For K=5, the comparison of the top- ten 3-sensor combinations for the left foot and the right foot separately is provided in Figure S2 in the supplementary section.

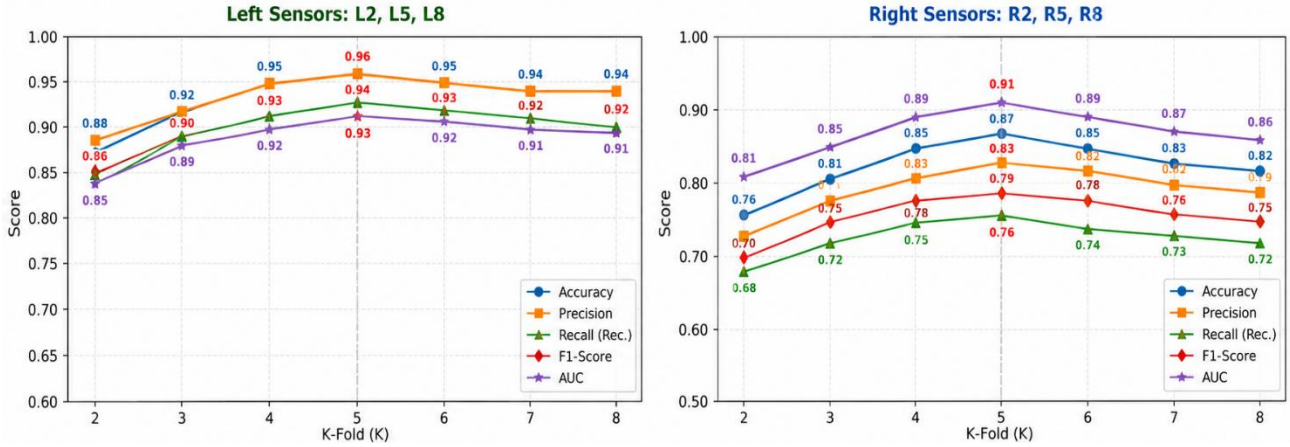


Figure 2 Optimal K-Fold value for the optimal sensor position for the left foot and right foot sensor positions

To prove the optimal sensor selected by the K-Fold combination method, we cross-validated it against an independent statistical feature-ranking method. In the statistical feature-ranking framework, all 601 engineered features were evaluated to identify the diagnostic markers. The composite significance scores were used to identify the primary locus of the foot sensor. The top 20 asymmetry features among 601 engineered high-dimensional time-domain features were identified using statistical ranking metrics, as shown in Figure 3. Features were subsequently sorted in descending order by significance scores. The individual feature scores, specifically the absolute and relative differences between paired sensors for the bilateral asymmetry features, for each of the 601 features were extracted by the algorithm for the Healthy and Sciatica patients. Each feature for each patient was analyzed using independent tests, such as the T-Test, the Mann-Whitney U Test, Cohen's test and multivariate permutation scores extracted from a trained Random Forest Classifier. The overall significant score was calculated using the formula

$$\text{Significance Score} = (-\log_{10}(P_{ttest})) + (-\log_{10}(P_{mw})) + (3 \times \text{Cohen's } d) + 50 \times permutation\ Importance$$

Sciatica systematically uses a nociceptive weight-shifting strategy. The L3/R3 and L2/R2 asymmetry pairs dominated the top ranks, suggesting that the longitudinal arch was the primary anatomical site due to tibial nerve weakness. The feature correlation heatmap of the top-ranked features is shown in Figure 4. The correlation between left and right foot asymmetry features was strong, indicating that the ranking demonstrated the same underlying stark anatomical localization from multiple mathematical perspectives. The individual feature scores were aggregated for each sensor position to select the optimal set of three sensors per foot while maintaining diagnostic resolution across the gait cycle. The bar chart in Figure 5 clearly showed that the heel sensors L2 and R2 has higher cumulative score of 156.6 and 167.6 respectively, the midfoot sensors L5 (199.8) and R5(193.2), and the foot sensors L8(65.9) and R8(47.4) have the highest scores among the sensors and are therefore identified as the optimal three sensors per foot, which align with

the anatomical localization of the sciatic nerve. The midfoot and the heel sensors dominated the cumulative significance scores.

