Joint CSCE Construction Specialty & CRC Conference 2025
Conférence conjointe spécialisée en construction de la SCGC et CRC-2025

Montreal, Quebec
July 28-31, 2025 / *28-31 juillet 2025*

Automated Inferences on Walking Barriers Based on Human Bipedal Keypoint Detection Using CCTV Video Data

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ABSTRACT: Identifying walking barriers is crucial for ensuring pedestrian safety and mobility, especially in high-risk environments like construction sites. These barriers pose serious safety hazards, such as falls, compromising pedestrian stability and accessibility. Traditional closed-circuit television (CCTV)-based object tracking methods have been used to detect pedestrian movements in response to obstacles to infer their presence but often lack the precision required for detailed motion analysis. This study proposes a method for detecting walking barriers by analyzing pedestrian foot movements in response to barriers using Openpose-based keypoint detection and a long short-term memory autoencoder anomaly detection model. Foot pixel coordinates were extracted from CCTV footage and analyzed to identify gait abnormalities caused by obstacles. Experimental results demonstrated that the proposed method successfully detects gait anomalies, which correlate with the locations of physical barriers in both controlled and actual construction environments. The model achieved an accuracy of 86.4% and an F1-score of 0.897 for inferring barriers, indicating reliable performance in distinguishing normal from abnormal walking patterns. However, errors were observed when pedestrians and obstacles were far from the camera owing to the reduced accuracy of keypoint detection at greater distances. Despite these limitations, this approach enables real-time identification of high-risk zones and enhances pedestrian safety. In addition to its application in construction sites, this method shows potential for broader use in urban environments for monitoring public infrastructure and improving pedestrian mobility. Future research could focus on advanced data preprocessing to enhance further model performance and generalizability.

1. INTRODUCTION

Walking is a fundamental aspect of human mobility, yet walking barriers undermine safety and accessibility. These barriers can include uneven surfaces, poorly maintained sidewalks, cluttered pathways, and obstacles like construction debris or improperly placed equipment. These issues are particularly pronounced in high-risk environments, such as construction sites, where hazards (like tripping and falling) can lead to severe safety accidents. Beyond construction sites, walking barriers also pose threats to pedestrian safety in everyday environments, making the effective identification and resolution of these obstacles essential.

Studies using wearable sensors have provided valuable insights into pedestrian safety and behavior. Kim (2020) explored the relationship between walking stability and environmental factors by evaluating pedestrian mobility through wearable sensor data. Kim et al. (2022) analyzed pedestrian distress in urban environments using wearable sensors, collecting electrodermal activity, electrocardiogram, heart rate, and skin temperature time-series data to detect and explain stress responses. Oluwatobi et al. (2025) investigated the benefits and challenges of adopting wearable safety technologies to improve health and safety on construction sites. They highlighted the usefulness of wearable devices in mitigating risks such as falls, slips, and collisions, as well as in monitoring environmental factors and worker stress in real time. However, major barriers to the widespread adoption of wearable safety devices remain, including increased implementation costs, maintenance requirements, and privacy concerns.

Video-based monitoring technologies offer complementary advantages by focusing on locations rather than individuals. These systems are particularly effective in monitoring spaces for safety and mobility. While blind spots may pose limitations, the increasing installation of closed-circuit television (CCTV) cameras in urban areas and construction sites enhances the feasibility of video-based approaches. Lee et al. (2021) analyzed pedestrian behaviors and responses to identify environmental factors that negatively affect pedestrians. Shen et al. (2022) measured walking characteristics at varying speeds, and examined gait transitions and instability. Majeed et al. (2021) conducted a study to analyze lower-body walking data and detected walking trajectories using CCTV footage. Gu et al. (2024) analyzed walking patterns utilizing three-dimensional joint coordinates. Additionally, Lee et al. (2021) proposed an approach to quantify unpredictability in pedestrian movements using entropy-based analysis and detected environmental obstacles.

Following advancements in deep-learning-based image processing technologies, detecting pedestrians and analyzing their movements through CCTV footage has become feasible. The number of relevant studies has increased; these studies have focused on inferring walking discomfort factors based on pedestrian trajectories (Kanu-Asiegbu et al., 2021; Kim et al., 2024). However, existing object recognition techniques often struggle to track individual footsteps or detailed movements, limited by a nuanced understanding of how pedestrians respond to specific environments.

