A Cross-Scene Person Re-Identification through Gait Recognition using Silhouette-based Deep Learning Model

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ABSTRACT
Person Re-Identification (Re-ID) through gait analysis is gaining attention as a powerful and practical method for recognizing people across different camera views without depending on facial features or what they are wearing. Since the way a person walks are distinctive and tends to stay consistent even with changes in clothing, lighting, or camera angles, gait offers a reliable biometric for long-distance surveillance and security. In this study, a simplified and effective framework for person Re-ID that relies on analyzing how people walk in video footage is presented. The system works by first extracting a person's silhouette and then using Deep Learning (DL) to understand both how their body looks and how it moves over time. To do this, Convolutional Neural Networks (CNNs) to capture visual details with Recurrent Neural Networks (RNNs) to track motion across frames are combined. This combination helps the system better recognize and tell individuals apart based on their unique walking patterns. The system is tested on publicly available gait datasets and found that it performs exceptionally well, even under different conditions. The system also includes a detection component to automatically identify and track people across different scenes before applying the gait recognition process. Our experimental results show that the method is highly robust in real-world situations, making it a promising tool for applications like surveillance, access control, and forensic analysis. This research moves forward the development of non-intrusive, reliable technologies for person Re-ID using gait.

Keywords
Convolutional Neural Networks, Deep Learning, Gait Analysis, Person Re-identification, Recurrent Neural Networks.

1. INTRODUCTION
Gait recognition is a biometric technique that identifies persons based on their body form and walking pattern. Unlike other biometrics such as face, fingerprint, and iris, gait can be collected at a range employing off-the-shelf sensors in a hidden manner. For these factors, gait is a viable biometric attribute for situations in which the face is not visible clearly enough to be recognized. With the rapid growth of video devices, greater monitoring systems are being implemented in everyday situations and performing an increasingly important role in defending our society's security. Numerous security technologies, like face recognition, person re-identification, and gait recognition, have emerged as a result of advancements in artificial intelligence (AI) and broad demand in the area of social security. These advancements greatly minimize the amount of data and increase social security's efficiency. The detection and characterization of a person's walking pattern and kinematics is typically the first step in the investigation of human gait periodic movement. The gait cycle insight can be extracted from data collected by sensors methods and modelled using various data-driven methodologies [1][2]. Yet, two components are required for accurate gait analysis: a suitable wearable gait mobility data gathering system and methodologies for reliable gait tracking, evaluation, and recognition. A wearable device having sensors, a unit for processing, and connectivity built into a tiny lightweight housing is typically preferred for long-term everyday use. A wearable device must also have minimal power consumption, adequate external memory storage, and a user interface for web-based information display and monitoring. Many Machine Learning (ML) approaches now include feature extraction capabilities.

The process of detection and recognition of Person Re-ID through gait analysis using CNN and RNN involves multiple stages. First, CNNs extract spatial features from gait silhouettes or motion sensor data, capturing unique walking patterns for each individual. Then, RNNs, particularly Long Short-Term Memory (LSTM) or Gated Recurrent Units (GRU) [3], model the temporal dependencies in gait sequences, ensuring the system learns how movement evolves over time. The extracted gait embeddings are compared with stored profiles using metric learning techniques like Triplet Loss or Cosine Similarity for re-identification. This approach enables cross-camera tracking, allowing individuals to be recognized across different locations. Advanced feature engineering and augmentation techniques help improve recognition accuracy despite variations in clothing, lighting, or walking surfaces. In real-world circumstances, the end targets of Re-ID and gait recognition remain identical, that is, identify the intended person among cameras, as illustrated in Figure 1.

