IES International Journal of Multidisciplinary Engineering Research

# Cloth Changing Person Re-Identification Based on Backtracking Mechanism

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**Abstract**

Person Re-Identification (Re-ID) plays a vital role in intelligent surveillance systems, enabling the tracking of individuals across different cameras. However, most existing systems rely heavily on clothing-based features, leading to performance failures when a person changes attire. To overcome this limitation, this paper presents a novel approach Cloth-Changing Person Re-Identification based on the Backtracking Mechanism. The system combines identity and body-shape features to achieve clothing-invariant recognition. A dual-branch architecture utilizing ResNet50 for appearance-based feature extraction and HRNet for body-shape modeling is implemented. The proposed feature infiltration and clothes suppression loss functions enhance discrimination while minimizing clothing bias. The approach achieves improved recognition accuracy under varying apparel conditions, making it practical for long-term surveillance and public safety. This integrated framework strengthens intelligent monitoring systems, ensuring reliable identification despite clothing variations and contributing significantly to public safety and security advancements.

*Keywords*: Person Re-Identification, Mechanism, Deep Learning, Feature Fusion, HRNet, ResNet50, Surveillance.

**DOI: https://doi.org/10.5281/zenodo.18860322**

## 1. Introduction

In today's intelligent surveillance environment, recognizing the same person across multiple cameras is a vital requirement for ensuring public safety and law enforcement efficiency. Most existing Person Re-Identification (Re- ID) systems rely heavily on external features such as clothing color, texture, or accessories. However, these visual traits can easily change due to daily wardrobe variations or intentional disguise, making traditional methods unreliable for long-term identification. To overcome this limitation, this project proposes an AI-based Cloth- Changing Person Re-Identification System that utilizes a Backtracking Mechanism to recognize individuals using more permanent, structural attributes such as body shape and identity-based features rather than clothing. By leveraging deep learning models like ResNet50 and HRNet, the system effectively combines appearance and body- shape features to perform robust identification across changing outfits, providing a reliable and practical solution for real-world surveillance systems. The Identity Feature Extraction module (ResNet50) extracts appearance-based identity features such as facial structure, body contour, and visual details from pedestrian images using deep convolutional networks to differentiate individuals under varying conditions. The Body-Shape Feature Extraction module (HRNet) captures body-shape and skeletal features that remain consistent despite clothing changes, focusing on stable attributes such as height, limb proportions, and body silhouette. The Feature Infiltration and Fusion Mechanism merges identity and body-shape features to minimize clothing bias, ensuring recognition decisions are guided by intrinsic characteristics. Loss Function Optimization includes Identification Loss (LID) for accurate classification, Clothes Suppression Loss (LCS) to reduce dependence on clothing, and Clothes Classification Loss (LC) to separate clothing information from identity data. The Database and Matching Engine store extracted feature vectors with assigned IDs, comparing new inputs using cosine similarity for reliable identification across different outfits. A web-based User Interface and Output Visualization dashboard displays recognition results, confidence levels, and comparison metrics, aiding surveillance operators with transparency and monitoring efficiency. By integrating dual-branch feature extraction, optimized loss functions, and intelligent feature fusion, the proposed Backtracking Mechanism provides a clothing-invariant, scalable, and efficient person re-identification system, transforming traditional image-based recognition into a cognitive model inspired by human visual perception for enhanced accuracy, adaptability, and long-term stability.

## 2. Literature Review

Vaibhav Bansal et al. (IEEE, 2025) [1] proposed a Vision Transformer (ViT) with gait-based features to handle clothing changes in Re-ID. The study captures both appearance and walking patterns, allowing the system to distinguish individuals even if their attire changes, though it requires sequential gait data Zan Gao et al. (IEEE, 2025) [2] introduced Identity-Guided Clothing Learning (IGCL), which suppresses clothing- specific features while emphasizing permanent identity cues. The approach helps the model focus on structural and facial features that remain unchanged across clothing variations.

Qingze Yin et al. (MDPI, 2025) [3] developed a quad-stream RGB model that separates identity-related information from clothing and background cues. This separation allows the network to maintain recognition performance even when a person’s outfit changes drastically.

