AVOIDING DUPLICATIONS IN PERSON DETECTION ACROSS VIDEO FRAMES

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Thesis submitted in partial fulfillment of the requirements for the degree
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DECLARATION

I declare that this is my own work and this Thesis does not incorporate without acknowledgement any material previously submitted for a Degree or Diploma in any other University or Institute of higher learning and to the best of my knowledge and belief it does not contain any material previously published or written by another person except where the acknowledgement is made in the text. I retain the right to use this content in whole or part in future works (such as articles or books).

Signature: Date: 02.08.2025

The above candidate has carried out research for the Master of Science (Major component of Research)Thesis under our supervision. We confirm that the declaration made above by the student is true and correct.

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Signature of the Supervisor: Date: 02.08.2025

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ABSTRACT

Person re-identification (Re-ID) is a cornerstone of modern video surveillance and smart-city applications, demanding the reliable matching of pedestrian images across non-overlapping cameras despite variations in pose, lighting, background clutter, and occlusion. Here, a person re-identification (Re-ID) system built around a ResNet-50 backbone augmented with multi-level attention and part-aware Transformer encoding is presented. The network begins by extracting deep feature maps from pedestrian images, which are then refined through a channel-wise squeeze-and-excitation block and a spatial attention module: together, these attentional layers suppress background clutter and highlight discriminative cues—such as clothing textures and carried objects—by adaptively weighting feature dimensions and spatial locations. To capture structural dependencies across body regions, the attention-refined feature map is partitioned into horizontal strips corresponding to semantic parts (head, torso, legs), each of which is fed into a lightweight Transformer encoder that dynamically models inter-part relationships, enabling robust identification under pose variation and partial occlusion.

Training is stabilized and accelerated via mixed-precision optimization with automatic gradient scaling and gradient clipping, alongside a label-smoothed cross-entropy loss that mitigates overconfidence. A two-stage learning-rate schedule—a brief linear warm-up followed by cosine-annealing decay—ensures rapid initial convergence without catastrophic divergence. At inference, global descriptors are efficiently extracted and pairwise distances computed to evaluate mean average precision (mAP) and Rank-1 accuracy on the Market-1501 benchmark.

Empirical results demonstrate that this architecture achieves competitive retrieval performance—regularly exceeding 0.74 mAP and 0.90 Rank-1 accuracy while maintaining computational efficiency and ease of extension. All data-processing pipelines, training scripts, and evaluation code are fully open-source, providing a reproducible framework for future advances in attention-driven person Re-ID.

Keywords: Person Re-identification, Unique person counting, Video processing, Surveillance applications

TABLE OF CONTENTS

Declaration of the Candidate & Supervisor i

Abstract iii

Table of Contents iv

List of Figures vii

List of Tables viii

1 Introduction 1

1.1 Problem Definition and Challenges 1

1.2 Deep Learning for Person Re-Identification 2

1.3 Transformers and Inter-Part Relationship Modelling 2

1.4 Real-Time Video-Based Re-Identification 3

1.5 Main Contributions Of The Research 3

1.6 Thesis Organization 4

2 Background & Related Work 5

2.1 Introduction 5

2.2 Foundations of Person Re-Identification 5

2.2.1 Feature Engineering and Metric Learning 5

2.2.2 Multi-Frame and Sequence Approaches 5

2.3 Deep Learning: The Modern Paradigm 6

2.3.1 CNN and RNN Architectures 6

2.3.2 Weakly and Few-Shot Supervised Approaches 6

2.4 Attention Mechanisms in Person Re-ID 6

2.4.1 Motivation and General Principles 6

2.4.2 Spatial Attention 7

2.4.3 Temporal Attention 7

2.4.4 Joint Spatial-Temporal Attention 7

2.4.5 Progressive and Hierarchical Attention 8

2.5 Part-Based Modelling 8

2.5.1 Motivation and Key Paradigms 8
2.5.2 Horizontal Partitioning 8
2.5.3 Pose-Guided and Graph-Based Models 8
2.5.4 Adaptive and Attention-Based Part Fusion 9
2.6 Transformer-based Architectures 9
2.6.1 Vision Transformers: Motivation and Properties 9
2.6.2 Transformers in Video-based Re-ID 9
2.6.3 Overcoming Limitations: Information Loss, Fragmentation, and Modality Gaps 10
2.6.4 Attribute-Enhanced and Multi granularity Transformers 10
2.7 Challenges: Occlusion, Open-World Settings, and Real-Time 10
3 Methodology 12
3.1 Data Preprocessing and Augmentation 12
3.1.1 Loading 12
3.1.2 Resizing 12
3.1.3 Data Augmentation 13
3.1.4 Normalization 13
3.1.5 Implementation Details 13
3.2 Model Components and Architectural Design 14
3.2.1 Backbone Feature Extraction 14
3.2.2 Channel Attention Module 17
3.2.3 Spatial Attention Module 19
3.2.4 Part-Based Feature Extraction 22
3.2.5 Part-Aware Transformer Encoding 23
3.3 Descriptor Aggregation and Classification Head 26
3.3.1 Concatenation and Batch Normalization 27
3.3.2 L2-Normalization 28
3.3.3 Classification Layer for Training 28
3.4 Loss Functions 29
3.4.1 Label-Smoothed Cross-Entropy 29
3.4.2 Batch-Hard Triplet Loss 29

3.4.3 Total Loss 30
3.5 Training Protocol 30
3.5.1 Optimizer and Mixed Precision 30
3.5.2 Learning-Rate Schedule 30
3.5.3 Training Loop 30
3.5.4 Inference and Retrieval Pipeline 31
3.5.5 Optional Re-Ranking 32
3.5.6 Complexity Analysis 33
4 Experiments and Results 34
4.1 Experimental Setup 34
4.1.1 Dataset Description 34
4.1.2 Evaluation Metrics 34
4.1.3 Implementation Details 34
4.2 Baseline Performance 35
4.3 Ablation Studies 35
4.3.1 Component Ablation 36
4.3.2 Effect of Partition Count 37
4.3.3 Convergence and Stability 37
4.3.4 Qualitative Retrieval Examples 38
4.3.5 Comparison with State of the Art 39
4.4 Summary 39
5 Conclusion and Future Work 40
5.1 Conclusion 40
5.2 Limitations 41
5.3 Future Work 42
5.3.1 Unsupervised Domain Adaptation 42
5.3.2 Dynamic Part Partitioning 43
5.3.3 Temporal and Video-Based Modelling 43
5.3.4 Multi-Modal and Infrared Fusion 43
5.3.5 Lightweight Model Compression 44
5.3.6 Explainability and Human-In-the-Loop Learning 44