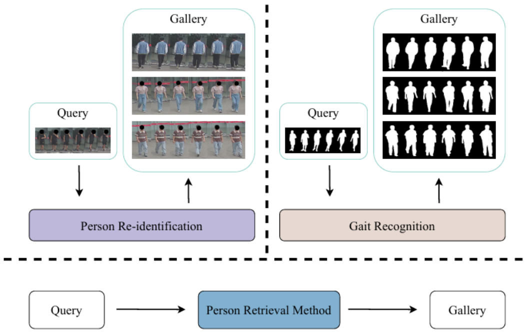


Figure 1: Comparison of Person Re-ID and Gait Recognition for Person Retrieval

2. RELATED WORK

Previous research [5,6] compared the results of video-based Re-ID and recognition of gait on video-based Re-identification datasets that were cloth-unchanged. There is little research on these cloth-changing situations, and no comparable experiments have been undertaken using video-based Re-identification and gait recognition. The primary problem is the absence of a cloth-changing standard for comparing cloth-changing situations. So, it's time to create a cloth-changing dataset for video-based Re-ID and gait identification. According to Leightley et al. [7], computational models should not rely on individual interpretation, and the way decisions are made should help medical professionals. Innovations in research have assisted physicians in improving physical and behavioral approaches for their patients. Sok et al. [4] reported that biomechanical gait studies were beneficial in diagnosing gait abnormalities and defining treatment plans for individuals with more than fixed, complicated classifications, but interaction with a wide range of motor system input was extremely hard. To analyze relevant logo equipment input combinations having precision ranges greater than 80%, ML models are utilized to depict various behaviors in healthy and afflicted patients. The created optimization models lowered study duration and can also help physicians choose the important pathological category variables [8, 9].

Most gait photographs are taken with static cameras on a basic background or perhaps in close proximity to a green screen to make it easier to obtain pedestrian silhouettes. Certain data sets are acquired in interior spaces to improve ambient illumination regulation. Such constraints limit the investigation of gait detection in real-world circumstances. More crucially, participants in these datasets are cooperative, and they are instructed to travel in a straight line toward the camera or the focal point of a camera array. As a result, the angle between the camera and the pedestrian's walking path remains unchanged. The extent of viewpoint relies on a set of cameras, which is typically below fifteen [8][9]. In 2021, numerous new datasets comprising gait data gathered in uncontrolled circumstances were made available. In paper [10], the authors provided the Re-ID gait dataset, which was gathered over a 15-month period as the patients walked independently in an indoor corridor. These two traits (long time period and free walking pattern) weren't previously present in earlier gait datasets. N. Nazmi et.al., [11] released the GREW dataset, an extensive gait dataset collected in real-life situations. As only a few gait systems built on both of these gait datasets were published, the focus of gait identification research has shifted from regulated to real-world circumstances.

Appearance-based gait detection systems typically process pedestrian photos using a deep CNN afterwards detect pedestrians using acquired gait embeddings. These techniques can be further separated into three groups depending on the input data: set-based methods, sequence-based methods, and template-based techniques. Template-based approaches, like the Gait Energy images (GEI) [12, 13] utilize CNNs to gather information from a single gait picture. CNNs with various designs were suggested by authors in paper [14] in order to enhance cross-view detection of gait ability. Related research is available in [15], [16], and [17]. In addition, models that are generative, such as those constructed using auto-encoders [18] and generative adversarial networks (GAN) [19][20][21], have been suggested as well to convert gait photos from one perspective to other.

Body motion is abstracted by template-based representations using basic processes. For a thorough examination of motion, sequence-based or video-based methods are created because this abstraction loses a lot of motion data. Three-dimensional (3D) CNN [25][26] and LSTM [22][23][24] are the models most frequently employed for periodic extraction of features of gait. A CNN was created by Lai et.al., for combining gait silhouette sequences [27]. For view-invariant gait identification, S. Adil et.al., suggested a 3D-CNN that concurrently records spatial and temporal data [28]. For cross-view gait identification, Li et al. [29] presented a thorough model that included both residual focus and LSTM elements. Improved illustrations of gait features are obtained because these investigations utilize both frame-level spatial and temporal data. Large gait data have demonstrated advanced accuracy with set-based methods. Identical modules are present in the Micro-motion Capture method [20], the LSTM attention method [31], and the Feature Map Pooling approach [30] Ferreira et.al., used LSTM attention algorithms in conjunction with CNNs to derive frame features [32]. A new parts-based system featuring a micro-motion recording module was presented by Goh et.al., [33].

