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Detection of the Leg-Crossing Position Using Pressure Distribution Sensor and Machine Learning

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Abstract: Humans often cross their legs unconsciously while sitting, which can lead to health problems such as shifts in the center of gravity, lower back pain, reduced blood circulation, and pelvic distortion. Detecting unconscious leg crossing is important for promoting correct posture. In this study, we investigated the detection of leg-crossing postures using machine learning algorithms applied to data from body pressure distribution sensors. Pressure data were collected over 180 s from four male subjects (25.8 ± 6.29 years old) under three conditions: no leg crossing, right-leg crossing, and left-leg crossing. Seven classifiers, including support vector machine (SVM), random forest (RF), and k-nearest neighbors (k-NN), were evaluated based on accuracy, recall, precision, and specificity. Among the tested methods, k-NN demonstrated the highest classification performance, suggesting it may be the most effective approach for identifying leg-crossing postures in this study.

Keywords: pressure distribution sensor; leg crossing; machine learning; posture estimation

Citation: Yuda, E.; Ando, T.; Yoshida, Y. Detection of the Leg-Crossing Position Using Pressure Distribution Sensor and Machine Learning. *Information* **2024**, *15*, 810. https://doi.org/10.3390/info15120810

Academic Editor: Zoran H. Perić

Received: 1 November 2024
Revised: 7 December 2024
Accepted: 9 December 2024
Published: 17 December 2024

1. Introduction

It is known that many people unconsciously cross their legs in everyday life. However, maintaining the leg-crossing posture for long periods of time can have a variety of negative effects on the body. For example, if the center of gravity of the body shifts to one side or the other due to leg crossing, the pelvis may become distorted, leading to lower back pain and body twisting. Decreased blood flow has also been associated with coldness and circulatory disorders in the lower limbs [1–4]. For this reason, it is important to detect the unconscious act of crossing legs at an early stage and encourage improvements in posture to maintain good health.

In addition, prolonged sitting is a significant factor contributing to increased health risks in modern society. Japanese individuals, in particular, spend considerable amounts of time sitting [5]. A global survey of 20 countries reported that the average sitting time on weekdays in Japan is 7 h (420 min) per day, the longest among the surveyed countries. This is approximately three times longer than the 2.5 h (150 min) observed in Portugal, the country with the shortest sitting duration [6]. Prolonged sitting has been associated with reduced muscle metabolism, decreased blood flow, and increased risks of obesity, diabetes, cancer, cerebrovascular diseases, and dementia, which may ultimately shorten life expectancy.

Moreover, sitting with legs crossed is well known to cause elevated blood pressure [7–15]. This rise in blood pressure occurs due to the compression of blood vessels passing through the hip joint. Additionally, the peroneal nerve, which controls leg sensation, branches behind the knee and may become compressed when legs are crossed. This compression can signal the heart to compensate for a perceived lack of blood flow throughout the body, resulting in an increased heart rate and elevated blood pressure.

Although sitting with a straight back does not negatively affect posture, crossing the legs can lead to a forward-leaning posture. Consequently, the ability to detect unconscious leg crossing is desirable to mitigate its potential health impacts and promote better sitting habits.