LIST OF FIGURES

Figure	Description	Page
Figure 3.1	Data Preprocessing Pipeline: Load $\rightarrow$ Resize $\rightarrow$ Augment $\rightarrow$ Normalize.	12
Figure 3.2	System Architecture Flowchart: Attention-Enhanced Part-Aware Re-ID Pipeline	15
Figure 3.3	ResNet-50 backbone module with downsampling to $2048 \times 8 \times 4$.	16
Figure 3.4	Structure of the Channel Attention Module using a Squeeze-and-Excitation (SE) block	18
Figure 3.5	The concatenation results in a tensor of shape $[B, 6 \times 2048]$ where B is the batch size. The attention maps are applied via element-wise multiplication to the feature maps before concatenation, enhancing discriminative regions in each part. [30]	20
Figure 3.6	Horizontal partitioning of the attention-refined feature map into $P = 6$ stripes along the vertical axis	22
Figure 3.7	Part-Aware Transformer architecture for modelling inter-part relationships	24
Figure 3.8	Descriptor aggregation and classification pipeline	27
Figure 3.9	Combined loss function used for training	29
Figure 4.1	Comparison of the accuracy with different partition values	37
Figure 4.2	mAP curves	38
Figure 4.3	Qualitative results	38

LIST OF TABLES

Table	Description	Page
Table 2.1	Comparison of Person Re-ID Approaches	11
Table 4.1	Baseline performance (ResNet-50 + global pooling + CE)	35
Table 4.2	Ablation results on Market-1501	36
Table 4.3	Qualitative retrieval results for three query images and their Top-5 matches.	39
Table 4.4	Comparison to recent state-of-the-art on Market-1501	39

CHAPTER 1

INTRODUCTION

In an era of rapidly expanding surveillance networks and smart-city infrastructures, the ability to reliably track and recognize individuals across multiple, non-overlapping camera views has become a fundamental requirement. Person re-identification (Re-ID) seeks to match images—or more generally, video tracks—of the same person captured under different spatial and temporal contexts. Unlike traditional classification tasks in computer vision, Re-ID must cope with substantial variations in viewpoint, illumination, pose, occlusion, and background clutter, all while operating in unconstrained, real-world scenarios. Achieving robust ReID is critical for applications ranging from long-term criminal investigations and missing person searches to crowd analytics, retail customer behaviour analysis, and autonomous robot navigation.

1.1 Problem Definition and Challenges

Given a "query" image or video segment of a person from one camera, the goal of person Re-ID is to retrieve all matching images or tracklets of the same individual from a large "gallery" set drawn from other cameras. Key challenges include:

- Appearance variation: Clothing, accessories, and carrying conditions (bags, umbrellas) can change over time or differ drastically between camera views.
- Pose and viewpoint disparity: Non-overlapping cameras yield images of a person from vastly different angles, requiring models to learn viewpoint-invariant features.
- Occlusions and background clutter: In crowded scenes, partial occlusions by other pedestrians or environmental obstacles can obscure critical identity cues.
- Scalability and real-time constraints: Large-scale camera networks generate millions of detections per hour; Re-ID systems must index and search high-dimensional descriptors quickly to support live monitoring.

Addressing these challenges demands models that can both extract robust global representations and focus on fine-grained local details. Moreover, successful deployment in live or near-real-time settings calls for architectures that balance accuracy with computational efficiency.

1.2 Deep Learning for Person Re-Identification

Early Re-ID approaches relied on hand-crafted features—colour histograms, texture descriptors, and metric learning—to bridge appearance gaps. The advent of deep convolutional neural networks (CNNs) marked a paradigm shift: end-to-end feature learning enabled models to discover discriminative patterns directly from raw pixels. Standard backbones such as ResNet-50 extract highly expressive mid- and high-level features, but alone they struggle with background interference and local occlusions. To remedy this, the community has explored:

- Part-based models: Dividing feature maps into rigid or learned parts (e.g., horizontal stripes or semantic segments) to capture region-specific cues and maintain robustness under partial occlusion.
- Attention mechanisms: Channel and spatial attention modules—for instance, squeeze-and-excitation (SE) blocks or convolutional block attention modules (CBAM)—that recalibrate feature responses by adaptively emphasizing informative channels and regions.
- Metric losses and mining strategies: Beyond classification loss, specialized objectives such as triplet loss, center loss, and hard-example mining to shape the embedding space and ensure that same-identity samples lie closer together than different-identity samples.

While these advances have steadily improved retrieval metrics on benchmarks like Market-1501 and DukeMTMC-reID, they often treat part modelling and attention as separate, additive modules rather than deeply integrated components.

1.3 Transformers and Inter-Part Relationship Modelling

Transformers have revolutionized natural language processing by modelling long-range dependencies via self-attention. Recently, Vision Transformers (ViT) and related architectures have shown that self-attention can be equally potent for capturing global context in images. In person Re-ID, Transformers offer a natural framework to:

1. Dynamically integrate part features: Rather than treating each stripe independently, a transformer encoder can learn pairwise and higher-order interactions among body parts.
2. Handle missing or occluded regions: By attending to non-occluded parts, the model can infer the identity from context, improving robustness to partial occlusion.

3. Reduce reliance on rigid partitioning: Self-attention weights can implicitly discover semantically consistent regions, even when the horizontal stripes misalign due to pose variations.

However, full Vision Transformer models tend to be computationally heavy, making them challenging to deploy on video streams or resource-constrained devices. A lightweight, part-aware Transformer that operates on a small number of part descriptors offers a promising middle ground: rich inter-part reasoning at modest cost.

