Original Article

Fundamental study on walking environment classification using insole-type gait sensors for smart tourism

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Abstract

This study classified walking environments (hallway, grass, sandy beach, uphill slope, downhill slope) using an insole-type gait sensor and conducted a fundamental investigation of walking environment estimation technology with an eye toward applications in the tourism sector. Diverse walking environments exist in tourist destinations, parks, and historic streetscapes, where mobility load and safety directly impact the comfort and accessibility of the tourist experience. This study constructed walking environment classification models using five methods: Random Forest, SVM, XGBoost, 1D-CNN, and Transformer Encoder, and evaluated them via cross-validation among subjects. The results showed that the deep learning models 1D-CNN and Transformer Encoder demonstrated relatively high classification accuracy, maintaining strong generalization performance even for unseen subjects. Furthermore, through misclassification tendency analysis and visualization using t-SNE, we clarified differences in feature distributions and challenges in environmental identification. These findings suggest potential applications in barrier-free evaluations of tourist destinations, fatigue risk estimation, and route recommendation/mobility support within smart tourism.

Keywords

gait analysis, insole-type sensor, environmental classification, smart tourism, deep learning

1. Introduction

In recent years, the global aging population has been increasing, making falls among the elderly and declines in motor function critical social issues. Falls can lead to the need for long-term care and a decline in quality of life (QOL), emphasizing the necessity of preventive measures and adaptive mobility support [Matikainen-Tervola et al., 2025]. Conventional gait analysis technologies have mainly focused on walking in indoor or flat, paved environments, with the aim of evaluating gait ability or detecting abnormalities. However, in real-world contexts, people often walk on various outdoor surfaces such as slopes, grass, and sandy ground, where walking characteristics differ markedly.

Recent studies using in-shoe motion sensors and pressure-sensing insoles have revealed that gait parameters such as foot clearance, stride length, and heel roll angle vary significantly depending on surface type [Wolff et al., 2024; Warmerdam et al., 2024; Shimizu et al., 2025]. Walking on uneven or compliant surfaces such as grass or sand requires greater postural control and muscle activation, influencing stability and energy expenditure [Sikandar et al., 2023]. These findings highlight the importance of estimating walking environments automatically to support fall prevention, rehabilitation, and daily mobility.

In addition, the concept of smart tourism, which integrates mobility sensing technologies to enhance user experience and accessibility, has been gaining attention. Walking activities at tourist destinations or parks directly influence visitors' satisfaction and safety, and understanding walking environments could contribute to reducing fatigue and optimizing route design [Huang and Lau, 2020]. Wearable navigation systems for older adults—such as augmented-reality glasses or bone-conduction headsets—have been shown to improve navigation performance and user experience by providing intuitive sensory feedback [Montuwy et al., 2019].

Therefore, technologies capable of recognizing environmental conditions from walking data are expected to play a fundamental role not only in health and mobility assistance but also in designing inclusive urban and tourism infrastructures.

This study focuses on developing environmental classification models using insole-type gait sensors. Our previous study demonstrated the feasibility of environmental estimation using insole-type gait sensors and Random Forest classification based on gait features [Nakagawa, Sato, and Kawanami, 2024]. However, challenges remained, including limited subject diversity, insufficient data volume, and a lack of deep learning applications. In this research, we construct classification models using Random Forest, SVM, XGBoost, 1D-CNN, and Transformer Encoder architectures, evaluating their accuracy on multi-subject data and testing inter-subject generalization performance. We further investigate the effect of data augmentation on model robustness and interpret model outputs through feature-importance and t-SNE visualization.

By exploring these approaches, this study aims to validate the feasibility of environment estimation using insole gait sensors and discuss its potential applications in safe walking support and smart tourism.

2. Related research

A large body of research has shown that walking environments, such as surface type and slope, substantially affect gait parameters. For instance, walking on slopes or uneven ground changes lower-limb joint motion, stride timing, and stability [Matikainen-Tervola et al., 2025; Wolff et al., 2024]. Studies using in-shoe motion sensors and inertial units have reported that walking on grass or dirt increases swing time, roll angle, and foot clearance compared with indoor or asphalt surfaces [Warmerdam et al., 2024; Shimizu et al., 2025]. Such variations provide important features for distinguishing environmental conditions based on gait dynamics.