This study aims to address these limitations by proposing a method to identify walking barriers with a deeper understanding of human physical responses to barriers using keypoint detection technology. Keypoint detection is a computer vision technique that identifies and localizes specific anatomical landmarks, such as joints, from images or video frames. By extracting the positions of these key body points, it enables detailed analysis of human posture and movement (Li et al. 2023). Keypoint detection has been successfully applied in various fields to analyze human motion and detect physical limitations or hazards. For example, Wang et al. (2021) utilized keypoint detection to monitor rehabilitation progress by tracking lower-body joint movements and optimizing rehabilitation models for precise physical therapy assessments. Similarly, Altieri et al. (2020) applied keypoint detection in ergonomic risk assessment using the Openpose library to monitor body postures and reduce the risk of musculoskeletal disorders in workplace environments. In pedestrian research, Li et al. (2023) demonstrated the utility of keypoint detection combined with long short-term memory (LSTM) models to recognize pedestrian poses and predict movement patterns with high accuracy.

By tracking the positions of critical body parts, such as joints, keypoint detection has the potential to analyze pedestrian movements and provide valuable insights into walking behaviors and environmental interactions. However, it is necessary to verify whether keypoint detection can be effectively utilized to analyze detailed pedestrian movements to identify barriers.

This study utilizes keypoint detection technology on CCTV footage to extract key coordinates of pedestrians, particularly focusing on the left and right feet. The extracted time-series data of foot positions are then analyzed using an LSTM autoencoder network to detect anomalies, which may indicate barriers. The study validates its approach by examining whether considerable anomalies are detected in coordinates corresponding to sections with obstacles in various barrier environments.

2. RESEARCH METHODS

Figure 1 describes the framework of this study. First, the person's keypoints, which are specific anatomical landmarks representing the posture and movement of the body, are extracted from CCTV video data, followed by the extraction of the coordinates of both feet and their spatial relationships. After training for the normality of the coordinate change data using an LSTM autoencoder anomaly detection model, an optimal threshold is determined by examining the reconstruction errors. The model then assesses whether anomaly points are concentrated in areas with obstacles to infer the locations where pedestrians experience discomfort due to obstacles.

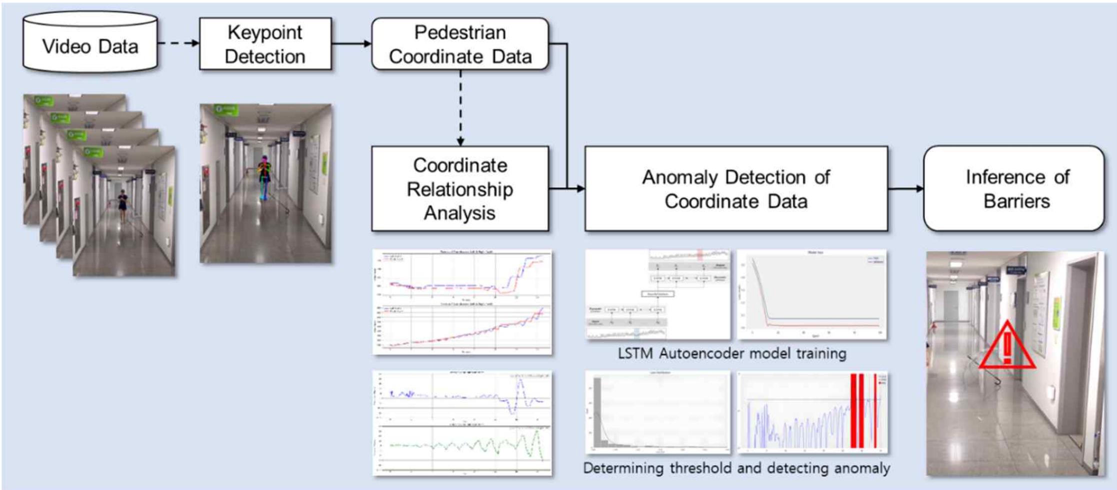

Figure 1: Research Framework

2.1 Data Collection and Processing

This study utilized both prerecorded videos and newly recorded footage tailored to the research objectives. The prerecorded videos consisted of CCTV footage captured in actual urban environments, reflecting naturally occurring pedestrian activities. Additionally, new recordings were conducted in a controlled experimental setting where specific obstacles were intentionally placed to meet the study's requirements. The study collected 25 datasets, including 8 normal walking datasets and 17 abnormal walking datasets recorded in the presence of barriers, across three different environments. By combining these two types of data, the study was able to analyze normal and barrier-responding walking patterns across various scenarios.