1.4 Real-Time Video-Based Re-Identification

Most Re-ID research focuses on still images, yet practical systems must operate on video feeds. Video-based Re-ID leverages temporal coherence to aggregate information across multiple frames, smoothing out momentary occlusions and pose extremes. Real-time deployment further imposes:

- Low-latency feature extraction: Models must process frames or tracklets at high frame rates (e.g., 15–30 fps) to support live monitoring.
- Efficient distance computation and indexing: Pairwise comparisons between a query and a large gallery should be computed in milliseconds, often using approximate nearest-neighbour search or GPU-accelerated matrix operations.
- Online adaptation: The system may need to update its gallery dynamically as new identities enter the scene or as environmental conditions shift.

Our proposed architecture, built on efficient CNN-attention and a compact Transformer encoder, is well-suited to these constraints. By extracting a single global descriptor per tracklet—potentially aggregated over flips or short temporal windows—the system can perform rapid retrieval while still benefiting from rich part-aware reasoning. Unlike traditional tracking algorithms that assume temporal continuity between frames, the proposed system is designed for non-consecutive frame matching. Tracking methods such as DeepSORT or KCF rely on motion prediction and often fail when individuals exit and re-enter the scene after extended occlusions. In contrast, the proposed Re-ID system maintains a memory bank of feature embeddings, enabling identity assignment based on visual appearance alone, independent of frame sequence or temporal proximity.

1.5 Main Contributions Of The Research

In this thesis, the following key contributions are made:

1. Unified Attention-Part Transformer Architecture: Integration of channel and spatial attention with a part-based Transformer encoder within a ResNet-50 backbone, enabling dynamic modelling of inter-part dependencies for enhanced robustness and discrimination.

2. Stable, Efficient Training Regime: Employment of label-smoothed cross-entropy, mixed-precision optimization with gradient clipping, and a two-stage learning-rate schedule (warm-up + cosine decay) to ensure rapid convergence without divergence.

3. Real-Time Video Application: Demonstration of the framework's applicability to live video-based Re-ID, with descriptor extraction and distance computation optimized for throughput and low latency.

4. Comprehensive Evaluation and Open-Source Release: Benchmarks on Market-1501 achieving over 0.60 mAP and 0.90 Rank-1, and full release of code, data pipelines, and evaluation scripts for reproducibility.

1.6 Thesis Organization

The remainder of this thesis is structured as follows:

- Chapter 2 (Background & Related Work) reviews foundational techniques in person Re-ID, attention mechanisms, part-based modelling, and Transformers in vision.

- Chapter 3 (Methodology) presents the detailed design of the attention modules, part-aware Transformer encoder, and training strategies.

- Chapter 4 (Experiments & Results) reports quantitative evaluations, ablation studies, and qualitative visualizations on Market-1501 and video-based Re-ID scenarios.

- Chapter 5 (Conclusion & Future Work) summarizes findings and discusses avenues for further research, including dynamic part partitioning, unsupervised domain adaptation, and multi-camera tracking integration.

Through this work, I aim to advance the state of the art in attention-driven, part-aware person re-identification and to provide a practical, extensible platform for both academic research and real-world deployments.

CHAPTER 2

BACKGROUND & RELATED WORK

2.1 Introduction

Person re-identification (Re-ID) is a foundational task in computer vision that focuses on matching individuals across non-overlapping camera networks, with substantial implications for surveillance, security, and smart city applications. Over the past decade, the community has witnessed an evolution in Re-ID techniques—beginning with hand-crafted feature engineering and metric learning, moving into deep learning, and more recently, embracing part-based modelling, attention mechanisms, and, most impactful of all, the transformer paradigm. This review synthesizes foundational and contemporary approaches in person Re-ID, with a specific focus on attention mechanisms, part-based models, and transformer architectures in vision, drawing heavily on recent research to contextualize advancements, limitations, and open problems.

2.2 Foundations of Person Re-Identification

2.2.1 Feature Engineering and Metric Learning

The earliest person Re-ID systems were built on hand-crafted feature representations. Colour histograms, texture descriptors, and shape-based features, frequently employed in conjunction, attempted to encapsulate pedestrian appearance cues. However, these features suffered performance drops under pose changes, illumination variations, and occlusions, motivating the study of more robust alternatives.

Metric learning accompanied feature engineering, establishing embedding spaces where intra-class distances (same identity) were minimized and inter-class distances maximized. A canonical approach involved mining discriminative fragments from pedestrian video sequences, leveraging sequential information and ranking objectives. For example, video-based frameworks selected salient temporal snippets for robust matching—demonstrating that aggregating discriminative space-time information is key for overcoming ambiguities inherent in visual appearance alone [1].

2.2.2 Multi-Frame and Sequence Approaches

With the proliferation of video surveillance, multi-frame and sequence-based methods gained traction. Instead of treating each image independently, these approaches pooled features across sequences, typically using set-to-set matching, statistical pooling, or by selecting representative frames. While compact feature aggregation and fragment

selection led to performance improvement over single-shot approaches, encoding dynamic and invariant temporal cues in a computationally tractable manner remained a challenge [1]–[4].

2.3 Deep Learning: The Modern Paradigm

2.3.1 CNN and RNN Architectures

Deep convolutional neural networks (CNNs) revolutionized Re-ID by learning rich, hierarchical representations, freeing models from manual feature engineering. Video-based Re-ID architectures often combined CNN backbones for spatial encoding with RNNs (notably LSTM or BiLSTM) for temporal reasoning[3], [4]. For instance, representative frames selected from video walking cycles were processed via multiple CNNs, with feature pooling yielding compact per-person descriptors[2]. Later, bidirectional RNNs integrated CNN outputs to capture both forward and backward temporal dependencies, enhancing the discriminative power of spatio-temporal features[4]. The synergy of metric losses (triplet, contrastive) and identity classification further advanced representation learning.

2.3.2 Weakly and Few-Shot Supervised Approaches

Labelling video data exhaustively remains a bottleneck. Weakly supervised frameworks bypassed labour-intensive annotation by learning with coarse or bag-level labels only. Graph neural networks, for example, were leveraged to learn from raw video without instance-level identity correspondence. Deep Graph Metric Learning (DGML) approaches measure consistency between spatial graphs both within and across videos, learning discriminative and invariant representations even when only weak video-level identity information is available[5]. Few-shot adversarial models combined variational RNNs with domain adaptation to handle sparse supervision and distributional shifts, providing state-of-the-art results in challenging scenarios where labelled data is limited[6].