In the field of gait sensing, insole-type systems are widely used for measuring acceleration, angular velocity, and plantar pressure in daily environments. The distribution of plantar pressure and the center of pressure (COP) trajectory reflect characteristic patterns depending on the walking condition—such as level walking, slopes, or stairs—and can be leveraged for environment recognition [Horie et al., 2006]. Recent domestic research has also demonstrated road-condition estimation from insole pressure data, confirming that foot-pressure signals contain rich contextual information about walking surfaces [Wakabayashi and Shiraishi, 2022].

Deep learning approaches have recently advanced environmental recognition from wearable sensors. Studies have shown that inertial and in-shoe sensor data can be used to classify different surface types and walking conditions, and that the optimal number and placement of sensors play an important role in classification accuracy [Sikandar et al., 2023; Fujii et al., 2025]. These findings suggest that high-level representations from sensor fusion and deep feature extraction are effective for recognizing irregular walking environments.

In addition to health and rehabilitation contexts, environment recognition is also relevant to tourism and urban mobility systems. Montuwy et al. [2019] examined wearable navigation aids for older pedestrians, showing that sensory feedback through augmented reality (AR) or haptics can enhance spatial awareness and emotional comfort. Similarly, Huang and Lau [2020] proposed gamified mobile applications to improve accessibility and experience for visually impaired tourists. These studies suggest that environment-aware sensing can contribute not only to gait analysis and fall prevention but also to inclusive mobility design and user-centered tourism experiences.

Figure 1: NEC insole-type gait sensor

In summary, prior studies have established that walking environments significantly influence gait dynamics and that wearable sensors can effectively capture these differences. However, few studies have rigorously assessed inter-subject generalization or compared multiple learning models for environmental estimation. This research addresses these gaps by constructing and evaluating environment-classification models across diverse subjects and exploring explainable visualization methods.

3. Proposed methodology

3.1 Insole-type gait sensor

In this study, walking data was measured using the NEC insole-type gait sensor shown in Figure 1. This sensor can measure a total of 24 discrete walking parameters shown in Table 1, such as walking speed, stride length, foot angle, foot lift height, and foot pressure, calculated based on the values of the built-in acceleration sensor and gyro sensor. Although this

Table 1: Measurable parameters

Description (Unit)	
Walking speed (km/h)	Stride length (cm)
Maximum foot sole angle in plantarflexion (deg)	Maximum foot sole angle in dorsiflexion (deg)
Foot height (cm)	Circumduction (cm)
Toe-in/out angle (deg)	Hallux value angle (deg)
Minimum toe clearance (cm)	Foot clearance (cm)
Roll angle at heel contact (deg)	Roll angle at toe-off (deg)
Peak angular velocity during swing phase (deg/s)	Maximum speed during swing phase (m/s)
Duration of loading response (sec)	Duration of preswing (sec)
Stance phase time (sec)	Swing phase time (sec)
Duration from heel contact to foot flat (sec)	Duration from foot flat to heel release (sec)
Duration from heel release to toe release (sec)	Center of pressure exclusion index (%)
Cadence (step/min)	Frailty level (–)

sensor cannot utilize continuous raw data such as acceleration and angular velocity, it can be used continuously for several hours (or even for a year if the sampling cycle is lengthened), and it has the potential to estimate walking environments from everyday walking.

During measurement, insole-type sensors are placed inside both shoes and paired with a dedicated smartphone (Android) via Bluetooth. When the subject turns on the power while wearing the shoes, walking detection starts automatically, and the acquired parameters are sent to the smartphone in real time via a dedicated application. The application displays the number of steps, stride length, walking speed, etc. in chronological order, and outputs and saves the data in CSV format after measurement is complete.

Each CSV file corresponds to one walking trial and contains time-series gait parameters recorded frame by frame. Each row represents a single step frame, and each column corresponds to a parameter such as stride length, foot angle, or contact time. These CSV files were later used as input for preprocessing and training in this study.

Because it is an insole-type, subjects can acquire data simply by wearing their normal shoes, and it has the advantage of being able to measure natural walking conditions both indoors and outdoors. In addition, the sensor itself is lightweight and flexible, causing little discomfort when worn, and data can be acquired during free walking without special equipment or guidance.

3.2 Data collection

In this study, walking data was collected from 10 healthy adult males in five different environments: a hallway, lawn, sandy beach, uphill slope, and downhill slope, as shown in Figure 2. In each environment, subjects performed 10 sets of 30-second straight-line walking trials. Each subject contributed an average of approximately 500 gait data samples in total across all environments. The exact number of samples varied slightly between individuals.