The deep-learning-based keypoint detection algorithm Openpose was used to detect and extract coordinates of pedestrians' body joints. Openpose is particularly suitable for high-density environments, such as construction sites or urban areas captured in CCTV footage, as it can track multiple pedestrians simultaneously (Cao et al., 2017). One of the key strengths of Openpose is its ability to extract accurately lower-body joint coordinates, such as those of the ankles and knees, which are critical for analyzing foot movements. This capability provides a solid framework for collecting reliable walking pattern data even in multipedestrian environments.

Using keypoint detection on the video data, the body joint coordinates of pedestrians were extracted frame-by-frame, with the coordinates collected at the pixel level. Among the extracted coordinates, the ankle coordinates of the left and right feet were analyzed to evaluate pedestrian movements. The coordinates were tracked across frames to analyze changes over time, focusing on the relationship between the left and right ankle coordinates. In cases where pedestrians were either too far from or too close to the camera, major errors were observed in the extracted coordinates. Therefore, the initial and final sections of the data were removed to ensure accuracy. This approach helped identify deviations from normal walking behaviors, such as irregular gait patterns or sudden stops, which could indicate the presence of walking obstacles.

2.2 Barrier Zone Inferences Based on Anomaly Detection of Keypoint Data

Anomalies are observations that deviate considerably from other data points or do not conform to the overall pattern of a dataset, often resulting from unexpected variations within a system (Cook et al., 2019). Advances in deep learning, particularly deep-neural-network-based techniques, have greatly enhanced the ability to analyze anomalies in time-series sensor data. These techniques have been extensively applied in hierarchical learning and complex data pattern recognition, proving effective for anomaly detection and interpretation (Darban et al., 2022).

LSTM autoencoders have proven highly effective for anomaly detection of time-series data. These models encode input data into a lower-dimensional space and reconstruct it to approximate the original input (Githinji et al., 2023). Anomalies are detected by analyzing the reconstruction error; normal instances yield minimal errors, while anomalies yield considerably higher deviations. The reconstruction error distribution is evaluated to define an appropriate threshold above which data points are classified as anomalies. In this study, we apply an LSTM autoencoder-based anomaly detection method to analyze changes in walking patterns caused by walking barriers. By identifying these anomalies, we determine barrier zones, which represent areas where pedestrians frequently experience walking disturbances.

3. RESULTS

3.1 Keypoint Detection

Figure 2 shows the results of detecting pedestrians' keypoints from CCTV footage in indoor and outdoor environments. As shown in Figure 3, the x- and y-coordinates of the left and right feet were extracted using Openpose and visualized in Figure 2 over time. The left graph in Figure 3 shows the coordinates for the case in which there is no obstacle, and the right graph shows the coordinates when walking in the presence of an obstacle; the case in which an obstacle was encountered is indicated by a red box. In a normal walking situation without obstacles, the interval between the x-coordinates of the left and right feet was kept constant. Conversely, when an obstacle was encountered, the x-coordinates of the left and right feet intersected. This reflects an abnormal pattern that occurred in the process of pedestrians trying to avoid obstacles. The y-coordinates also showed a pattern in which the positions of the left and right feet regularly intersect, but irregularities in the crossing pattern were frequently found when obstacles appeared. This shows that comparing the coordinates of the left and right feet can detect abnormalities in the walking patterns of pedestrians and deduce inferences on walking discomfort factors.

To improve the identification of abnormalities in walking, the differences in coordinates between the left and right feet are shown in Figure 4. The left graph in Figure 4 shows the coordinate differences between the left and right feet in the case wherein there was no obstacle, and the right graph shows the coordinate differences between the left and right feet in the case wherein an obstacle existed; the case in which an obstacle was encountered is indicated by the red box. In these data, noticeable patterns different from normal can be observed in areas where obstacles are present.