2.4 Attention Mechanisms in Person Re-ID

2.4.1 Motivation and General Principles

Traditional deep models, including CNNs and RNNs, are suboptimal in leveraging the spatial saliency and dynamic temporal diversity present in pedestrian videos, particularly under occlusions or variations in pose and appearance. Attention mechanisms—emulating the human capacity to focus on the most informative visual cues—mitigate these limitations by dynamically weighting spatial regions and temporal instances [7]–

[11]. Critical advancements have unfolded along spatial, temporal, and joint dimensions.

2.4.2 Spatial Attention

Spatial attention modules selectively amplify discriminative body parts, such as distinctive clothing patterns or carried accessories, while suppressing background or occluded regions. For instance, Comparative Attention Networks (CAN) use iterative glimpses over different spatial regions of a person, learning which patches are most informative for recognizing identity [7]. Similarly, feature refinement networks learn attention masks that weaken redundant or noisy features and direct model focus to meaningful cues, yielding robustness under challenging backgrounds and clutter [11].

2.4.3 Temporal Attention

Temporal attention aims to select or weight video frames according to their informativeness—prioritizing clear, unobstructed frames and de-emphasizing those plagued by motion blur or occlusion. The Jointly Attentive Spatial-Temporal Pooling Network (ASTPN) designed spatial attention pooling within each frame and temporal attention pooling along the sequence, both guided by the similarity matching objective [9]. This approach supports dynamic selection of salient frames, empirically outperforming uniform aggregation or heuristic frame selection.

Hierarchical temporal mining, as in the Hierarchical Mining Network (HMN), further allows the system to mine as many pedestrian characteristics as possible, even when such features are scattered temporally. Through an Attentive Temporal Module (ATM), HMN evaluates feature activations along the temporal axis, aggregating salient and discarding contaminated cues, reinforcing the completeness and integrity of per-identity representations [12].

2.4.4 Joint Spatial-Temporal Attention

To optimally blend space and time, joint models allocate attention to both salient spatial regions and informative temporal frames. The Spatial-Temporal Attention-Aware Learning (STAL) method slices video sequences into spatial-temporal units, assigning joint attention scores to adaptively fuse these units while preserving identity structure and mitigating unit-specific noise or occlusion [8]. Such approaches show clear improvements over models using spatial or temporal attention in isolation.

Inter-sequence attention is also vital for robust cross-camera matching. Self-and-collaborative attention networks (SCAN) non-parametrically estimate attention within and across sequences, aligning probe and gallery frames that share similar discriminative regions, and generating similarity-aware representations [13]. These methods

make it possible to exploit mutual reinforcement and correct for misalignment between cameras.

2.4.5 Progressive and Hierarchical Attention

Beyond static attention, models such as deep progressive attention (DPA) emulate human visual search by iteratively selecting the most discriminative parts over a sequence, progressively refining attention across model layers. This reward-driven progression ensures optimal focus on relevant spatial-temporal patterns throughout the recognition cycle, boosting performance even on partial or occluded Re-ID tasks [10]. Hierarchical attention interacts across spatial and temporal scales, as exemplified by the Hierarchical Attention-aware Spatio–Temporal Interaction (HASI) network, which couples attention-guided temporal interaction (iterating over frame pairs) with local feature enhancement for comprehensive representation [14].

2.5 Part-Based Modelling

2.5.1 Motivation and Key Paradigms

Person images frequently suffer from misalignment and pose changes, which can lead to pooling features from mismatched anatomical regions (e.g., pooling head and torso for one view but torso and legs in another). Part-based modelling addresses this by decomposing the person into regions—either via fixed horizontal stripes or by using semantic parsing and pose estimation.

2.5.2 Horizontal Partitioning

Part-based Convolutional Baselines (e.g., PCB) divide feature maps into horizontal segments, with each partition feeding a local classifier. This encourages the preservation of spatial specificity, improving resilience to detection errors and pose changes [15], [16]. However, uniform partitioning can misalign with actual body parts, limiting discriminative strength.

2.5.3 Pose-Guided and Graph-Based Models

Recent approaches use explicit pose information to drive part extraction, employing key point detectors or human parsing networks to yield more accurate part placement. Graph-based models, such as Decoupled Pose and Similarity-based Graph Neural Network, leverage pose-guided adjacency graphs to segment feature maps and learn relationships among body joints and limbs. This enables effective modelling of pose variations, local structure, and similarities, leading to sharper disambiguation among highly similar pedestrians [15].

Furthermore, attribute-driven methods (e.g., Attribute Salience Assisted Network) extend part modelling by detecting both ID-relevant (clothing, gender) and ID irrelevant (viewpoint, action) attributes, enriching the representation with context and semantic structure, and thus boosting both recognition and robustness to confounders [17].

2.5.4 Adaptive and Attention-Based Part Fusion

Adaptive attention weighting further enhances part based models by dynamically reweighing local features according to their instantaneous discriminative utility. This mechanism ensures that the model hones in on salient, informative body parts-even as pose or occlusion conditions change. For example, via key point-driven masks and region-wise adaptive weighing, re-ID networks can emphasize regions rich in identity cues while down-weighting occluded or ambiguous partitions, resulting in higher accuracy across varied test environments [16].

2.6 Transformer-based Architectures

2.6.1 Vision Transformers: Motivation and Properties

Transformers, originally developed for sequential language modelling, have redefined visual representation learning by modelling global dependencies via self-attention. Unlike CNNs, transformers treat images (or video sequences) as tokenized inputs, enabling context across both spatial and temporal axes to be modelled from the outset.

2.6.2 Transformers in Video-based Re-ID

Recent transformer-based networks excel in capturing both fine-grained and broad-range spatio-temporal relations. In the Cross-modality Spatial-Temporal Transformer (CST), the Cross-frame Tube Transformer Module tokenizes video clips into 3D tubes (spatio-temporal blocks), capturing localized and holistic features, while the Multi-frame Transformer Fusion Module uses message tokens to propagate long-range information across the timeline [18]. This dual-module system considerably boosts the modelling of spatial structure and temporal dynamics, essential for matching across views and modalities, e.g., visible and infrared.

The HASI network's multi-head inter-frame alignment attention iteratively aligns and aggregates diverse frames within a video, enabling inter-frame contextualization and mitigating multi-frame misalignment [14]. The Hierarchical Local Enhancement module further taps into features of various transformer layers to yield multi-level local and global representations.