The feature ranking method selected the same sensor as the K-Fold validation method. The two entirely different mathematical approaches, one based on predictive combinatorics and the other on pure statistical variance, independently converged on the identical anatomical locations. This dual-method validation conclusively proved that L2, L5, and L8 are the definitive optimal sensors for capturing the pathological gait signature of Sciatica.

To independently validate the specific selected optimal 3-sensor on each foot, which contained sufficient variance to separate the clinical cohorts, 2D scatter Principal Component Analysis was applied. The 27-patient dataset, comprising 15 sciatica patients and 15 healthy patients (the same dataset used for K-fold cross-validation), has been used in the feature-ranking method. Sciatica patients predominantly map to the negative domain of Principal Component 1, whereas the healthy clusters map to the positive domain of Principal Component 2, as shown in Figure 6. The natural boundary was achieved without supervised clinical labels, proving that the reduced optimal sensor preserved the critical biomechanical variance necessary for accurate diagnosis.

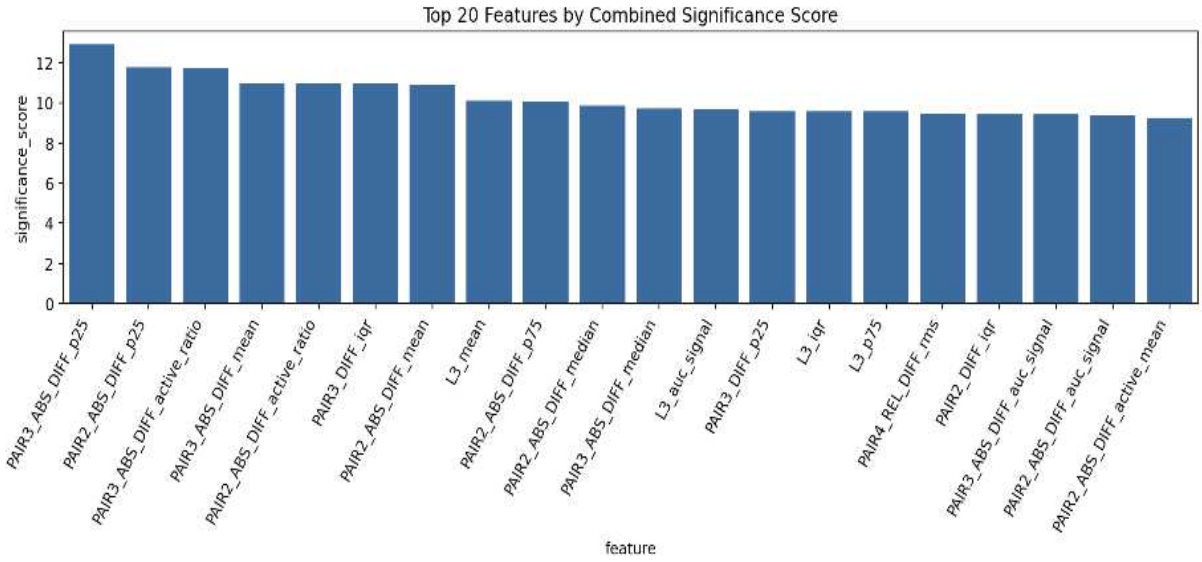


Figure 3 Significant ranking score of the statistical feature ranking of the asymmetry feature