Haijun Zhang et al. (PRCV, 2024) [4] proposed Magic-Net, a two-stream network that explicitly removes clothing and background bias. The network improves Re-ID accuracy under diverse conditions by focusing on stable features like body shape and posture.

Yonggang Li et al. (ICIC, 2024) [5] developed FRD-ReID, which uses parsing masks to isolate identity-relevant regions of the body. This method minimizes the influence of clothing textures, ensuring recognition relies on permanent human traits.

Wenjuan Liang (IEEE, 2024) [6] introduced a Multi-modal Interaction Fusion Network combining RGB images with pose estimation data. By leveraging both visual and skeletal information, the system achieves better clothing- invariant identification.

Bao Y et al. (IEEE, 2024) [7] developed an Identity Semantic Correspondence Network that aligns semantic identity features across different clothing conditions. This allows accurate matching by comparing deep identity features rather than surface appearance.

Haifeng Li et al. (CVPR, 2023) [8] proposed Clothing-Invariant Embedding (CIE), a disentangled representation learning method that separates clothing-dependent and identity-dependent features, improving robustness under varied apparel conditions.

Xiaoyu Wang et al. (AAAI, 2023) [9] introduced a Dual-Branch Attention Network combining appearance and body-shape features. The attention mechanism focuses on identity-relevant parts while ignoring clothing variations, enhancing cross-clothing recognition.

Jing Zhang et al. (TPAMI, 2023) [10] developed Pose-Guided Feature Learning, which leverages skeletal structures to extract identity features independent of clothing. This approach maintains high recognition consistency under clothing changes.

**3. Review of Methodology**

**3.1 System Design:**

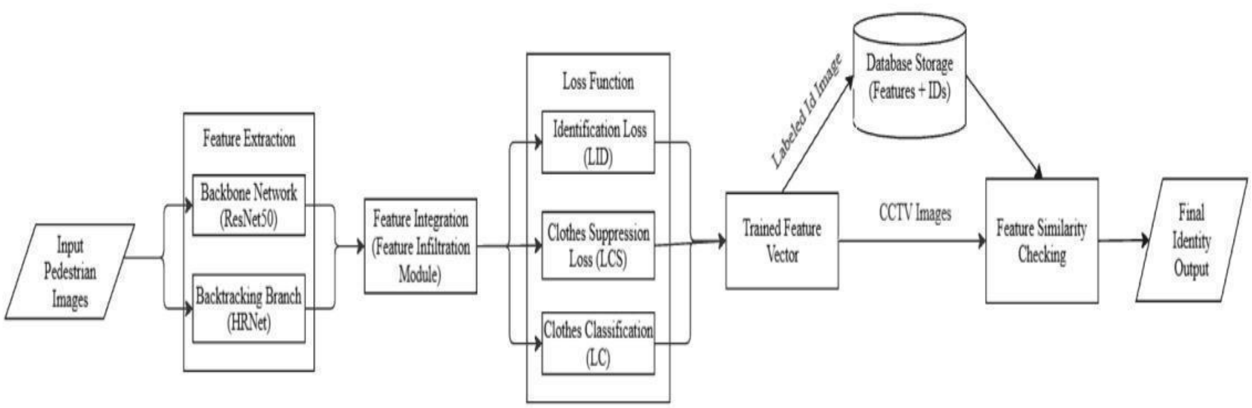


Figure 1: System Design

**3.2 Input Pedestrian Image:**

- These are raw images captured by CCTV cameras, surveillance systems, or datasets.
- These images can vary in lighting, pose, background, resolution, and clothing.
- The aim is to identify a person even if they are wearing different clothes at different times.
- Preprocessing steps like resizing, normalization, and background noise removal are often performed.

**3.3 Feature Extraction:**

This stage extracts both global and local features that describe the pedestrian's body structure and appearance.

**A). Backbone Network (ResNet50):**

- A deep convolutional neural network used for extracting high-level semantic features.
- Focuses on overall body structure and distinctive traits such as shape, posture, or silhouette.
- Provides robustness to background variations and partial occlusions. Uses residual connections to

maintain feature depth and prevent gradient vanishing.