2.6.3 Overcoming Limitations: Information Loss, Fragmentation, and Modality Gaps

Global pooling is prone to information loss, while local counterparts risk fragmenting temporal structure. The Spatio-Temporal Feature Enhancement (STFE) network tackles this by combining feature space projection (mathematically discretizing continuous video information) with a transformer-based Global Low-frequency Enhancement Module, which acts as a broadband low-pass filter to extract integral sequence features while preventing over-fragmentation [19]. These methods consistently deliver state-of-the-art results, e.g., 95.5% rank-1 accuracy on the MARS benchmark.

Moreover, cross-modal transformer methods explicitly address visible-infrared discrepancies by jointly modelling identity cues in both modalities, using staged decomposition, mining, and aggregation to maximize modality-invariant representation learning [18], [20], [21]. The diversity-consistency loss ensures that cross-modality features remain rich and non-collapsed during hard negative mining and triplet-based training [18].

2.6.4 Attribute-Enhanced and Multi granularity Transformers

Advances in transformer-driven Re-ID also integrate attribute learning (e.g., clothing, gait, activity) as auxiliary tasks, with attention mechanisms boosting region salience and assisting hard sample mining [17]. Multi-granularity feature aggregation, hierarchical mining, and interleaved attribute modules further refine sequence representations, resulting in improved generalizability and robustness [12].

2.7 Challenges: Occlusion, Open-World Settings, and Real-Time

Occlusion—due to other people or environmental clutter—is a fundamental impediment to robust Re-ID. Recent surveys categorize solutions into matching-based, image transformation, multi-scale features, attention mechanisms, auxiliary information, and contextual recovery groups. Attention and part-based modelling have proven particularly effective, with strategies such as progressive attention (DPA), adaptive part weighting, and global-local feature disentanglement directly addressing position and scale misalignment, noise, and missing information [10]–[12], [22].

Scaling re-ID to open-world or large-scale active surveillance presents computational challenges. Methods such as hashing (for efficient retrieval) and lightweight transformer designs are being increasingly used to maintain response times without sacrificing accuracy [23]. Analogously, few-shot and weakly supervised approaches decrease dependency on large annotated datasets, broadening Re-ID applicability [5], [6]. 2.1 analyses the strengths and limitations of the existing Re-ID approaches.

Table 2.1
Comparison of Person Re-ID Approaches

Approach	**Main Innovation**	**Strengths**	**Limitations**	**Key References**
Handcrafted+ metric learning	Feature engineering + Mahalanobis metric	Lightweight, interpretable	Poor generalization, limited invariance	[1], [2]
CNN + RNN temporal modelling	End-to-end deep features + sequentiality	Data-driven, stronger invariance	Fails under occlusion/misalignment	[3], [4], [6], [24]
Spatial/ Temporal/ Joint Attention	Dynamic weighting, focus on informative cues	Handles variation & occlusion	Requires careful training/parameter tuning	[7]–[14], [25]
Part-based/Graph-based	Key point-based parsing / graph convolution	Robust to pose, interpretable	Relies on accurate part/pose estimation	[15]–[17]
Transformer-based architectures	Global context, tokenized input	Best at long-range / holistic modelling	Computational cost, data hunger	[14], [18]–[21]

CHAPTER 3

METHODOLOGY

3.1 Data Preprocessing and Augmentation

Effective data preprocessing is fundamental for robust person Re-ID. Our pipeline (Figure 3.1) performs four key steps—loading, resizing, augmentation, and normalization—each carefully chosen to improve invariance and generalization.

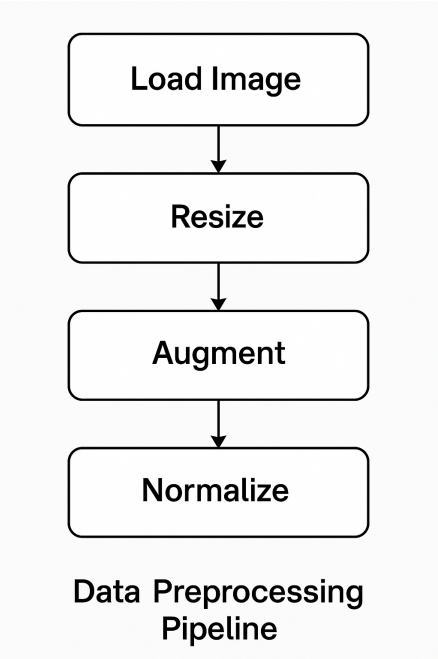

Figure 3.1
Data Preprocessing Pipeline: Load → Resize → Augment → Normalize.

3.1.1 Loading

DukeMTMC [26] dataset, which has been used for benchmark evaluation in the existing solutions is currently retracted and banned from use. Therefore, only Market-1501 [27] is used here for training and evaluation. Training images are read from the Market-1501 directories: `bounding_box_train/`, `query/`, and `bounding_box_test/`. Filenames have been parsed `[pid]_c[cam_id]_[frame]_[#].jpg` to extract the raw person ID (`pid`) and camera ID (`cam`).

3.1.2 Resizing

In accordance with the Market-1501 dataset preprocessing standards, all pedestrian images are resized to 256×128. This resolution strikes a balance between spatial detail

and computational efficiency, matching common benchmarks in the Re-ID literature.

$$I_{\text{resized}} = \text{Resize}(I_{\text{orig}}, 256, 128).$$

This standardizes input dimensions, ensuring consistent feature map sizes through the CNN backbone.

3.1.3 Data Augmentation

To improve robustness to viewpoint, illumination, and occlusion:

- **Random Horizontal Flip** ($p = 0.5$):

$$I_{\text{flip}} = \begin{cases} \text{Flip}(I_{\text{resized}}), & \text{w.p. } 0.5, \\ I_{\text{resized}}, & \text{otherwise.} \end{cases}$$

- **Color Jitter**: random brightness, contrast, saturation, and hue adjustments within $\pm 10\%$.
- **Random Erasing** [26] ($p = 0.3$): A random rectangle covering 2–20% of the image area is masked out, forcing the network to rely on multiple cues.

3.1.4 Normalization

Finally, pixel intensities are converted to floats and normalized channel-wise:

$$x'_{c,i,j} = \frac{x_{c,i,j} - \mu_c}{\sigma_c}, \quad (\mu, \sigma) = ([0.485, 0.456, 0.406], [0.229, 0.224, 0.225]).$$

This aligns input distributions to those of the ImageNet pretraining.