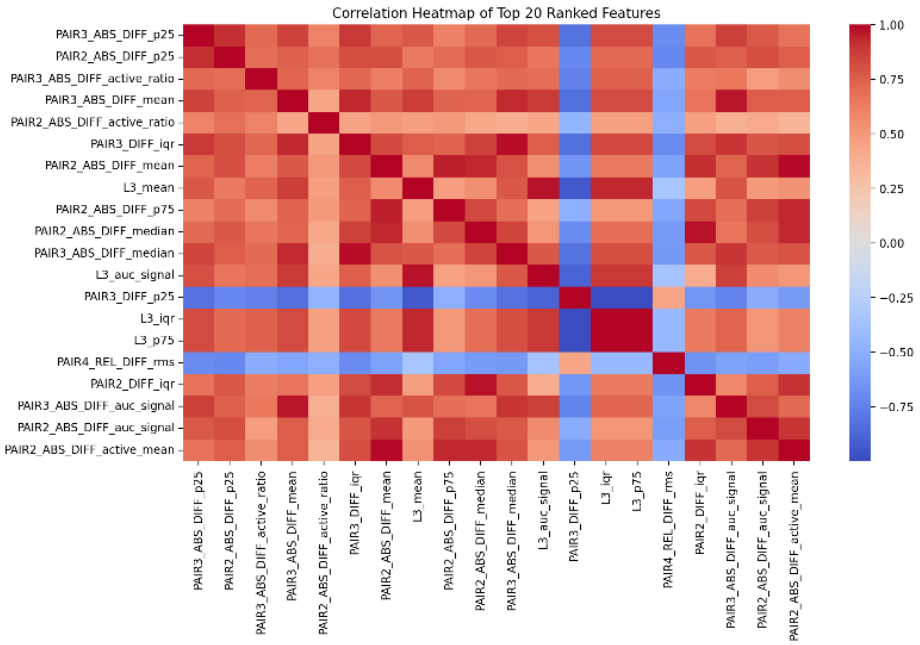
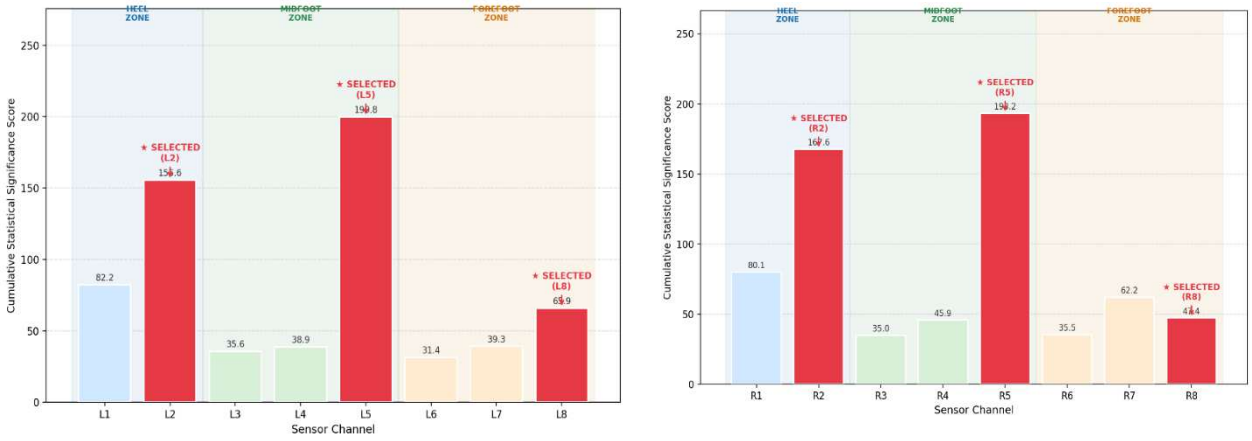


Figure 4 Correlation Heatmap of the top-ranked features of the asymmetry feature



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Figure 5 Sensor Ranking (a) Left foot Sensor Ranking; (b) Right foot Sensor Ranking