Figure 2: Keypoint Detection in Indoor and Outdoor Environments

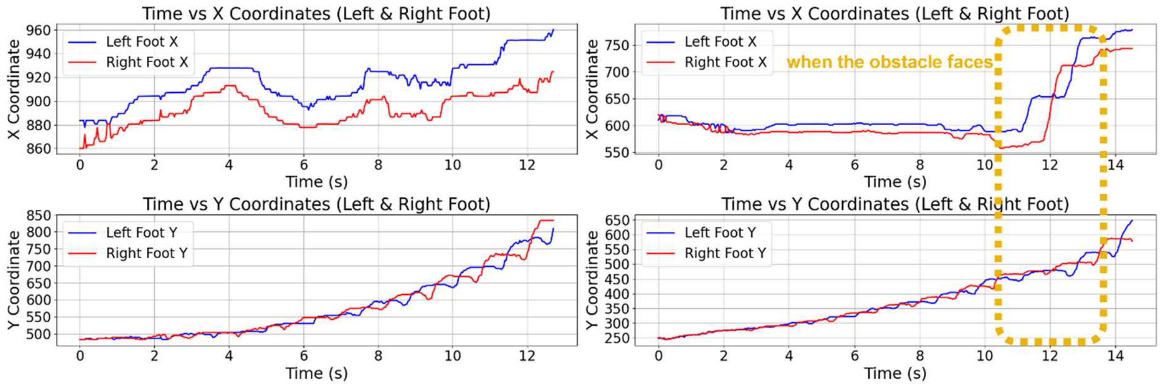

Figure 3: Graphs of X-coordinate and Y-coordinate of the left foot (blue) and the right foot (red) in normal (left graphs) and abnormal (right graphs) gait cases

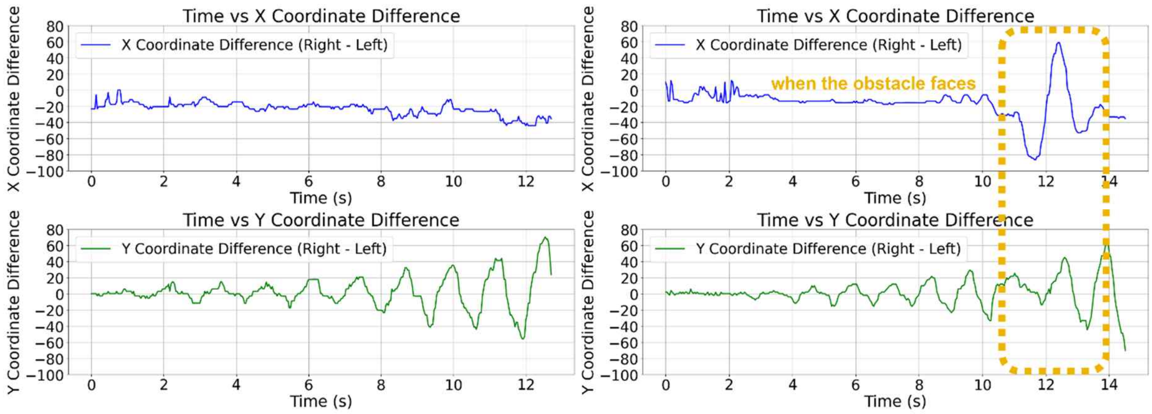

Figure 4: Graphs of X-coordinate differences and Y-coordinate differences between left and right ankles, normal (left graphs) and abnormal (right grapths) gait cases

3.2 Anomaly Detection Results

Figure 5 presents the anomaly detection results using the differences in x-coordinates between the left and right feet, captured from a front-view perspective of a walking pedestrian, while Figure 6 shows the results using data from a rear-view perspective. The top graphs display the anomaly detection results for normal data using a model trained on normal walking patterns, whereas the bottom graphs show the results for abnormal data. It was confirmed that the detected anomalies corresponded to the actual obstacle locations.