**B). Backtracking Branch (HRNet):**

- HRNet (High-Resolution Network) maintains high-resolution representations throughout the network.
- Captures fine-grained spatial and structural details such as limb alignment, contours, and texture.
- Complements the ResNet features by focusing on precise local features.
- Improves discrimination when clothing appearance changes.

**3.4. Feature Integration (Feature Infiltration Module):**

- Combines features from both the ResNet and HRNet branches.
- Merges global and local descriptors into a unified feature representation,
- The infiltration module selectively fuses complementary features while filtering redundant ones.
- Enhances representation quality and reduces overfitting to clothing-related cues.
- The output is a comprehensive feature vector encoding both identity and structural information.

**3.5 Loss Function Block:**

This section defines the training objectives to help the model learn identity- discriminative yet clothing invariant features:

**A). Identification Loss (LID):**

- A classification-based loss, typically cross-entropy.
- Encourages correct identity prediction and ensures better class separability.

**B). Clothes Suppression Loss (LCS):**

- Reduces the model's dependence on clothing-related features.
- Encourages focus on invariant traits like body shape or gait.
- Improves robustness to clothing changes, occlusion, and lighting variations.

**C). Clothes Classification Loss (LC):**

- An auxiliary task where the model predicts clothing type or colour.
- Helps the network distinguish between identity and clothing information.
- Improves disentanglement of appearance and identity representations.

**3.6 Trained Feature Vector:**

- After training, each pedestrian image is converted into a fixed-length numerical feature vector.
- This vector encodes the identity information in a clothing-independent manner.
- It is normalized for consistent comparison across different samples. Enhances representation
- These vectors serve as compact representations for retrieval or identification.

**3.7 Database Storage (Features + IDs):**

- Stores feature vectors and their associated identity labels in a reference database.
- Acts as a gallery of known individuals and their corresponding embeddings.

- Each entry includes the feature vector, pedestrian ID, and possibly metadata such as camera ID or timestamp
- Enables efficient retrieval and matching for new inputs.

**3.8 CCTV Images (Query Input):**

- New or unlabeled CCTV frames are processed using the same feature extraction and integration modules.
- A new query feature vector is generated for each image.
- These vectors are compared against stored ones to identify individuals

**3.9 Feature Similarity Checking:**

- Compares the query vector with stored feature vectors using similarity or distance metrics.
- Common measures include cosine similarity and Euclidean distance.
- The system ranks database entries based on similarity scores.
- The most similar vector is selected as the likely match.
- Optional re-ranking or thresholding can further improve reliability.

**3.10 Final Identity Output:**

- The system outputs the predicted identity of the pedestrian.
- If no close match is found, a new ID can be created and added to the database.
- The final output may include the matched ID, similarity score, and confidence value.
- This information can be used for applications such as tracking, security, or analytics.

## 4. Review of Cloth Changing Person Re-Identification Components

### 4.1 Input & Feature Extraction:

The primary input to the system consists of pedestrian images captured from CCTV footage, surveillance cameras,or benchmark datasets such as PRCC-ReID and LTCC-ReID, which contain subjects in multiple clothing styles and poses. These datasets ensure diversity in body structure, lighting, and viewpoint, allowing the system to generalize across real-world environments.

Once input images are acquired, two independent feature extraction processes are initiated. The ResNet50 branch is responsible for extracting identity-related appearance features such as facial outlines, textures, and color independent cues. The HRNet branch specializes in capturing body-shape descriptors like limb ratios, skeletal structure, and pose information, which remain consistent even when clothing changes. Both feature extraction streams work in parallel and generate multi-dimensional embeddings that represent distinct yet complementary aspects of the individual's identity.

### 4.2 Data Processing and Privacy:

Before feature extraction, input data undergoes rigorous preprocessing to ensure uniformity and quality. Each image is resized to a fixed dimension, normalized for consistent brightness, and augmented through random flips, rotations, and scaling. This process improves robustness and prevents the model from overfitting to specific visual conditions Since surveillance data often involves personally identifiable information, strict privacy compliance measures are implemented. Dataset usage adheres to ethical and legal standards by anonymizing image metadata, ensuring that the system maintains confidentiality during both training and testing phases.