In previous research on posture estimation, the main methods used were those that used cameras and image analysis [16,17]. While these methods can analyze the position and posture of the skeleton using image processing technology, they have the problem that it takes time to perform advanced image processing and load model data [18–20]. In addition, there are environments where it is difficult to use cameras from the perspective of protecting human privacy. In recent years, some studies have suggested that the crossed leg sign may indicate a good outcome after a severe stroke [21]. In addition, research is being conducted on applying the comfort of leg crossing to interior design [22], and there are various potential applications for detecting the action of crossing one's legs from the pressure of sitting. In addition to the specific application of pressure distribution sensors for detecting leg-crossing postures, the integration of machine learning and sensor technologies has broader implications across various fields, including environmental and ecological toxicology, industrial applications, and healthcare. For instance, Manduca et al. (2023) [23] employed machine learning algorithms to detect postural changes and movement abnormalities in flies exposed to minimal amounts of harmful substances, demonstrating the potential for similar techniques in environmental toxicology. These methods highlight how sensor-based data collection and machine learning can be applied to monitor the impact of environmental stressors on living organisms' behavior and physiology, offering valuable insights into ecological health risks. In the industrial sector, Fernandes et al. (2022) [24] reviewed the application of machine learning for predictive maintenance in real-world manufacturing environments. Their work emphasizes how machine learning techniques, like those used for posture detection, can be adapted for detecting mechanical failures and predicting maintenance needs. This cross-disciplinary approach suggests that pressure distribution sensors could be similarly employed in industrial environments to monitor worker posture and prevent musculoskeletal disorders, improving workplace ergonomics and safety. In healthcare, Javaid et al. (2022) [25] underscored the importance of machine learning in the healthcare sector, particularly for disease prediction and patient monitoring. The application of similar sensor-based technologies in healthcare could enable the early detection of posture-related health issues, such as those caused by prolonged sitting or improper posture, offering a new avenue for preventive care. These developments align with the increasing trend toward personalized health monitoring, where real-time data from wearable sensors can inform healthcare decisions and interventions. By exploring these diverse applications, we can better understand the broader implications of pressure distribution sensing technologies and machine learning, not only in detecting leg-crossing postures but also in addressing complex challenges across multiple domains.

In this study, we focus on a non-contact body pressure distribution sensor that enables immediate data processing and evaluate the accuracy of leg posture detection using this sensor. Specifically, we propose a method for detecting leg posture with high accuracy by applying machine learning to the data acquired from the body pressure distribution sensor. The aim of this research is to provide the basis for a system that can detect the leg-crossing posture in real time and contribute to improving the sitting posture.

2. Materials and Methods

2.1. Data Collection

In this study, we aimed to verify the extent to which leg-crossing postures can be detected using pressure distribution sensors. Seat pressure was measured using a pressure distribution sensor (Azwil, Takano Corporation, Nagano, Japan) designed in the shape of a seat. This sensor is equipped with 16×16 pressure sensors, totaling 256 sensors, arranged in a grid-like configuration. The external dimensions of the sensor are 600 mm square, with a detection area of 397 mm square, capable of detecting pressures up to 200 mmHg. The pressure data were sampled at a frequency of 5 Hz.

The pressure distribution sensor was placed on a flat chair, and participants were instructed to sit naturally without adjusting their posture excessively. Data collection involved recording pressure distribution data for three specific leg position patterns:

- No leg crossing (center position, labeled as "C")—participants sat with their feet flat on the ground, ensuring no leg crossing.
- Right leg crossed (labeled as "R")—participants crossed their right leg over the left leg.
- Left leg crossed (labeled as "L")—participants crossed their left leg over the right leg.

For each condition, participants maintained the assigned posture for at least 120 s to ensure sufficient data for analysis. A minimum of two male subjects (25.8 ± 6.29 years old) participated in the experiment, each contributing data for all three leg position patterns.

During data acquisition, the pressure distribution from the 256 sensors was recorded in real time as heatmaps, which visualized the variation in seat pressure over time. These heatmaps served as the primary data source for the subsequent analysis, where machine learning classifiers were applied to identify and differentiate the three leg-crossing postures based on the collected pressure data.

The sensor placed on the floor of the chair, and the subject on. (Figure 1 shows the central position, with no legs crossed.) The pressure sensor is connected to a computer, and the data are measured in real time.

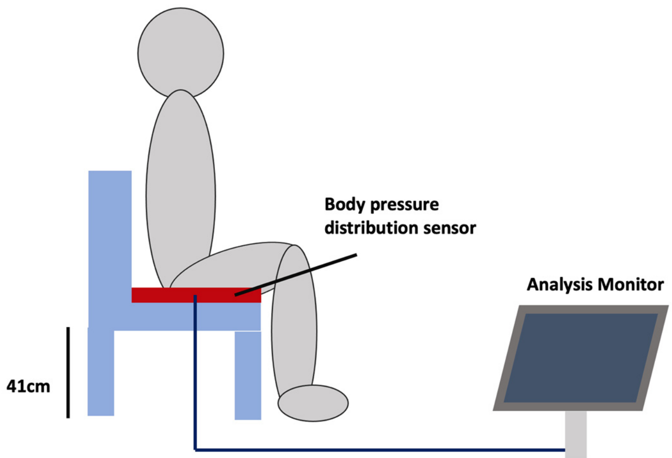


Figure 1. Measurement of pressure distribution in seated position.