3. METHODOLOGY

3.1 Data Collection

The datasets provided contain sensor data collected from real world actions worn by individuals performing various physical activities. The training set includes 7,352 observations, while the test set contains 2,947, each with 563 features. These features capture measurements from accelerometers and gyroscopes, including means, standard deviations, maximums, and angles across time and frequency domains. Each row represents a snapshot of a subject's movement, identified by the subject column, and is labeled with the corresponding physical activity such as "STANDING" or "WALKING". This data is typically used for human activity recognition tasks in ML.

3.2 Data Preprocessing

To prepare the dataset for applying CNN and RNN algorithms, several preprocessing steps are essential. First, normalize or standardize the feature values to ensure uniformity in scale, which helps neural networks converge efficiently. Then, reshape the data appropriately where CNNs usually require a 2D or 3D input shape, while RNNs require sequential data formatted as time steps with features. Convert categorical labels, such as activities, into one-hot encoded vectors for classification. Lastly, to accurately assess model performance, divide the dataset into training, validation, and testing sets.

3.3 Techniques Used

The detection and recognition of person Re-ID through gait analysis using CNN and RNN involve multiple stages. CNNs are utilized to extract spatial features from gait silhouettes or skeleton-based representations, capturing unique walking patterns. These extracted gait features are then fed into RNNs, such as LSTMs GRUs to model the temporal dependencies in human motion across frames. By combining CNNs and RNNs, the system leverages both spatial and temporal information, significantly improving gait recognition accuracy. This integrated approach is robust to challenges such as changes in viewpoint, clothing, and partial occlusions. To further enhance recognition, metric learning techniques like Triplet Loss or Contrastive Loss are applied. These methods help refine the feature representation by increasing the difference between features of different individuals while minimizing differences for the same individual under various conditions.

For person Re-ID, the extracted gait signatures are compared with a pre-stored database. Similarity measures such as Cosine Similarity and Euclidean Distance are used to determine the closest match. Finally, the system supports cross-camera tracking and recognition, allowing continuous monitoring of individuals across different camera views and locations. This makes it highly suitable for applications in security surveillance, forensic investigations, and smart monitoring environments.

3.4 Proposed Architecture

Figure 2 illustrates the overall workflow of a person Re-ID system, broken down into two main phases: training phase and testing phase. In the training phase, the process starts by collecting people's data from multiple cameras (Camera 1, 2, …, n). Once people are detected, key features are extracted from these individuals. This important information such as visual patterns or unique characteristics is then processed to learn and store meaningful patterns. The learned features are saved into a database for future use. In the testing phase, the system tries to re-identify a person. It begins by detecting a person from one or more cameras (Camera 1, 2, …, m). Key features are then extracted from the detected individuals, just like in the training phase. These features are described using the previously learned format, and then compared against the saved information in the database. Finally, the system matches the data and returns a result, indicating the identity or closest match of the person. Overall, the process uses a combination of detecting, learning, storing, and matching to recognize individuals effectively across different camera views.

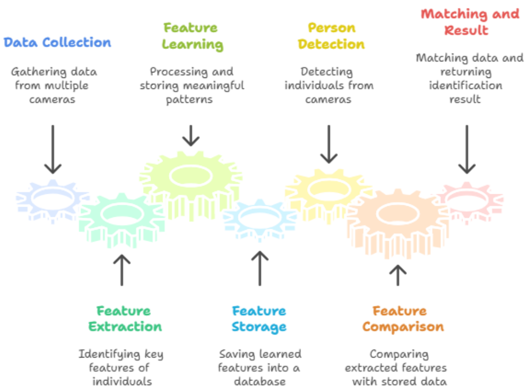


Figure 2: Flow diagram of Person Re-ID using Gait analysis

4. RESULTS AND DISCUSSIONS

Figure 3 box plot visualizes the importance of the accelerometer magnitude mean across different physical activities. The vertical axis represents the normalized mean values of acceleration, while the horizontal axis lists the activities. Static activities like standing, sitting, and laying show low and tightly grouped values, indicating minimal movement, whereas dynamic activities like walking and stair use exhibit higher and more variable values. The dashed green and magenta lines likely represent threshold levels used to distinguish between low and high activity intensity.