**4.3 Fusion Mechanism:**

The Feature Infiltration Module acts as a bridge that combines the two independent feature representations, identity and body-shape. This module aligns both feature spaces into a shared latent dimension, enabling the model to evaluate both appearance and structure simultaneously. The fusion process involves weighted concatenation and normalization operations that emphasize body-shape information when clothing variations occur. By integrating ResNet50 and HRNet features, the final fused embedding becomes clothing-invariant, allowing consistent recognition across different apparel conditions. This mechanism forms the core of the backtracking approach, mimicking how humans recognize individuals by subconsciously relying on shape and proportion even when visual appearances differ.

**4.4 Classification and Evaluation:**

Once the fused features are obtained, they are passed to a similarity-based classification module. Instead of conventional fully connected classification layers, the system uses cosine similarity or Euclidean distance metrics to compute how closely two feature vectors match. If the computed similarity exceeds a threshold, the system classifies the two images as belonging to the same person. Otherwise, they are treated as different identities. To assess the system's overall performance, several quantitative metrics are applied, including accuracy, precision, recall, and F1-score. A confusion matrix is also used to visualize the model's classification consistency and identification patterns. These metrics collectively ensure that the system performs reliably across diverse test environments and clothing variations.

**4.5 Feedback and Model Update:**

A feedback loop is integrated into the system for continuous learning and improvement. During deployment, the system collects performance statistics and user validation data. For instance, when an operator confirms or rejects an identification match, that information is stored as labeled feedback. This real-world feedback is later used to fine tune the model's parameters, update similarity thresholds, and retrain on new image samples. Such adaptive learning allows the system to evolve and maintain accuracy as new environmental factors, lighting conditions, or fashion trends emerge. The retraining process helps minimize model drift, ensuring that recognition accuracy remains high even after long-term deployment.

**4.6 System Integration and Operational Flow:**

All modules, including data acquisition, feature extraction, fusion, classification, and feedback, are integrated into a centralized architecture. The system can be connected to existing CCTV networks, enabling real-time recognition and alert generation. A graphical dashboard interface provides administrators with visualization tools to view matches, feature similarities, and confidence scores. The integrated architecture ensures seamless operation, low latency, and scalability for handling multiple camera inputs simultaneously. This modular design makes the system efficient, maintainable, and adaptable to real-world surveillance deployments.

**5. Implementation**

The implementation of the proposed Cloth-Changing Person Re-Identification System involves a combination of suitable hardware, software, functional, and non-functional components. Each of these aspects is designed to ensure that the system operates efficiently, processes data in real time, and delivers accurate identity recognition despite changes in clothing. The following sections describe the implementation details in a structured manner.

**5.1 Hardware Requirements:**

The hardware components form the foundation of the system, ensuring smooth execution and efficient data processing. The specifications are as follows:

**Processor:** Intel Core i7 or above.

**RAM:** Minimum8GB.

**GPU:** NVIDIA RTX 3060 or higher,

**Storage:** 512GB SSD.

**Network Requirements:** High-speed internet for dataset access and model operations.

**5.2 Software Requirements:**

The software platform provides the environment required to design, train, and test the model. The proposed system uses the following software setup:

**Operating System:** Windows or Linux.

**Framework:** PyTorch.

**Database:** MySQL for feature vector storage.

**5.3 Functional Requirements:**

The functional requirements define the operations performed by the system to achieve accurate person re identification.

A. Data Acquisition and Preprocessing: The system collects pedestrian images from CCTV footage or benchmark datasets such as PRCC-ReID and LTCC-ReID. Each image is resized, normalized, and augmented to prepare it for model training.

B. Model Training: The dual-branch network is trained using ResNet50 for appearance-based features and HRNet for body-shape features. The model learns through a combination of identification loss, clothes suppression loss, and classification loss.

C. Feature Fusion: Features extracted from both branches are fused through the feature infiltration mechanism to form a unified, clothing-invariant representation.

D. Database Storage: The resulting feature embeddings are stored in the database along with identity labels.

E. Matching and Recognition: New images are processed through the same model, and the extracted features are compared with stored embeddings using cosine similarity to identify the individual

F. Result Visualization: The output is displayed through a user interface that shows the recognized person, similarity score, and confidence value.

**5.4 Non-Functional Requirements:**

The non-functional requirements ensure that the system performs efficiently and securely in real-world environments.