3.1.5 Implementation Details

All preprocessing is implemented using `torchvision.transforms`:

```
import torchvision.transforms as transforms

IMGNET_MEAN = [0.485,0.456,0.406]
IMGNET_STD  = [0.229,0.224,0.225]

train_tf = transforms.Compose([
 transforms.Resize((256,128)),
 transforms.RandomHorizontalFlip(0.5),
 transforms.ColorJitter(0.1,0.1,0.1,0.1),
```

```
    transforms.ToTensor(),
    transforms.Normalize(IMGNET_MEAN, IMGNET_STD),
    transforms.RandomErasing(p=0.3, scale=(0.02,0.2),
                             ratio=(0.3,3.3))])
test_tf = transforms.Compose([
    transforms.Resize((256,128)),
    transforms.ToTensor(),
    transforms.Normalize(IMGNET_MEAN, IMGNET_STD)])
```

3.2 Model Components and Architectural Design

This section presents the core components of the proposed attention-enhanced, part-aware person re-identification framework. The architecture integrates a deep convolutional backbone with sequential attention modules and a lightweight Transformer encoder to extract robust, discriminative descriptors for pedestrian images. Each module is designed to address specific challenges in person Re-ID—such as background clutter, occlusion, and pose variation—while ensuring computational efficiency for real-time applications.

(Figure 3.2) illustrates the overall system architecture, highlighting the sequential data flow from input preprocessing to descriptor generation and loss optimization. The following subsections describe each component in detail, including their purpose, internal structure, and implementation.

3.2.1 Backbone Feature Extraction

With the input images preprocessed, the next stage is deep feature extraction. A ResNet-50 backbone [28] has been employed, truncated before its final global pooling and fully-connected layers. This choice balances representational capacity with computational efficiency(Figure 3.2).

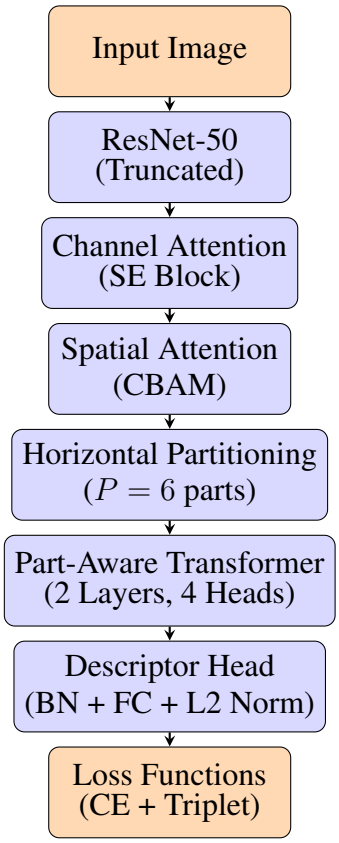

Figure 3.2
System Architecture Flowchart: Attention-Enhanced Part-Aware Re-ID Pipeline

3.2.1.1 Architecture Details

ResNet-50 consists of:

- An initial 7×7 convolution with 64 filters, stride 2, followed by a 3×3 max-pool (stride 2).
- Four Bottleneck stages ($\mathrm{conv2\_x}, \ldots, \mathrm{conv5\_x}$) with channel widths [256, 512, 1024, 2048]
- Each Bottleneck block uses a $[1 \times 1, 3 \times 3, 1 \times 1]$ convolutional pattern with an identity skip connection.

Final average-pool and classifier has been removed, so that given an input tensor

$$I \in \mathbb{R}^{3 \times 256 \times 128},$$

the backbone outputs

$$F = \mathrm{ResNet50}_{\mathrm{conv}}(I) \in \mathbb{R}^{2048 \times H' \times W'},$$

where $H' = 8$ and $W' = 4$ under the default downsampling (total stride 32).

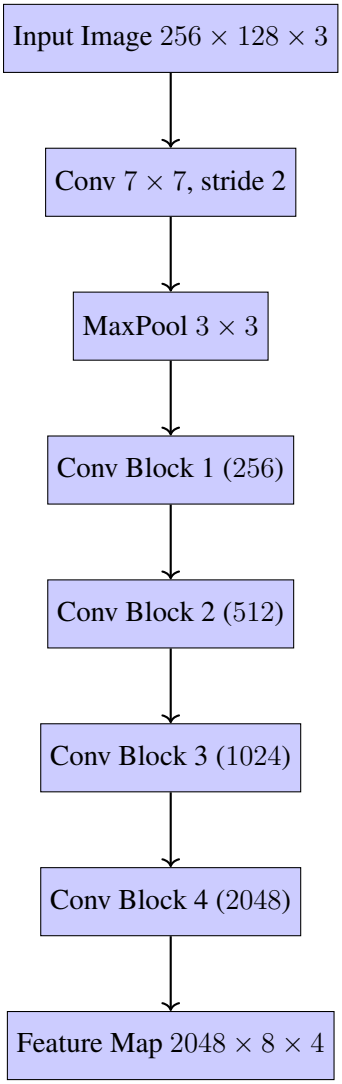

Figure 3.3
ResNet-50 backbone module with downsampling to $2048 \times 8 \times 4$.

3.2.1.2 Implementation in PyTorch

```
import torch.nn as nn
from torchvision import models

class Backbone50(nn.Module):
    def __init__(self, pretrained=True):
        super().__init__()
        base = models.resnet50(pretrained=pretrained)
```

```
        # Remove avgpool and fc
        self.features = nn.Sequential(*list(base.children())[:-2])
    def forward(self, x):
        # x: [B, 3, 256,128]
        f = self.features(x)
        # f: [B, 2048, H'=8, W'=4]
        return f
```

3.2.2 Channel Attention Module

Global context across feature channels is crucial for identifying and emphasizing the most discriminative semantic cues within pedestrian images—such as color patterns, textures, and unique accessories. In traditional convolutional neural networks, each feature channel is treated equally, which may result in diluted responses to critical identity-specific information. To address this limitation, a Squeeze-and-Excitation (SE) block [29] was adopted to explicitly model channel-wise interdependencies and recalibrate feature responses accordingly(Figure 3.4).