This study was conducted following review and approval by the Ethics Review Committee of Kanazawa Institute of Technology (Approval No. 2502011).

3.3 Data preprocessing

In this study, we applied a common preprocessing step to all models. Specifically, we first performed smoothing to reduce sensor noise, applied data augmentation for some environments, and then split the data into training and evaluation sets. Furthermore, we standardized the features to reduce scale differences before inputting them into each model. For deep learning models (1D-CNN, Transformer Encoder), since fixed-length time series are required as input, additional segmentation processing was performed.

3.3.1 Smoothing

Since walking data contains high-frequency noise originating from sensors, a moving average with a window width of w = 5 was applied to each feature time-series x_t to reduce short-term fluctuations.

$$\tilde{x}_t = \frac{1}{W}\sum_{i=0}^{w-1} x_{t-i} \tag{1}$$

3.3.2 Segmentation

Since walking is a continuous motion, it must be divided into segments of a fixed length for analysis. Therefore, walking is divided into fixed-length segments of one step (or L samples), and the segment start is extracted by shifting (sliding window) by Δ samples. In this paper, L = 50 and Δ = 5 are assumed.

3.3.3 Standardization

When the scales of features differ across subjects or environ-

Figure 2: Walking environments

ments, some features may exert an excessive influence during model training. Therefore, Z-score normalization was applied using the mean μ and standard deviation σ of the training data D_{train}.

The same μ and σ were then applied to the evaluation data.

$$z = \frac{x - \mu}{\sigma} \tag{2}$$

This processing was performed independently for each fold to prevent information leakage. Note that among the 24 indicators shown in Table 1, "frailty level (estimated value)" was not used for training; instead, the remaining 23-dimensional feature vector was input to each model.

3.3.4 Data extension

To mitigate the impact of insufficient data, the following extensions were implemented specifically for slope environments:

- Sliding window extension: Increase the number of segments using the above Δ (allowing overlap).
- Addition of small Gaussian noise: For the segment matrix $X \in R^{L \times d}$, add noise to each component.

$$X' = X + \varepsilon,\ \ \varepsilon_{ij} \sim \mathrm{N}\,(0, \sigma^2_{\text{noise}}) \tag{3}$$

Add σ noise to each feature to avoid scale differences, making it proportional to the standard deviation σ_j within the training fold.

$$\sigma_{\text{noise},\,j} = \alpha\sigma_j \tag{4}$$

The default α value was set to 0.02. Expansion was performed only on the training data and not applied to the evaluation data.

3.3.5 Data extension validation

The validity of the augmented data was confirmed by verifying its consistency with the actual data distribution using t-SNE visualization and cluster validity metrics. As a result, it was determined that the augmented data does not significantly compromise the characteristics of the actual data and is suitable for use as training data.

3.4 Model building

3.4.1 Random forest (RF)

RF is an ensemble learning method that constructs multiple decision trees and performs classification based on majority voting among them. Since each individual decision tree is built based on a randomly sampled subset of the training data, it has the characteristic of achieving stable prediction performance while suppressing overfitting. In this study, we used a 23-dimensional feature vector derived from walking data as input. The model was implemented using scikit-learn's RandomForestClassifier with 300 trees (n_estimators = 300), no restriction on maximum depth, and a fixed random seed (random_state = 42) for reproducibility. Tree depth was automatically adjusted during training, ensuring stable classification performance.

Given its ease of implementation, RF was adopted as the baseline model for environmental estimation.

3.4.2 Support vector machine (SVM)

SVM is a classification method that maximizes the margin between classes. Even when linear separation is difficult, it can map data to a high-dimensional feature space using kernel functions and learn nonlinear boundaries. In this study, the RBF kernel was used as the kernel function, with the hyperparameter C set to 1.0 and the gamma value automatically adjusted.

We used the SVC implementation in scikit-learn with kernel = 'rbf', C = 1.0, gamma='scale', and random_state = 42 to ensure reproducibility.

Since SVM is robust to high-dimensional data and performs well even with a small number of samples, it was positioned as a comparison target against RF.