2.2. Selection of Machine Learning Methods

In this study, multiple machine learning methods were employed to classify leg-crossing postures based on pressure distribution data. The choice of these methods was guided by their ability to handle high-dimensional data and their widespread application in related research fields. Support vector machine (SVM) was selected due to its effectiveness in finding optimal hyperplanes for classification, especially in datasets with non-linear separability. Random forest (RF), on the other hand, was chosen for its robustness and ability to handle feature importance, making it suitable for datasets with complex interactions between variables. K-nearest neighbors (KNN) was included, as it is a simple yet effective method for multi-class classification problems and performs well with smaller datasets. Additionally, other methods such as neural networks and AdaBoost were incorporated to explore their potential for capturing non-linear patterns in the data. Quadratic discriminant analysis (QDA) and naïve Bayes classifiers were also tested as baseline models due to their simplicity and computational efficiency. The diversity of classifiers allowed for a comprehensive evaluation of the suitability of different approaches for this specific application. The ultimate goal of selecting these methods was to identify the most effective algorithm for classifying leg-crossing postures with high accuracy and reliability while also providing insights into the underlying patterns in the pressure distribution data.

2.3. Data Analysis

The collected data were analyzed using seven different classifiers. The classifiers used were support vector machine (SVM), random forest (RF), K-neighbors (KNN), multi-layer perceptron (MLP), AdaBoost (ADB), quadratic discriminant analysis (QDA), and naïve Bayes (NAB). We calculated the pressure data obtained from the 256 pressure sensors as features and performed classification for each posture. The features were classified into three categories in advance: C (center position, no leg crossing), R (right leg crossed over left leg), and L (left leg crossed over right leg). To evaluate the accuracy of the classification, we performed K-fold cross-validation. First, we trained the classifier using 90 s of data for each posture, and then we verified the accuracy using 10 s of test data. As evaluation metrics, we calculated Accuracy (percentage of correct answers), Recall (reproduction rate), Precision (accuracy), and F-score and used Python to compare the performance of each classifier. Machine learning was performed in Python (Ver 3.6.5) using Spyder (editor, Ver 3.2.8) obtained from the open data science platform Anaconda. The machine learning library used was scikit-learn. Table 1 shows the hyperparameters for each classifier. *n_estimators* and *max_depth* for RF are the number of decision trees and the maximum depth of decision trees, respectively. *n_neighbors* for KNN is the value of k and is an odd number. The *max_iter* of MLP is the maximum number of iterations, and the *n_estimators* of ADB is the maximum number of estimators when boosting is finished. The hyperparameters of QDA and NAB are set to their default values. We adjusted the hyperparameters using grid search and calculated the AUC of the ROC curve for Accuracy, Precision, Recall, F-score, True Positive Rate, and False Positive Rate, as well as the AUC of the Precision–Recall curve (PR curve) for the optimal hyperparameters. These six indices were used as the accuracy indices. Accuracy, Recall, Precision, and F-score are defined by the following Equations (1)–(4).

$$Accuracy = (TP + TN)/(TP + TN + FP + FN) \quad (1)$$

$$Recall = TP/(TP + FN) \quad (2)$$

$$Precision = TP/(TP + FP) \quad (3)$$

$$F\text{-}score = 2 * Recall * Precision/(Recall + Precision) \quad (4)$$

Table 1. Hyperparameters for each classifier.

Classifier	Hyperparameter	
SVM	*C*	0.001, 0.01, 0.1, 1, 10, 100, 1000
	gamma	0.001, 0.01, 0.1, 1, 10, 100, 1000
RF	*n_estimators*	16, 32, 64, 128, 256, 512, 1024
	max_depth	16, 32, 64, 128, 256, 512, 1024
	criterion	gini
KNN	*n_neighbors*	3, 5, 7, 9, 11, 13, 15, 17, 19, 21
MLP	*alpha*	0.001, 0.01, 0.1, 1
	max_iter	16, 32, 64, 128, 256, 512, 1024
ADB	*n_estimators*	16, 32, 64, 128, 256, 512, 1024
	algorithm	SAMME.R