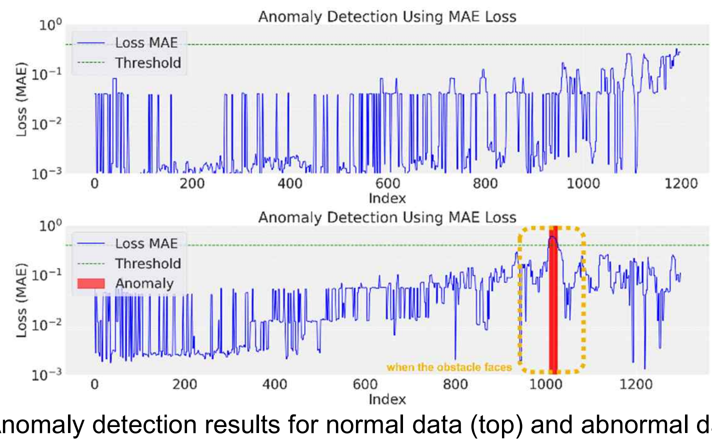

Figure 5: Anomaly detection results for normal data (top) and abnormal data (bottom) in a front-view walking scenario

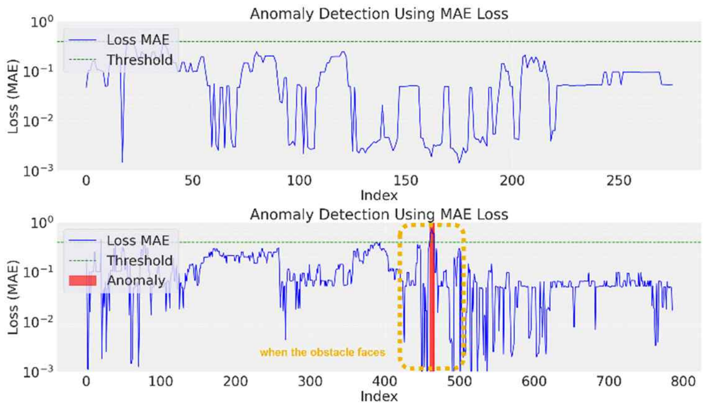

Figure 6: Anomaly detection results for normal data (top) and abnormal data (bottom) in a rear-view walking scenario

In this study, an LSTM-based anomaly detection experiment was conducted using a trained model with a single normal dataset displaying a highly stable walking pattern. When the trained dataset was used for testing, any detected anomalies were considered part of the normal pattern and were ignored. As a result, if a considerably different anomaly cluster appeared in other test data, it was identified as abnormal; otherwise, it was classified as normal. As shown in the left graph of Figure 7, the accuracy of detection of this abnormal pattern is 86.4%, and the F1-score reached the value of 0.897. Notably, the precision was 1.000, indicating a very high level of reliability in detecting abnormal walking patterns. However, the recall was 0.813, indicating that some abnormal data instances were misclassified as normal.

The anomaly ratio for normal data ranged between 0% and 19.23% among the total number of coordinate data points, with most values falling below 10%. The median was approximately 5%, indicating low variance and a relatively stable state. There were almost no anomaly points, and the range of values was narrow, indicating that the data exhibited minimal fluctuations. In contrast, the anomaly ratio for abnormal data ranged from 2.29% to 27.94%. The median exceeded 20%, which is higher than that of normal data, and the values exhibited greater variance and a broader range. Some data points recorded an anomaly ratio of >25%, reflecting changes that can occur in abnormal situations. These data exhibited a larger spread and included more anomaly points compared with those of normal data.

The anomaly ratio in abnormal data is typically higher than that of normal data and exhibits a greater range of variation. The boxplot in the right graph of Figure 7 illustrates the distribution differences between normal and abnormal data, making anomaly points in conditions with obstacles more noticeable.