3.4.3 eXtreme gradient boosting (XGBoost)

XGBoost is an algorithm that efficiently implements Gradient Boosted Decision Trees (GBDT), characterized by fast training and high generalization performance. Boosting is a sequential method where later models focus on learning samples misclassified by earlier models, taking a different approach from RF based on bagging. In this study, we implemented the model using default settings: learning rate 0.1, number of decision trees 100, and maximum depth 6.

Specifically, we used the XGBClassifier implementation with learning_rate = 0.1, n_estimators = 200, max_depth = 6, subsample = 0.8, colsample_bytree = 0.8, random_state = 42, and eval_metric = 'mlogloss'.

The objective was to verify the effectiveness of different ensemble learning methods—bagging and boosting—by comparing them with RF.

3.4.4 One-dimensional convolutional neural networks (1D-CNNs)

1D-CNNs are excellent models for extracting local patterns in time-series data. In this study, we input walking data as a matrix of "feature dimension × time-series length," treating 23 feature types as the channel dimension and 50 steps of walking data as the sequence dimension. This enables simultaneous capture of temporal variations and local dependencies between features.

The network architecture followed a simple structure: Conv1D → MaxPooling1D → Flatten → Dense. Specifically, we used a Conv1D layer with 32 filters, a kernel size of 3, and ReLU activation, followed by a max pooling layer with pool size 2. The extracted features were flattened and passed through a fully connected layer with 64 ReLU units, and then classified into five classes using a softmax output layer.

The model was trained for 20 epochs with a batch size of 8 using the Adam optimizer and categorical cross-entropy loss. CNNs excel at extracting features from spatially adjacent inputs and are expected to learn local temporal variations in gait data (e.g., peak and trough patterns within a gait cycle). Therefore, this study introduced a 1D-CNN as a model capable of capturing temporal dependencies more precisely than machine learning models.

3.4.5 Transformer encoder

Transformer Encoder is a model based on the self-attention mechanism, widely used primarily in natural language processing, characterized by its ability to efficiently learn long-term dependencies in sequential data. In this study, we input walking data as a matrix of "feature dimension × sequence length," treating 23 types of features as embedding vectors and unfolding the 50-step sequence in the sequence dimension. This enables tokenizing and processing the walking state at each time step.

Specifically, we applied a multi-head self-attention layer with 4 heads and key dimension 16, followed by layer normalization, a fully connected layer with 64 ReLU-activated units, dropout (rate = 0.3), and global average pooling over the time axis. The final output layer was a softmax classifier over five classes.

Compared to 1D-CNNs, Transformer Encoder can learn flexible dependencies across the entire input. This offers the advantage of dynamically emphasizing features that vary across subjects or environments. Therefore, this study introduced Transformer Encoder as the model most capable of broadly representing temporal dependencies.

As described above, this study implemented and compared a total of five models: machine learning models (RF, SVM, XGBoost) and deep learning models (1D-CNN, Transformer Encoder). Machine learning models represent widely used conventional techniques, and their performance was evaluated using direct input of gait features. Deep learning models, on the other hand, were introduced to capture time-series dependencies and interactions between features more flexibly. By employing these multiple models, we aim to clarify the characteristics and limitations of each approach in environmental estimation.

3.5 Evaluation method

In this study, cross-validation was employed to evaluate the model's generalization performance. This method uses data from subjects not involved in training as test data, offering the advantage of measuring environmental classification performance independent of individual learner characteristics. Specifically, GroupKFold was used to divide subjects into groups, repeating the procedure of training 9 subjects and assigning 1 for verification within each division. This ensured every subject served as a validator at least once.

The primary evaluation metric was classification accuracy. Furthermore, to analyze misclassification tendencies in detail, confusion matrices were calculated. Using confusion matrices allows for quantitative comparison of the difficulty in distinguishing between specific environments and differences in misclassification patterns across models.

4. Experimental results

4.1 Comparison of classification accuracy

In this study, we first compared classification accuracy between randomly splitting the entire dataset and using cross-validation (GroupKFold). Table 2 shows the average accuracy for each model. When evaluating the entire split dataset, 1D-CNN achieved 100 % accuracy and RF achieved 97 %, both demonstrating very high accuracy. However, accuracy decreased significantly when subject-wise cross-validation was performed. This indicates that the models' generalization performance is insufficient for data from subjects not included in training. On the other hand, 1D-CNN and Transformer Encoder maintained relatively high accuracy compared to other models, confirming the effectiveness of deep learning models.