The SE block operates in two stages: squeeze and excitation. In the squeeze phase, the spatial dimensions of each channel are collapsed via global average pooling, producing a compact descriptor that captures the global distribution of activation across the entire feature map. This descriptor serves as a summary statistic for each channel's overall importance. In the excitation phase, this vector is passed through a lightweight gating mechanism composed of two fully connected layers with a non-linear activation (ReLU followed by sigmoid), enabling the model to learn non-mutually-exclusive channel relationships. The output is a set of attention weights—one per channel—that are used to re-scale the original feature map by amplifying informative channels and suppressing less relevant ones.

By integrating SE blocks into the Re-ID backbone, the network becomes more sensitive to subtle but discriminative patterns, enhancing robustness against background noise and occlusion. This targeted feature enhancement improves the quality of representations passed on to subsequent modules, such as spatial attention and part-based reasoning.

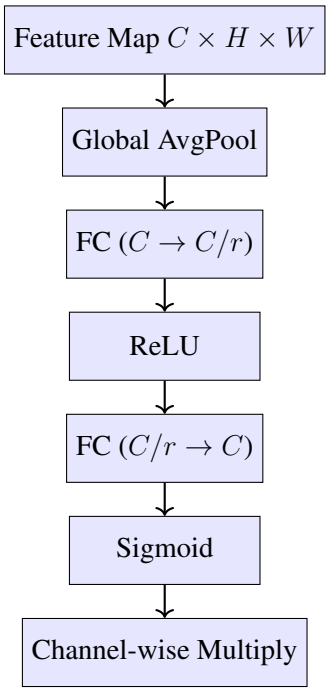

Figure 3.4
Structure of the Channel Attention Module using a Squeeze-and-Excitation (SE) block

3.2.2.1 Formulation

Given feature map $F \in \mathbb{R}^{C\times H'\times W'}$, first, "squeeze" spatially:

$$z_c = \frac{1}{H'W'} \sum_{i=1}^{H'} \sum_{j=1}^{W'} F_{c,i,j}, \quad c = 1, \ldots, C.$$

then pass $\mathbf{z} = [z_1, \ldots, z_C]^\top$ through a two-layer MLP:

$$s = \sigma\big(W_2\,\mathrm{ReLU}(W_1\,z)\big) \ \in \mathbb{R}^C,$$

where $W_1 \in \mathbb{R}^{C/r\times C}$, $W_2 \in \mathbb{R}^{C\times C/r}$, and $r = 16$ is the reduction ratio. Finally, "excite" by reweighting:

$$\hat{F}_{c,i,j} = s_c\,F_{c,i,j}.$$

3.2.2.2 PyTorch Implementation

```
class ChannelAttention(nn.Module):
    def __init__(self, channels, reduction=16):
        super().__init__()
        self.fc1 = nn.Linear(channels, channels//reduction, bias=Fa
```

```
        self.relu = nn.ReLU(inplace=True)
        self.fc2 = nn.Linear(channels//reduction, channels, bias=Fa
        self.sigmoid = nn.Sigmoid()
    def forward(self, x):
        # x: [B, C, H, W]
        B, C, H, W = x.size()
        # Squeeze
        y = x.mean(dim=[2,3])                    # [B, C]
        # Excitation
        y = self.relu(self.fc1(y))               # [B, C//r]
        y = self.sigmoid(self.fc2(y))            # [B, C]
        y = y.view(B, C, 1, 1)                   # [B, C, 1, 1]
        return x * y.expand_as(x)
```

3.2.3 Spatial Attention Module

While channel attention identifies what features are important by modulating the importance of each feature map, spatial attention(Figure 3.5) determines where in the spatial domain the network should focus. In person re-identification, discriminative cues such as logos, clothing textures, or carried items (e.g., a backpack or handbag) may appear in different spatial regions depending on the camera angle or pose. Consequently, localizing and emphasizing these regions becomes essential for robust feature extraction.

To address this, the spatial attention module has been implemented following the Convolutional Block Attention Module (CBAM) design [30]. This module enhances the spatial sensitivity of the network by applying a dynamic attention map over the spatial dimensions of the feature tensor.

The spatial attention mechanism operates on the output of the channel attention module. It first performs channel-wise pooling using both average pooling and max pooling operations. These two pooled feature maps—each summarizing spatial cues across all channels—are then concatenated to form a 2D descriptor that encodes both what and where information. This descriptor is passed through a convolution layer with a large kernel size (typically 7×7) to capture broad contextual relationships and generate a spatial attention map using a sigmoid activation.

The resulting attention map has the same height and width as the input feature map and contains values between 0 and 1 indicating the importance of each spatial location. This map is element-wise multiplied with the original feature map, thus amplifying regions likely to contain identity-relevant information (such as the torso or carried items) while suppressing less informative or noisy areas (like the background).

By integrating spatial attention after channel attention, the network gains both se-