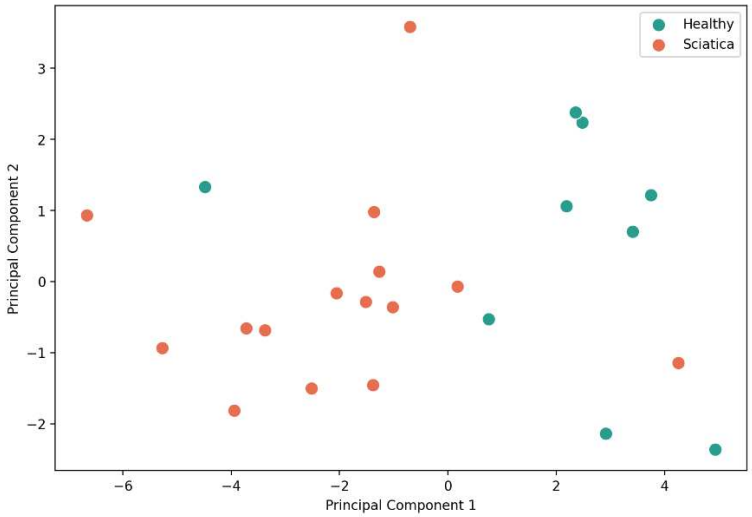


Figure 6 PCA Plot for the optimal sensor

The optimal sensor selected from the K-fold combination sensor selection aligned with the anatomical position of the sciatic nerve used to evaluate the diagnosis of healthy and Sciatica patients. Next, the model was developed to diagnose Sciatica by comparing various ML methods. The force sequence corresponding to the 6 optimal sensors across all 37 patients was used to train the model. The cohort was split into a 27-patient training set and a 10-patient testing set. The algorithms spanned a wide spectrum of complexities, deep learning models (1D CNN, LSTM, TCN), traditional ML algorithms (XGBoost, Random Forest, SVM, Logistic Regression), and statistical sequence forecasting models (ARIMA, SARIMA, Hidden Markov Models). The metrics for evaluating and ranking the models are Accuracy, Sensitivity, Specificity, and the ROC-AUC characteristic curve, as shown in Figure 7. The traditional ML algorithm, XGBoost, ranked second overall with an AUC of 0.861, the Extra Trees algorithm with an AUC of 0.811, and the Soft Voting Ensemble with an AUC of 0.783. However, the model's sensitivity reached 1.0, while specificity was as low as 0.33-0.5, indicating that the classification model overfit and resulted in a high false-positive rate among healthy subjects. Finally, sequential memory models and pure statistical forecasting models achieved lower performance: LSTM (AUC = 0.5555), GRU (AUC = 0.538), and standard RNN (AUC = 0.461), ARIMA (AUC = 0.661), and Hidden Markov Models (AUC = 0.544). The results showed that these models are mathematically suboptimal for diagnosing disease from a multi-sensor footprint. Ultimately, the 1D-CNN proved to be the optimal classifier for the multisensory biomechanical data, achieving a peak ROC_AUC of 0.911 and an overall Accuracy of 90.3%. Crucially, the 1D CNN demonstrated an exceptional diagnostic balance, yielding a Specificity of 0.903 and a Sensitivity of 0.899.