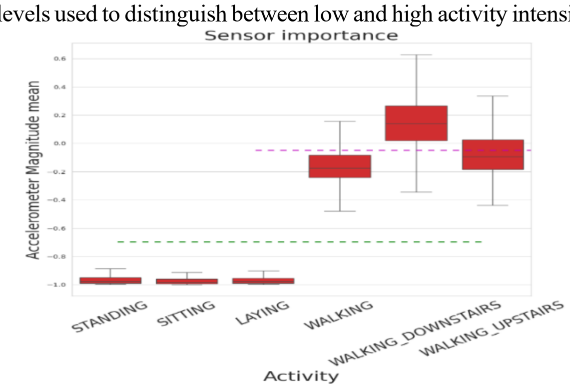


Figure 3: Box Plot of Accelerometer Magnitude Mean Across Physical Activities

Figure 4 pie chart displays the distribution of different physical activities in the dataset. Each colored segment represents a specific activity such as laying, standing, sitting, walking, walking upstairs, and walking downstairs. The percentage values indicate how much each activity contributes to the total dataset, with laying being the most frequent (19.1%) and walking downstairs the least (13.4%). This visualization helps understand the balance or imbalance of activity samples used in analysis or ML models.

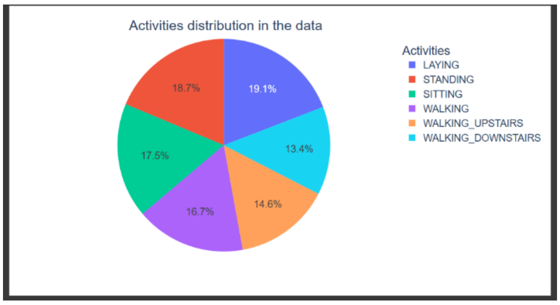


Figure 4: Proportion of Activities in Collected Data

The classification report shown in Figure 5 indicates that the CNN model performs exceptionally well across all activity classes, with precision, recall, and F1-scores close to or equal to 1.00, indicating highly accurate predictions. Activities like "LAYING" and "WALKING_DOWNSTAIRS" are predicted perfectly, while minor confusion exists between similar actions like "SITTING" and "STANDING". The overall accuracy is 98%, reflecting strong generalization to unseen data. The macro and weighted averages confirm consistent performance across both frequent and less frequent activity classes.

	precision	recall	f1-score	support
LAYING	1.00	1.00	1.00	280
SITTING	0.96	0.96	0.96	262
STANDING	0.96	0.96	0.96	276
WALKING	0.97	0.97	0.97	247
WALKING_DOWNSTAIRS	0.99	0.99	0.99	206
WALKING_UPSTAIRS	0.97	0.99	0.98	200
accuracy			0.98	1471
macro avg	0.98	0.98	0.98	1471
weighted avg	0.98	0.98	0.98	1471

Figure 5: The Classification Report for CNN

The normalized confusion matrix demonstrated in Figure 6 shows the classification performance of a gait-based activity recognition model, revealing some noticeable misclassifications. While LAYING and WALKING are identified with high accuracy (100% and 95% respectively), significant confusion exists between SITTING and STANDING, and between WALKING_DOWNSTAIRS and WALKING_UPSTAIRS. WALKING_DOWNSTAIRS is particularly misclassified, with only 63% correctly identified. Overall, the model performs moderately well but struggles with differentiating between visually and biomechanically similar activities.