Table 1. *Cont.*

Classifier	Hyperparameter
QDA	Default
NAB	Default

In secondary discriminant analysis (QDA), no regularization is applied and 'full' was used for the covariance matrix estimation. Naive Bayes (Gaussian naive Bayes), smoothing parameter var_smoothing = 1×10^{-9} (default setting). In this study, grid search was used to adjust the hyperparameters, and the grid search method was used to search for a predefined set of hyperparameters to identify the optimal combination for optimal model performance. For each classifier, the search space for parameters such as the number of estimators, maximum depth, and learning rate was defined. When the hyperparameter space is large, random search, which randomly samples the search space as opposed to grid search, is more efficient. This method can speed up convergence to the optimal parameter set by exploring a more diverse region of the parameter space without the exhaustive calculations required for grid search. However, in this study, random search was not implemented because the number of parameters was not large.

The feature values used 196 pressure values (100 s each) for each of 3 postures for each person ($196 \times 100 \times 5$ Hz = 98,000 pressure values for each posture). In addition, the first 10 s of measurement and the last 10 s before the end of measurement were removed. TP, TN, FP, and FN are true positive, true negative, false positive, and false negative, respectively. In addition, the average value of the discrimination accuracy index was calculated for each value of k using the k-fold cross-validation method (k = 2, 5, 10) for each subject.

k = 2 (150 s learning, 150 s testing),

k = 5 (240 s learning, 60 s testing), and

k = 10 (270 s learning, 30 s testing).

The accuracy evaluation metrics were Accuracy, Precision, Recall, F-score, AUC-tpfp, and AUC-pr.

2.4. Feature Extraction and Dimensionality Reduction

For feature extraction, the raw data collected from the pressure distribution sensor were first transformed into a set of features suitable for machine learning models. These features included both temporal and spatial information, such as the variance of pressure over time, the mean pressure values, the distribution of pressure, and the overall pressure across the sensor grid. These features were critical for capturing the variations in leg posture and sensor data over time.

Given the complexity of the data, dimensionality reduction techniques are typically applied to prevent overfitting and to improve the efficiency of classification models. Well-established methods, such as principal component analysis (PCA), independent component analysis (ICA), and t-distributed stochastic neighbor embedding (t-SNE), are commonly used to reduce the feature space while preserving significant patterns and variances in the data. However, in this study, dimensionality reduction techniques were not necessary due to the manageable number of sensors used. The dataset, consisting of 256 pressure sensor points, was not large enough to require dimensionality reduction. Therefore, we did not apply methods such as PCA or t-SNE for feature reduction.

Moreover, we did not employ techniques for fine-tuning feature selection, such as recursive feature elimination (RFE) or mutual information, after feature extraction. These steps are generally used in scenarios where a higher number of features may lead to overfitting or where more precision in model selection is required. Since the dataset in this study was already well structured with a limited number of features, this additional step was not deemed necessary for model optimization. This method description keeps the explanation clear and detailed while adhering to scientific conventions, focusing on why certain techniques were or were not applied based on the dataset characteristics.

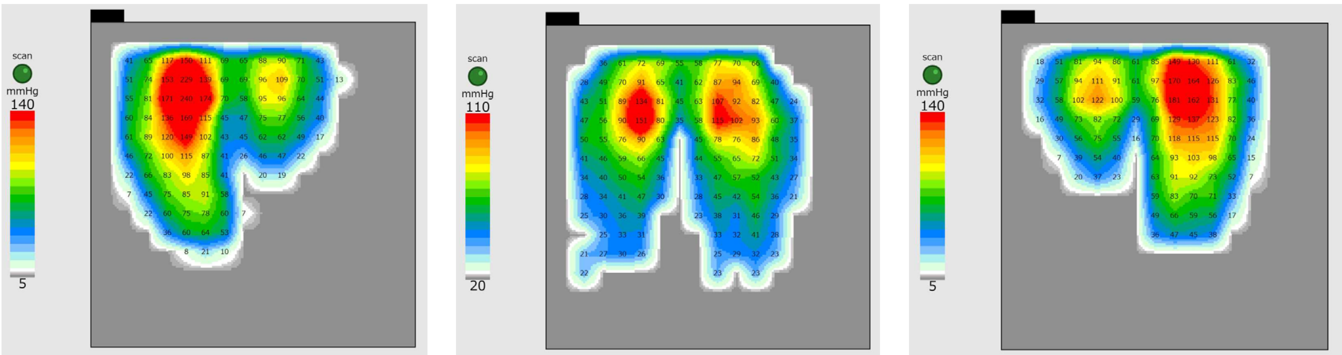
2.5. Ethics Review Committee

This research was conducted after receiving approval from the Ethics Review Committee of the Graduate School of Information Sciences, Tohoku University (approval date: 27 November 2023, approval number 85: 5-2).