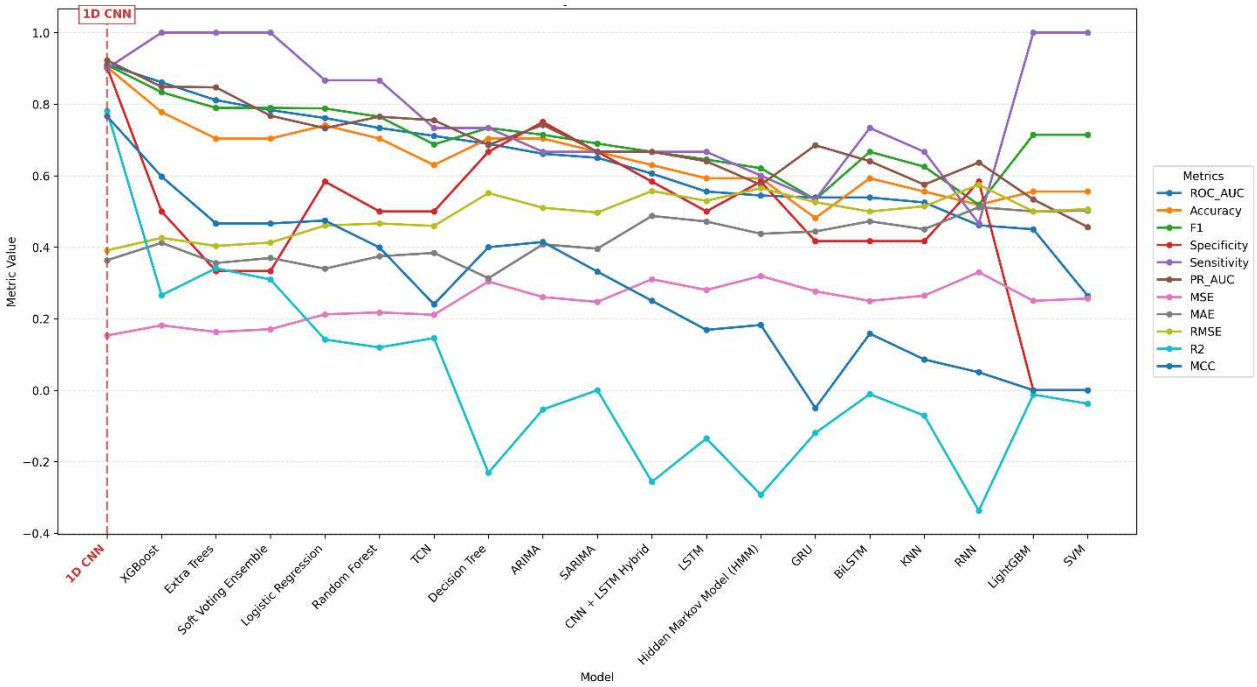


Figure 7 Metrics Comparison of the Classification Model

To ensure transparency and reliability in optimal sensor selection, Explainable AI(XAI) was introduced to visualize spatial features rather than operate as a black box. Figure 8 presented the continuous XAI heat distribution on the plantar surface. The analysis revealed a high concentration of the optimal sensor positions L2, L5, and L7 on the left foot, and R2, R5, and R7 on the right foot, among all eight positions on each leg. The heatmap relatively predicts the distinct pressure region on the foot. The high thermal intensity indicated the optimal sensor position, enabling the model to differentiate between subjects with healthy and Sciatica.

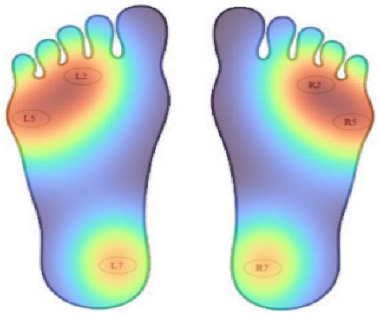


Figure 8 Explainable output of the classification model

The classification of Sciatica using a force sensor was cross-validated against the standard gait method of measuring Sciatica, which uses Independent Electromyography (EMG) and Inertial Measurement Unit (IMU) data. The wearable device described in the paper [39] contained EMG and IMU sensors. Hence, we utilize these data for validation. The 1D CNN sensor prediction is directly applied to the EMG and IMU data. The concurrent EMG and IMU dataset comprised 37 patients: 27 were used for training, and 10 for cross-Modality Agreement. The trained model achieved an accuracy of 85.2% (Figure 9), representing a direct measurement of neuromuscular firing and limb kinematics. The EMG model achieved high sensitivity, resulting in high false positives, and a lower specificity of 75%.

In contrast, the force sensor model demonstrated balanced classification, without sacrificing diagnostic specificity and accuracy. This confirms that the selected optimal force sensor was diagnostically powerful, similar to the muscle activation signals. Finally, the force sensor prediction is directly compared

with the EMG model and shown in Figure 10. The model demonstrated a cross-validation agreement of 81.48%, indicating that the force sensor model independently arrived at the same clinical diagnosis as the EMG model for the same patients in nearly 8 out of 10 cases, with an 81.7% correct diagnosis rate.