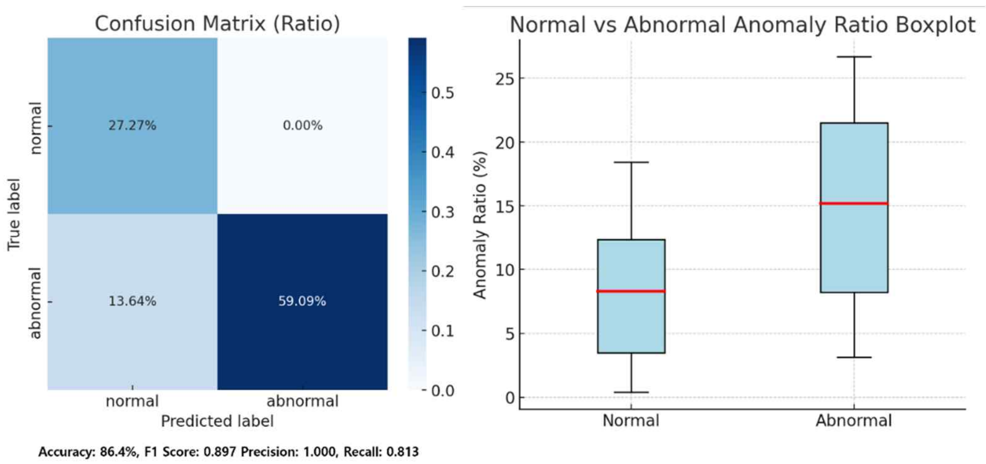

Figure 7: Confusion Matrix (Left) and Anomaly Ratio Boxplot (Right)

4. DISCUSSION AND CONCLUSIONS

This study proposed a method for detecting walking barriers by analyzing pedestrian foot movements based on CCTV footage. The study combined Openpose-based keypoint detection technology with an LSTM autoencoder-based anomaly detection model to identify effectively abnormal walking patterns caused by obstacles, demonstrating its feasibility based on experimental validation.

The experimental results confirmed the validity of this method, showing that gait anomalies tended to correspond to the actual locations of physical barriers. While the overall performance of the model was satisfactory, with an accuracy of the detection of abnormal movements in response to barriers of 86.4% and an F1-score of 0.897, the recall result of 0.813 indicates the possibility of misclassifying certain abnormal data as normal, highlighting the need for model optimization to minimize errors. In addition, variations in individual walking styles and external environmental factors can introduce noise, requiring further improvements in the model's generalization performance.

Errors were also observed when pedestrians and obstacles were located far from the camera, making keypoint detection difficult due to their smaller sizes in the footage, which in turn affected the anomaly detection accuracy. As this study was conducted under specific experimental conditions, additional validation is necessary in diverse construction site environments, such as those with varying lighting conditions and complex work zones.

This study demonstrated that pedestrian anomalies can be inferred solely based on the relative movement between the left and right feet, even without a bird's-eye view of the scene. Furthermore, the proposed approach offers a potential application in collective sensing, where data from multiple pedestrians passing through the same area can be accumulated. Although individual responses to obstacles may vary and different abnormal patterns may arise, aggregating multiple pedestrian reactions over time can highlight obstacle-prone areas, similar to a heatmap, providing visual cues for high-risk zones where walking barriers are likely present.

Future research could focus on advanced data preprocessing techniques to improve further the model's performance. For example, removing perspective-related trends in the data and applying downsampling techniques to minimize outliers could help reduce noise effects and enhance the reliability of anomaly detection. Incorporating these preprocessing steps may allow the model to handle larger, more diverse datasets while improving its robustness in different environments.

Additionally, further validation in real-world settings is necessary to confirm the applicability of the proposed method. In particular, testing in dynamic environments such as active construction sites, where barriers frequently change, is essential. Preliminary tests suggest that the method shows potential for adaptation under such dynamic conditions; however, broader real-world validation is needed to derive more generalized findings.

This study emphasizes identifying spatial patterns with a high likelihood of pedestrian instability rather than directly detecting specific causes and levels of discomfort. Future work could incorporate advanced keypoint detection techniques to enable more precise analysis of individual movement characteristics, allowing for not only the identification of barriers but also inferences regarding the types of discomfort experienced by pedestrians. Determining the optimal anomaly threshold will also help accurately assess the level of discomfort.

In conclusion, this study presents an approach that allows automatic inferences of walking barriers based on pedestrian movement analysis, contributing to improved pedestrian safety in construction sites and urban environments. The methods can be used for identifying barrier hotspots along walking paths and analyzing temporal changes in the presence of barriers and pedestrian discomforts.

ACKNOWLEDGMENTS

This research was supported by the National Research Foundation of Korea (NRF) grant funded by the government (Ministry of Science and ICT) (RS-2023-00210164).

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