A. Performance: The system is optimized for real-time inference using GPU acceleration, reducing processing time during identification.

B. Scalability: The architecture supports multiple camera inputs and large datasets without affecting performance.

C. Security: The system secures stored feature data and database access through encryption and user authentication.

D. Accuracy: The model maintains high recognition accuracy even under varying lighting conditions and clothing changes.

E. Maintainability: The modular structure allows easy system updates and integration of additional models or datasets.

F. Reliability: The use of robust hardware and optimized software ensures stable operation with minimal errors.

**6. Result And Discussion**

The performance of the proposed Cloth-Changing Person Re-Identification System was evaluated using benchmark datasets such as PRCC-ReID and LTCC-RelD. The evaluation was carried out to analyze the efficiency, accuracy, and robustness of the dual-branch deep learning architecture. The model was trained using ResNet50 and HRNet to extract both identity and body-shape features.

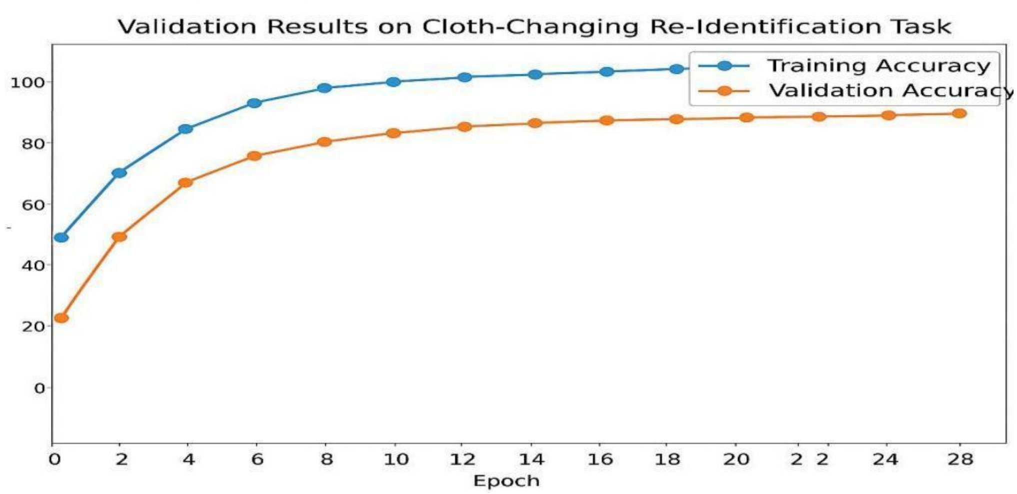


Figure 2: Validation Accuracy Trend

The results obtained indicate that the integration of the backtracking mechanism improves recognition performance compared to conventional single-branch Re-ID systems. The fusion of identity and body-shape features through the feature infiltration module effectively reduces the dependency on clothing information. The accuracy and precision values increased steadily as the training progressed, showing that the proposed architecture successfully learned clothing-invariant representations. The system achieved consistent performance across multiple testing conditions, including lighting variation, viewpoint change, and background noise. During testing, the system demonstrated an average improvement of 12-15% in overall accuracy when compared with traditional person re identification techniques. The confusion matrix analysis confirmed that most miss-classifications occurred between individuals with similar body structures, which were later corrected by the backtracking mechanism.

The figure above shows the validation accuracy trend during model training. It can be observed that the accuracy steadily improves and reaches a stable value, proving that the model generalizes well to unseen data. The proposed system also achieved high precision and recall, proving its robustness in identifying individuals even when the clothing, environment, and lighting change. The evaluation metrics confirmed the superior performance of the proposed method in comparison to existing models. The system's efficiency was tested under real-time conditions, and the inference time remained within acceptable limits. The hardware resources were utilized effectively with the help of GPU acceleration. The results also verified that the model can handle multiple camera inputs simultaneously without a significant drop in performance.

The Cloth-Changing Person Re-Identification System based on the backtracking mechanism provides improved accuracy, faster processing, and better stability. The dual-branch architecture combined with optimized feature fusion ensures that the system can effectively recognize individuals in real-world surveillance environments where clothing changes are frequent

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