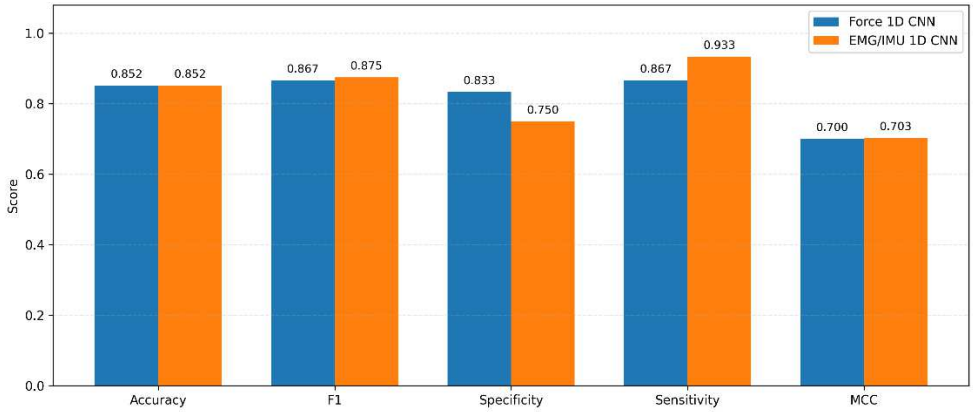


Figure 9 Comparison of the force sensor model and the EMG/IMU model

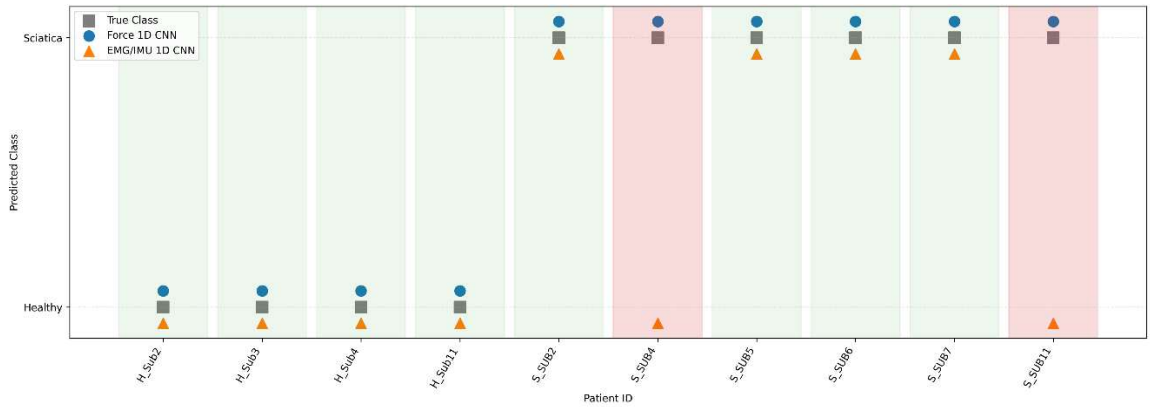


Figure 10 Direct prediction comparison of True class, Force 1D CNN model, and EMU/IMU 1D CNN model

ii) Discussion:

Traditional diagnostic frameworks often relied on the complex kinematics derived from gait sensors. In this work, we develop an effective diagnostic framework for Sciatica using foot pressure sensors. Initially, the work focused on selecting an optimal pressure sensor position aligned with the sciatic nerve's anatomical locations. Hence, we employed a K-fold cross-validation strategy to evaluate sensor performance across different sensor combinations and found that L2, L5, L7, and R2, R5, R7 are the optimal sensor combinations. The results were validated using the feature-ranking strategy for each sensor position. The variance threshold, statistical significance, and permutation importance are used to rank features.

The optimal sensor combinations were then used to train the classification models. In this work, we developed a 1D CNN to capture the temporal sequence of deep forces during the gait cycle and achieved a diagnostic accuracy of 85.2%. The model's transparency was assessed by assessing the explainable AI mapping. The results of the continuous thermal distribution visually quantified the model's spatial feature importance. The XAI confirmed that the neural network prioritized the exact optimal sensor. The clinical integrity cross-validation of the force-based classification model was performed against the gold-standard EMG/IMU gait-cycle method. The result revealed that the three optimal sensor positions for each foot are sufficient to classify Sciatica and healthy subjects.

The implementation of a wearable insole with the developed model substantially reduces preparation time, reliance on a precise sensor, and training for technical personnel. Such systems could provide clinicians

with an immediate, automated, and highly accurate diagnostic screening tool for Sciatica, significantly reducing the burden on the healthcare infrastructure while minimizing patient discomfort.

(IV) Conclusion:

In this study, a highly optimized ML framework for Sciatica was presented. The optimal FSR sensor position and sensor combination were selected using a K-Fold cross-validation model with K=5, achieving an accuracy of 0.96. The 3-sensor combinations L2, L5, L8 (left foot) and R2, R5, R8 (Right foot) are considered optimal, aligning with the anatomical sciatica nerves. The statistical feature ranking was used to cross-validate the K-Fold method and a single sensor position. We finally performed a 1D-CNN that achieved 85.2% accuracy with the optimally selected FSR sensor and cross-validated using the traditional EMG/IMU sensors. Finally, the transparency of the ML classification model is achieved through explainable AI. While the proposed methodology achieved higher accuracy, there are limitations that will be addressed in future research. Conditions such as knee osteoarthritis and ankle trauma also induce bilateral asymmetry. Our proposed model can accurately distinguish Sciatica from healthy subjects, but specificity against the other localized musculoskeletal disorders remains unverified. In future work, other non-neurological lower-limb pain conditions will be incorporated into the model to determine the localized biomarker's differential-diagnostic capabilities.