3. Results

3.1. Pressure Distribution Heatmap

The pressure distribution heatmap used to detect the cross-legged posture is shown in Figure 2. The heatmap visually illustrates the change in pressure distribution in three different sitting postures: C (middle position, legs uncrossed), R (right leg crossed), and L (left leg crossed). Notably, when legs are crossed, significant changes in pressure are observed on both the left and right sides. These changes indicate a noticeable shift in the center of gravity. This pressure change highlights the potential impact of crossing legs on posture and the overall equilibrium of the body, indicating the feasibility of detecting such postures for health monitoring purposes.



(**a**) (**b**) (**c**)

Figure 2. Heatmap of pressure distribution in the leg-crossed posture. (**a**) shows the heatmap for L (left leg crossed over), (**b**) for C (center position), and (**c**) for R (right leg crossed over). When the left leg is placed on the right leg, the right isthmus bears the weight, so the heatmap on the right side is displayed more intensely. The colors displayed on the color bar indicate higher pressure values as they become closer to red and lower pressure values as they become closer to light blue.

3.2. Comparison of Accuracy Evaluation Metrics

ROC curves (true positive rate and false positive rate) were used to evaluate the performance of the seven classifiers (Figure 3 and Table 2). And we calculated the evaluation index for each subject and then expressed the results as the average value for all subjects. As a result, the evaluation index for all classifiers except SVM was 99% or more when k was 5 or more. The discrimination accuracy improved as the training time increased. Therefore, a training time of around 240 s (80 s for each; center, right, and left) is appropriate. In addition, SVM proved to be difficult to classify, in particular, the center position was difficult to misclassify for SVM.