4.2 Misclassification Analysis

As representative models, we analyzed misclassification tendencies using the machine learning method RF and the deep learning method 1D-CNN. Results from cross-validation using GroupKFold showed RF's average accuracy was approximately 58 %, with significant accuracy variation across subjects (minimum 35 %, maximum 83 %). In contrast, the 1D-CNN achieved an average accuracy of 71.2 %, demonstrating overall higher accuracy than RF, though subject-specific differences remained evident.

To identify misclassification patterns, we aggregated confusion matrices across all folds and calculated the percentage of TRUE row environments misclassified into the PRED column. The results are shown in Table 3. Both models showed a high rate of misclassification between "hallway" and "lawn" (RF: hallway → lawn 38.2 %, 1D-CNN: hallway → lawn 25.4 %). This reflects the similarity in walking characteristics between these two environments and aligns with the t-SNE visualization results described later, where clusters for both environ-

Table 2: Average accuracy of each model (%)

Evaluation method	RF	SVM	XGB	1D-CNN	Trans-former
Hold-out	97.9	95.1	95.6	100	100
GroupKFold	58.2	59.3	60.5	71.2	69.4

Table 3: Average misclassification rate per subject for random forest and 1D-CNN

Random Forest					
True \ Pred	Hallway	Grass	Sand	Down	Up
Hallway	–	38.2	7.1	0.2	0.2
Grass	18.8	–	11.1	1.4	0.3
Sand	5.5	13.8	–	4.6	2.2
Down	2.1	17.8	9.7	–	2.5
Up	13.8	9.6	19.4	1.2	–
1D-CNN					
True \ Pred	Hallway	Grass	Sand	Down	Up
Hallway	–	25.4	11.2	0.3	0.0
Grass	1.1	–	7.2	1.6	0.0
Sand	6.0	1.6	–	0.0	0.0
Down	0.7	1.0	2.5	–	0.0
Up	2.0	1.0	2.0	0.0	–

ments are distributed close together.

On the other hand, while RF exhibited relatively high misclassification rates to other environments, such as "lawn → hallway," "uphill slope → sandy beach," and "downhill slope → lawn," 1D-CNN showed an overall reduction in misclassification rates, with particularly improved recognition performance for slope environments. This is likely because 1D-CNN, by learning temporal local patterns, more accurately captured differences between environments that are difficult for machine learning models to distinguish.

4.3 Visualization of feature space using t-SNE

To confirm the distribution patterns of each environmental data point in the feature space, t-SNE (perplexity = 30, learning rate = 200, random seed fixed) was applied for each subject, visualizing the cluster structure in the low-dimensional space. Figure 3 shows the visualization results for subjects F, N, O, S, and T. For all subjects, a certain degree of clustering was