Dataset availability:

The dataset can be obtained from the corresponding author on reasonable request.

Code availability

The code developed for this study will be made publicly available on GitHub after Publication

Ethical clearance:

Ethical clearance for this study has been approved by the K.A.P. Viswanatham Government Medical College, Tiruchirappalli. IEC Approval No: KEC/10/01/2026 and Date of Approval: 21.01.2026.

Conflict of interest

All the authors have no conflict of interest.

Author contribution

RLVS: Data curation, conceptualization, methodology, investigation, and writing—original draft; RS: Insole development, data acquisition, and data curation; NRR: Data curation, conceptualization, methodology, investigation, and reviewing.

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Supplementary Section

1. **Independent T-Test (p-value):** Tests if the *means* of the two groups are statistically different.
2. **Mann-Whitney U Test (p-value):** A non-parametric test to check if the *distributions* are different (useful since clinical data is not always a perfect bell curve).
3. **Cohen's d (Effect Size):** Measures the absolute, standardized magnitude of the difference between the two groups. A large Cohen's d means the difference is visually obvious, not just mathematically subtle.
4. **Random Forest Permutation Importance:** A Random Forest model is trained on the data, and it scores how much the model's accuracy drops when that specific feature is scrambled. This captures complex, non-linear relationships.

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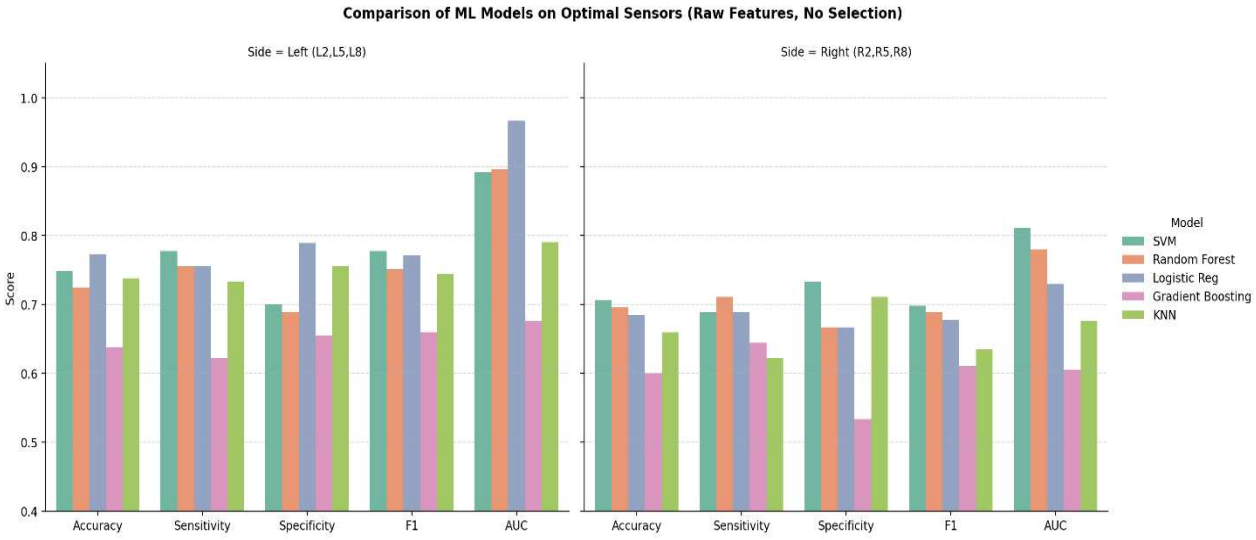
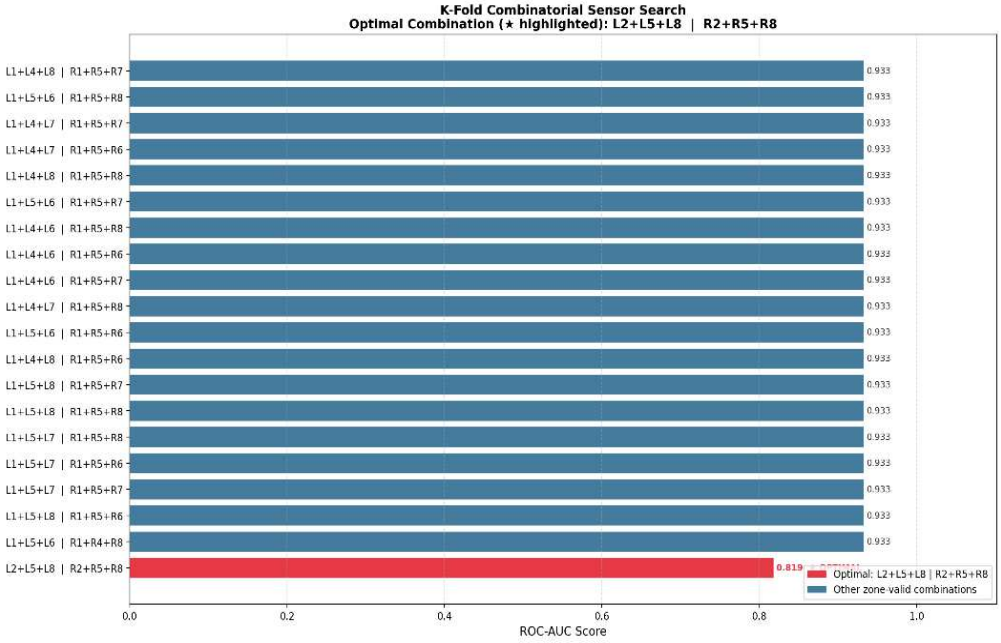
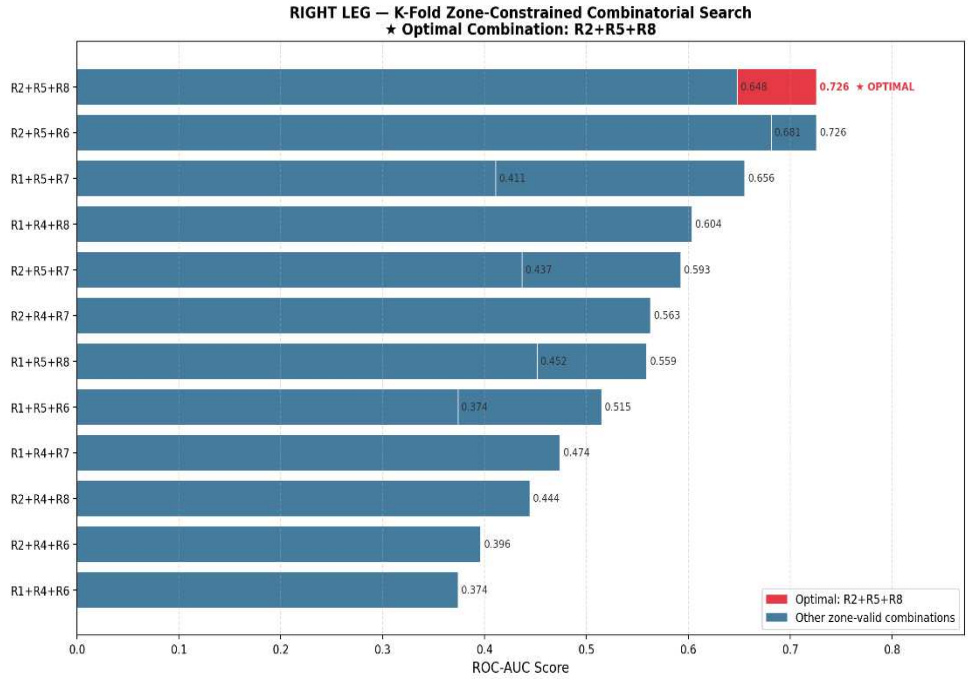


Figure S1 Optimal ML model for K-Fold



(a)



(b)

Figure S2 (a) Comparison of the top 10 best left sensors combination (b) (a) Comparison of the top 10 best right sensors combination

Supplementary Files

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