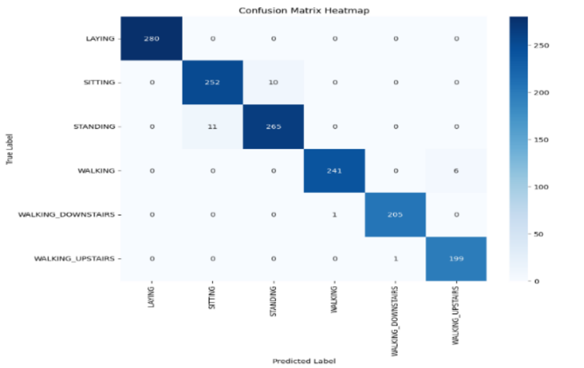


Figure 6: Confusion Matrix for CNN model performance

Figure 7 contains the training and validation accuracy and loss of a model over 10 epochs. The accuracy curve shows a steady improvement in both training and validation performance, reaching over 97%, showing good model performance. The loss graph shows a consistent decrease in both training and validation loss, suggesting effective learning without overfitting. Overall, the model demonstrates strong convergence and generalization across the dataset.

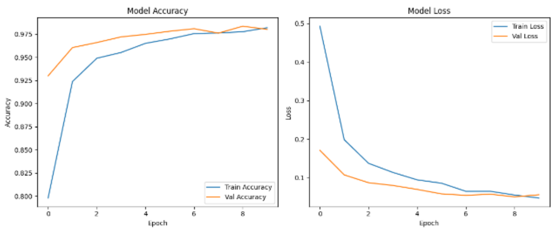
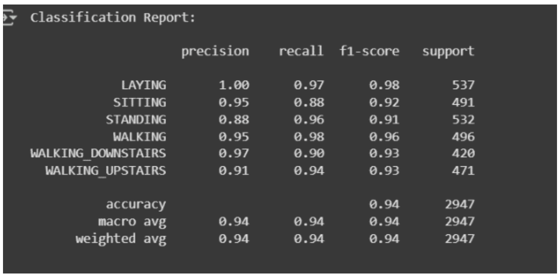


Figure 7: CNN model Accuracy and Loss Representation

The classification report shown in Figure 8 explains that the RNN model attained a high overall accuracy of 94% on the test dataset. Precision, recall, and F1-scores are consistently strong across all activity classes, with the best performance seen in detecting the LAYING and WALKING activities. The slightly lower F1-score for SITTING and STANDING suggests some overlap or confusion between these postures. Overall, the model generalizes well and performs robust activity recognition across all six classes.



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Classification Report:

                    precision    recall  f1-score   support

            LAYING       1.00      0.97      0.98       537
           SITTING       0.95      0.88      0.92       491
          STANDING       0.88      0.96      0.91       532
           WALKING       0.95      0.98      0.96       496
WALKING_DOWNSTAIRS       0.97      0.90      0.93       420
  WALKING_UPSTAIRS       0.91      0.94      0.93       471

          accuracy                           0.94      2947
         macro avg       0.94      0.94      0.94      2947
      weighted avg       0.94      0.94      0.94      2947
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Figure 8: Classification report for RNN

The confusion matrix in Figure 9 shows that most activities were correctly classified by the RNN model, with strong diagonal values indicating accurate predictions. Misclassifications are mostly seen between SITTING and STANDING, as well as between WALKING_DOWNSTAIRS and WALKING_UPSTAIRS, which are likely due to their similar motion patterns. For example, 54 instances of SITTING were misclassified as STANDING. Despite these confusions, the overall classification performance remains high with minimal off-diagonal errors.