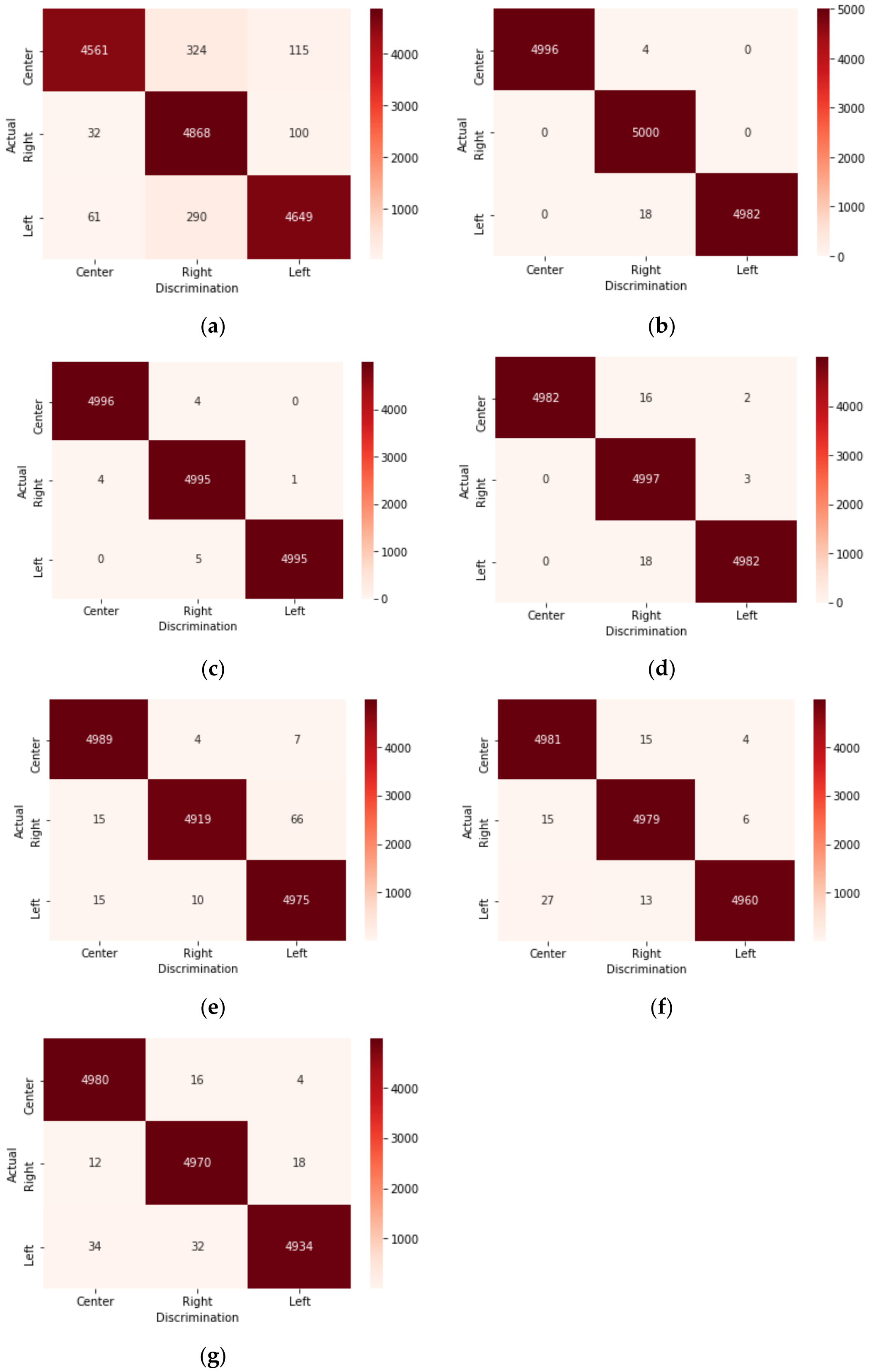


Figure 3. Confusion matrix by classifier. Figure shows the total sum of the confusion matrices for all subjects. The confusion matrices for each classifier are (**a**) SVM, (**b**) RF, (**c**) KNN, (**d**) MLP, (**e**) ADB, (**f**) QDA, and (**g**) NAB.

Table 2. Performance indicators for each classifier.

Accuracy			
Classifier	k-value		
	2	5	10
SVM	0.698 ± 0.039	0.881 ± 0.025	0.939 ± 0.010
RF	0.980 ± 0.009	0.996 ± 0.003	0.999 ± 0.001
KNN	0.992 ± 0.005	0.998 ± 0.002	0.999 ± 0.001
MLP	0.988 ± 0.007	0.993 ± 0.003	0.998 ± 0.001
ADB	0.983 ± 0.007	0.998 ± 0.002	0.992 ± 0.004
QDA	0.946 ± 0.014	0.995 ± 0.002	0.995 ± 0.002
NAB	0.962 ± 0.013	0.991 ± 0.004	0.992 ± 0.002
Precision			
Classifier	k-value		
	2	5	10
SVM	0.853 ± 0.015	0.910 ± 0.020	0.947 ± 0.011
RF	0.983 ± 0.007	0.997 ± 0.003	0.999 ± 0.001
KNN	0.993 ± 0.004	0.998 ± 0.001	0.999 ± 0.001
MLP	0.990 ± 0.005	0.995 ± 0.003	0.998 ± 0.001
ADB	0.986 ± 0.006	0.999 ± 0.001	0.995 ± 0.003
QDA	0.961 ± 0.010	0.996 ± 0.002	0.996 ± 0.001
NAB	0.971 ± 0.010	0.993 ± 0.003	0.994 ± 0.002
Recall			
Classifier	k-value		
	2	5	10
SVM	0.698 ± 0.039	0.881 ± 0.025	0.939 ± 0.010
RF	0.980 ± 0.009	0.996 ± 0.003	0.999 ± 0.001
KNN	0.992 ± 0.005	0.998 ± 0.002	0.999 ± 0.001
MLP	0.983 ± 0.007	0.993 ± 0.003	0.998 ± 0.001
ADB	0.983 ± 0.007	0.998 ± 0.002	0.992 ± 0.004
QDA	0.946 ± 0.014	0.995 ± 0.002	0.995 ± 0.002
NAB	0.962 ± 0.013	0.991 ± 0.004	0.992 ± 0.002
F-score			
Classifier	k-value		
	2	5	10
SVM	0.659 ± 0.046	0.853 ± 0.027	0.931 ± 0.012
RF	0.980 ± 0.009	0.995 ± 0.004	0.998 ± 0.001
KNN	0.992 ± 0.005	0.997 ± 0.002	0.999 ± 0.001
MLP	0.988 ± 0.007	0.992 ± 0.003	0.998 ± 0.001
ADB	0.983 ± 0.007	0.997 ± 0.002	0.991 ± 0.005
QDA	0.942 ± 0.016	0.995 ± 0.002	0.994 ± 0.002
NAB	0.961 ± 0.013	0.989 ± 0.004	0.992 ± 0.003
AUC_tpfp			
Classifier	k-value		
	2	5	10
SVM	0.788 ± 0.003	0.927 ± 0.017	0.959 ± 0.007
RF	0.991 ± 0.004	0.998 ± 0.002	0.999 ± 0.001
KNN	0.998 ± 0.001	1.000 ± 0.000	1.000 ± 0.000
MLP	0.996 ± 0.002	0.998 ± 0.002	0.999 ± 0.001
ADB	0.989 ± 0.005	0.999 ± 0.001	0.994 ± 0.003
QDA	0.954 ± 0.016	0.995 ± 0.004	0.995 ± 0.004
NAB	0.971 ± 0.015	0.993 ± 0.004	0.992 ± 0.004