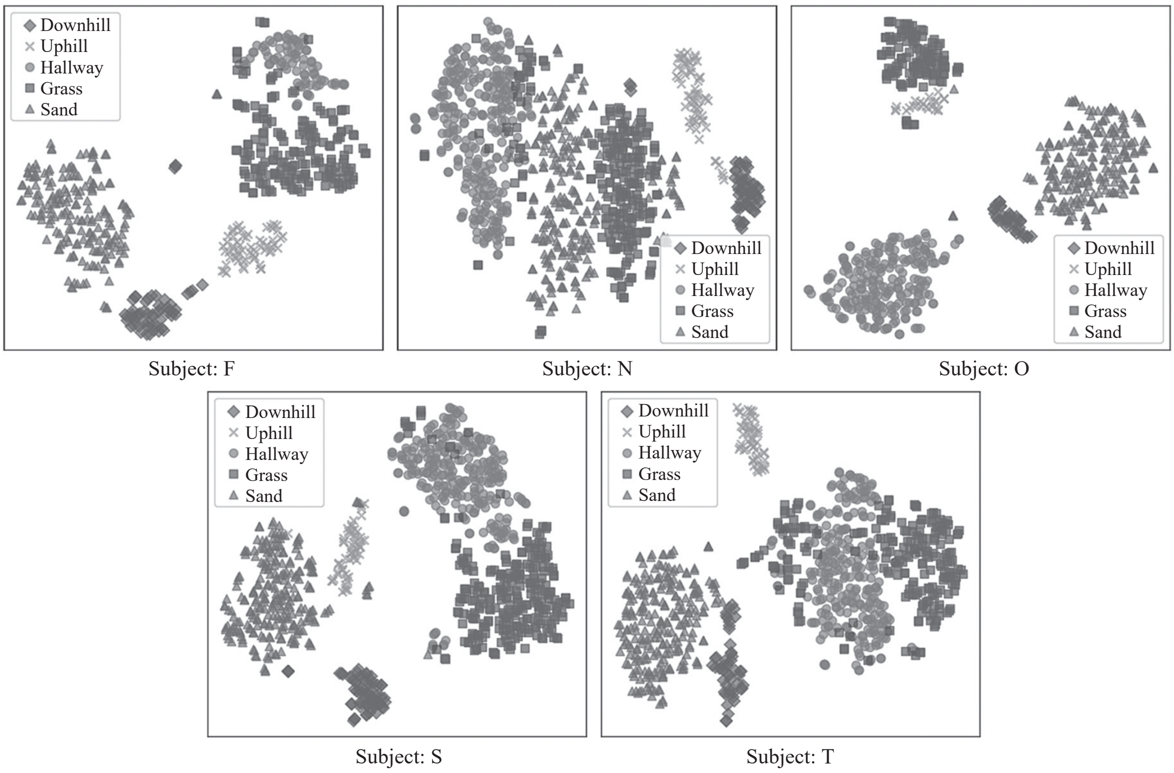

Figure 3: t-SNE visualization results for each subject

observed for each environment, with “beach” and “slope (up/down)” being particularly clearly separated. On the other hand, the clusters for ‘hallway’ and “lawn” tended to be distributed close to each other and partially overlap. This is consistent with the results of the misclassification analysis in the previous section, where many misclassifications were observed between these two environments, suggesting that the characteristics of both environments are similar.

5. Discussion

This study compared multiple machine learning models and deep learning models using gait data obtained from insole-type gait sensors to investigate the potential for gait environment estimation. The results yielded the following findings. First, in model accuracy comparisons, all models demonstrated high accuracy when data was randomly split, but accuracy significantly decreased when cross-validation between subjects was performed. Specifically, while machine learning models like RF and SVM remained at around 50-60 % accuracy, deep learning models such as 1D-CNN and Transformer Encoder maintained approximately 70 % accuracy, demonstrating their effectiveness in reducing subject dependency. Next, the misclassification tendency analysis revealed that both the RF and 1D-CNN models exhibited high misclassification rates for “hallway” and “lawn.” This reflects the similarity in walking characteristics between these two environments and was consistent with the t-SNE feature space visualization results showing closely clustered and overlapping clusters. Conversely, relatively clear separation tendencies were observed for “beach” and “slope (up/down)”, suggesting stable classification is possible when distinct environmental features are strongly present.

These results demonstrate that deep learning models exhibit improved generalization performance compared to traditional machine learning methods, indicating their potential for relatively accurate environment classification even for unknown subjects. However, distinguishing between environments with similar features, such as “hallway” and “lawn,” remains a challenge. Further refinement is needed, such as enhancing feature extraction and utilizing multimodal data.

6. Conclusion

This study attempted to estimate walking environments using machine learning and deep learning models based on walking data acquired with an insole-type gait sensor. We compared conventional machine learning methods such as RF, SVM, and XGBoost with deep learning methods like 1D-CNN and Transformer Encoder, evaluating their generalization performance through cross-validation among subjects.

Experimental results showed that deep learning models achieved higher accuracy than conventional machine learning models, with 1D-CNN achieving an average accuracy of 71.2 %. However, it was revealed that misclassifications were frequent and recognition was difficult between environments with similar feature distributions, such as “hallway” and “lawn.” Furthermore, analysis using t-SNE and cluster validity indices suggested that subject-specific walking characteristics may influence classification performance.

Future challenges include: (1) improving feature extraction methods to enhance classification performance between similar environments, and (2) introducing normalization and adaptive learning that account for inter-subject variation. These approaches are expected to further develop the insights gained in this study regarding walking environment classification.

Furthermore, the findings from this study are expected to be applicable in the context of smart tourism within the tourism sector. For example, technologies enabling real-time understanding of walking environments and support based on gait changes could potentially be utilized for accessibility support for elderly travelers and visually-impaired individuals, recommending comfortable tourist routes, and improving the quality of experience (QoE). Future research should aim for more practical implementation through deployment in tourist destinations and public spaces, coupled with user experience evaluations.

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