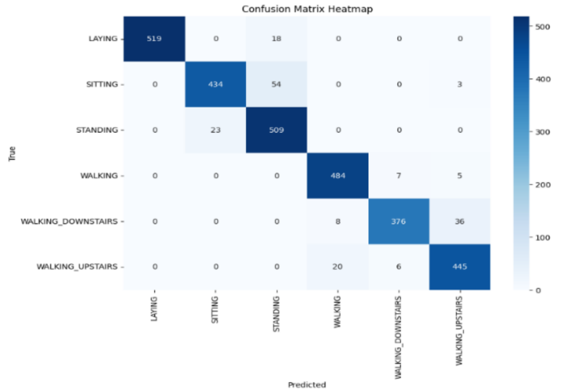

Figure 9: Confusion Matrix for RNN model performance

Figure 10 shows that the training accuracy steadily increases and reaches nearly 99%, while validation accuracy fluctuates around 93-94%, suggesting potential overfitting. The two accuracies rise at first as the model learns from the data, but between epochs 4 and 5, the train accuracy keeps increasing progressively while the validation accuracy reaches a plateau and then starts to slightly decrease. This suggests that the model is beginning to overfit by remembering the training data instead of extending effectively to unseen data.

Similar patterns are seen: the validation loss first drops but then varies and stays reasonably high, further supporting overfitting, whereas the train loss drops significantly and stabilizes at a low value. The model's performance on fresh, unknown data may suffer as a result of this discrepancy between train and validation parameters, which indicates that the model has grown excessively focused in fitting the training set. Techniques like regularization, early halting (around epoch 4–5), or diversifying the training data might be used to lessen this.

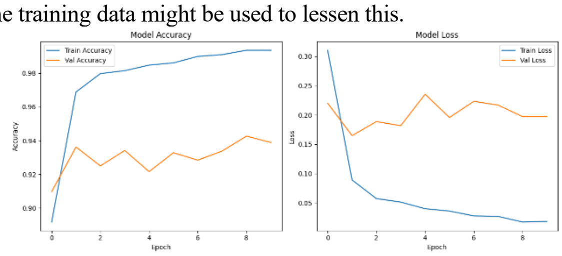

Figure 10: RNN model Accuracy and Loss Representation

Table 1 shows the model performance summary that compares the accuracy and loss of CNN and RNN. The CNN outperforms the RNN with a higher accuracy of 98.03% and a significantly lower loss of 4.31%. In contrast, the RNN shows a lower accuracy of 93.89% and a much higher loss of 19.74%, indicating it is less effective on this task. These results suggest that the CNN model generalizes better and makes more reliable predictions compared to the RNN.

Table 1. Problems with PDS

Model	Accuracy (%)	Loss (%)
CNN	98.03	4.31
RNN	93.89	19.74

5. CONCLUSION AND FUTURE SCOPE

In this study, we have proposed a simplified yet effective framework for person Re-ID through gait analysis, leveraging the unique and consistent nature of human walking patterns. By integrating CNN for spatial feature extraction and RNN for capturing temporal dynamics, the system successfully identifies individuals across varied scenes and camera views. Unlike traditional biometric methods that rely heavily on facial features or appearance-based cues, our approach demonstrates strong robustness under changes in clothing, lighting, and viewpoints. The inclusion of an automated detection and tracking module further enhances the practicality of the system for real-world applications. Experimental evaluations on publicly available gait datasets confirm the model's high accuracy and resilience, underscoring its potential for deployment in surveillance, access control, and forensic scenarios. Overall, this research contributes to the advancement of non-intrusive and reliable person Re-ID technologies and highlights gait analysis as a viable and scalable biometric approach for long-distance and unconstrained environments.

Future work in the field of person Re-ID should focus on developing more robust and comprehensive frameworks capable of handling the multitude of challenges posed by real-world surveillance environments. One promising direction is the integration of multi-modal data, such as combining gait, facial features, and clothing appearance, to improve recognition performance across varied viewpoints, lighting conditions, and occlusions. Additionally, leveraging DL models with domain adaptation techniques can significantly enhance the generalizability of Re-ID systems to unseen environments. Real-time implementation remains a key challenge; thus, future systems must aim to balance accuracy with computational efficiency, making use of lightweight models and hardware acceleration. Moreover, addressing the issue of clothing changes over time and introducing methods for long-term person Re-ID will be crucial. Finally, more extensive and diverse benchmark datasets, including those simulating real-world complexities like dense crowds and dynamic lighting, should be developed to evaluate and compare system performance more effectively.

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