Table 2. *Cont.*

AUC_pr			
Classifier	k-value		
	2	5	10
SVM	0.797 ± 0.037	0.937 ± 0.015	0.964 ± 0.007
RF	0.989 ± 0.005	0.998 ± 0.002	0.999 ± 0.001
KNN	0.997 ± 0.001	0.999 ± 0.001	1.000 ± 0.000
MLP	0.996 ± 0.002	0.997 ± 0.002	0.999 ± 0.001
ADB	0.985 ± 0.008	0.998 ± 0.002	0.993 ± 0.003
QDA	0.953 ± 0.015	0.995 ± 0.003	0.995 ± 0.003
NAB	0.970 ± 0.014	0.994 ± 0.003	0.992 ± 0.003

Evaluation index was calculated for each subject, and the average value for all subjects was shown. Each subject was measured 10 times (S.E. indicates the standard error.).

4. Discussion

In this study, we attempted to detect leg positioning posture using a body pressure distribution sensor and evaluated the accuracy of the detection using machine learning. As a result, classifiers other than SVM showed high classification accuracy and were confirmed to be effective for detecting leg positioning posture. The main points of the results obtained are discussed below.

First, regarding the significantly lower results of SVM compared to other classifiers: SVM is an algorithm that performs classification and regression by determining boundaries and hyperplanes to separate data into two classes. It is primarily designed for binary classification, requires preprocessing of data, and has relatively few parameters, but adjusting these parameters and interpreting the results can be challenging.

Next, the body pressure data acquired by the pressure sensor provided sufficient information to identify the leg-crossing posture even at a sampling rate of 5 Hz. The heat map not only visually confirmed significant changes in pressure distribution between the left and right sides of the body when crossing the legs but also demonstrated that these changes were effective as feature quantities for machine learning. In contrast to conventional posture estimation methods using depth cameras, which suffer from a delay when tracking posture changes in real time, the body pressure sensor can acquire data in real time without contact and so was considered to be superior in terms of efficiency and privacy protection.

In comparison with other classifiers, RF, KNN, and MLP also demonstrated high accuracy and were effective to some extent in identifying leg-crossing postures. These classifiers have the ability to capture complex data patterns and showed stable performance in identifying different pressure distributions. On the other hand, ADB and NAB showed a little poorer performance than the other classifiers excluding SVM. This is likely because these methods make specific assumptions about the data distribution, which may have limited their ability to capture the nonlinear and complex changes in pressure data.

The results of this study demonstrate the effectiveness of posture detection using body pressure distribution sensors. However, there are still further issues to be addressed before practical application. For example, the experiment classified static postures, but in real-life sitting postures, dynamic changes occur frequently. In order to be able to detect dynamic sitting postures in real time, it is necessary to collect more diverse data and improve the classification algorithm. In addition, since the number of subjects is limited, it is necessary to collect data from more subjects and improve the generality of the algorithm. For example, it is possible that elderly people and female subjects may show slightly different pressure distributions, so it is necessary to verify the effects of gender and age differences on the data. In our preliminary experiments, even for women and the elderly, the heatmap displays a load on the ischium of the leg that is on top (right side if it is the right leg), and there is no significant difference in the shape of the ischium of healthy people, so we can predict that there will be no significant difference [18], but it is also necessary to analyze the chronological changes due to long-term leg crossing. Future challenges include the complexity of data collection and the lack of publicly available datasets in this domain. To solve such problems, the leave-one-subject-out (LOSO) evaluation method could indeed enhance the robustness of our findings by simulating real-world scenarios where the system must classify data from individuals not included in the training set [26].

In future work, several key directions should be explored to enhance both the model's performance and its practical applicability. Given that the pressure data were collected over time, integrating techniques that capture temporal dynamics, such as recurrent neural networks (RNNs) or temporal convolutional networks (TCNs), could significantly improve the model's predictive accuracy by accounting for the sequential nature of the data. The impact of posture transitions on classification accuracy also warrants further investigation. Testing approaches that consider feature windows or sequential data could provide deeper insights into how changes between different postures influence model performance. Additionally, while the study utilized a range of evaluation metrics, including accuracy, recall, precision, F1-score, and AUC, understanding the potential class imbalance in the data is crucial. It would be beneficial to discuss the class distribution and explore techniques such as synthetic minority over-sampling technique (SMOTE) or weighted loss functions to alleviate class imbalance, which could improve model fairness and robustness. It is vital for end users, such as clinicians, to interpret how the model arrives at its predictions. Incorporating explained ability techniques, such as SHAP values or local interpretable model-agnostic explanations (LIME), can enhance transparency by highlighting which sensors or pressure zones contribute most to the model's predictions. This increased interpretability may facilitate the adoption of the model in real-world settings, particularly where understanding the reasoning behind decisions is essential for trust and clinical application. These future improvements address limitations and broaden the scope of this research, particularly in fields where precision and transparency are paramount, such as healthcare and ergonomic assessments.

5. Conclusions

In this study, we attempted to detect the leg-crossing posture in a sitting position using a body pressure distribution sensor and evaluated its accuracy using machine learning. As a result of comparing seven different classifiers, it was found that classifiers other than SVM can achieve high accuracy with an evaluation index of 95% or more when the number of clusters is set to 5 or more. It was also shown that the accuracy of identification improves as the learning time increases. This study demonstrated excellent performance in detecting the leg-crossing posture. In addition, RF, KNN, and MLP exhibited high classification accuracy, demonstrating that body pressure distribution data are effective features. Key features, including the variance of pressure over time (representing temporal changes), mean pressure, and pressure distribution across the sensor grid, provided essential information that allowed for accurate classification of the three postures: center position (C), right leg crossed (R), and left leg crossed (L). The results of this research will contribute to the development of a system that can detect unconscious leg-crossing posture in real time in everyday life. Since leg-crossing posture can cause a shift in the center of gravity of the body and back pain, the detection method verified in this research can detect posture without using a camera, ensuring privacy, and it is expected that this detection will encourage posture improvement.

Author Contributions: Conceptualization, E.Y. and Y.Y.; methodology, E.Y.; software, Y.Y.; validation, E.Y. and Y.Y.; investigation, E.Y. and T.A.; resources, E.Y.; data curation, E.Y.; writing—original draft preparation, E.Y.; writing—review and editing, E.Y.; visualization, Y.Y.; supervision, E.Y.; project administration, E.Y.; funding acquisition, E.Y. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by New Energy and Industrial Technology Development Organization (NEDO), Public-Private Support Program for Identifying Young Researchers, grant number P20004.

Institutional Review Board Statement: The study was conducted in accordance with the Declaration of Helsinki and approved by the Institutional Ethics Committee of Graduate School of Information Science, Tohoku University (protocol code 85:5-2 and approved on 27 November 2023).

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The original contributions presented in the study are included in the article, further inquiries can be directed to the corresponding author.

Conflicts of Interest: The authors declare no conflicts of interest.

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