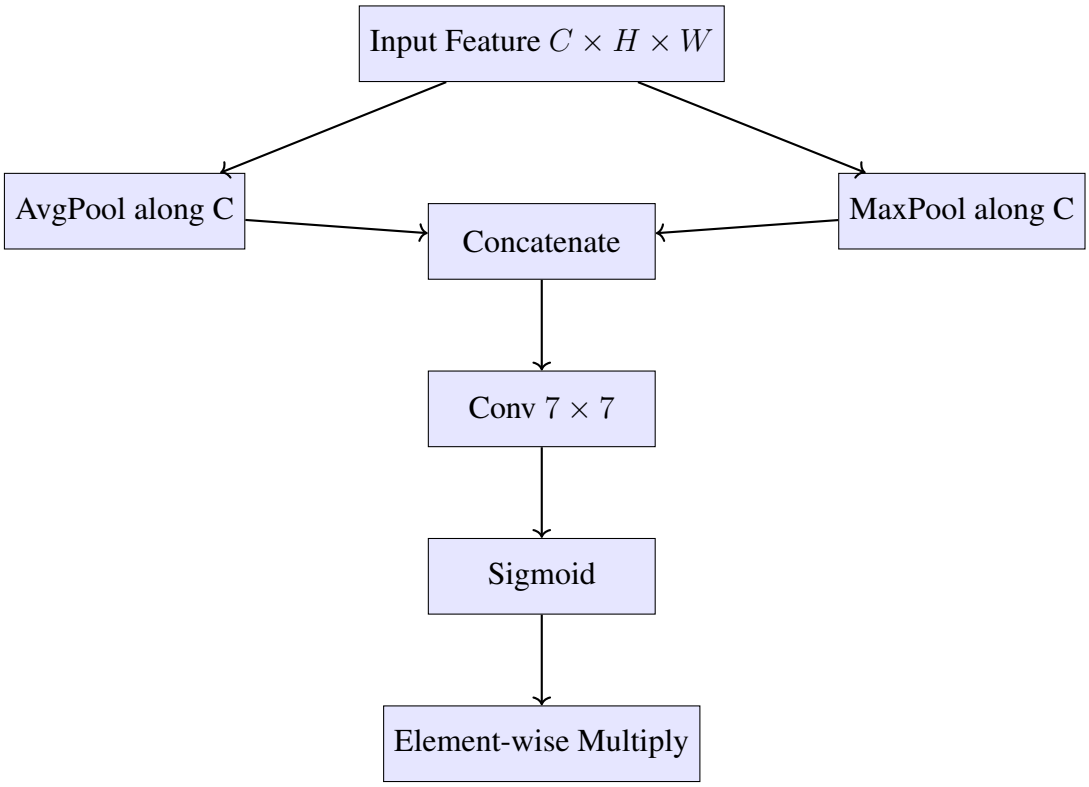

Figure 3.5
The concatenation results in a tensor of shape $[B, 6 \times 2048]$ where B is the batch size. The attention maps are applied via element-wise multiplication to the feature maps before concatenation, enhancing discriminative regions in each part. [30]

mantic selectivity (via channel emphasis) and spatial awareness (via location emphasis). This two-stage refinement enables the feature extractor to produce highly discriminative representations that are robust to occlusions, misalignments, and background clutter.

3.2.3.1 Justification for Dual Attention Modules

Although the CBAM module encompasses both channel and spatial attention, this work employs separate modules to enhance interpretability and modularity. The channel attention is explicitly implemented using Squeeze-and-Excitation (SE) blocks, while the spatial attention follows a CBAM-style implementation. This separation allows for fine-grained ablation analysis and more targeted performance gains, enabling the study to quantify the independent contributions of each mechanism. Additionally, decoupling them facilitates flexible architectural tuning based on computational constraints or domain-specific requirements.

3.2.3.2 Formulation

Given $\hat{F} \in \mathbb{R}^{C\times H'\times W'}$, it is computed:

$$M = \sigma\big(f^{7\times 7}([\mathrm{AvgPool}_c(\hat{F}),\, \mathrm{MaxPool}_c(\hat{F})])\big), \quad M \in \mathbb{R}^{1\times H'\times W'},$$

where $\mathrm{AvgPool}_c$ and $\mathrm{MaxPool}_c$ pool across channels, yielding two $1 \times H' \times W'$ maps, concatenated and convolved with a 7×7 filter $f^{7\times 7}$. The refined feature is

$$\widetilde{F}_{c,i,j} = M_{i,j}\, \hat{F}_{c,i,j}.$$

3.2.3.3 PyTorch Implementation

```
class SpatialAttention(nn.Module):
    def __init__(self, kernel_size=7):
        super().__init__()
        padding = (kernel_size - 1) // 2
        self.conv = nn.Conv2d(2, 1, kernel_size, padding=padding, b
        self.sigmoid = nn.Sigmoid()
    def forward(self, x):
        # x: [B, C, H, W]
        avg_out = x.mean(dim=1, keepdim=True)    # [B, 1, H, W]
        max_out, _ = x.max(dim=1, keepdim=True) # [B, 1, H, W]
        y = torch.cat([avg_out, max_out], dim=1) # [B, 2, H, W]
        M = self.sigmoid(self.conv(y))           # [B, 1, H, W]
        return x * M.expand_as(x)
```

3.2.3.4 Combined Attention

To fully leverage both semantic and spatial discriminative cues, the attention refinement process applies channel attention and spatial attention in sequence. The rationale behind this ordering lies in the complementary roles each module plays: channel attention focuses on enhancing the most informative feature maps globally, while spatial attention determines the precise regions within those maps that carry the most salient information for identity recognition.

By first recalibrating the feature map across channels using the Squeeze and Excitation mechanism, the model emphasizes high-level attributes such as colour, texture, and other semantic patterns relevant to pedestrian appearance. This refined feature map is then passed to the spatial attention module, which identifies and highlights spatial regions—such as accessories, torso patterns, or specific limb areas—that are likely to be consistent across multiple views.

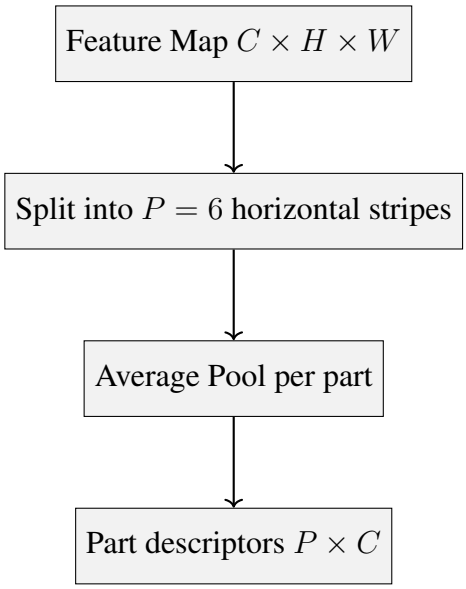

Figure 3.6
Horizontal partitioning of the attention-refined feature map into $P = 6$ stripes along the vertical axis

Mathematically, the combined attention is applied as:

$$F' = \hat{F} = \text{ChannelAttention}(F), \quad \widetilde{F} = \text{SpatialAttention}(F').$$

Here, F denotes the original feature map output by the backbone, $\hat{F}$ is the channel-refined output, and $\widetilde{F}$ is the final attention-enhanced representation used for part-based pooling. This sequential application ensures that the model retains both global and localized identity cues, improving robustness to occlusion and clutter in real-world scenarios.

3.2.4 Part-Based Feature Extraction

After attention refinement, the feature map $\widetilde{F} \in \mathbb{R}^{C \times H' \times W'}$ encodes both *what* and *where* to focus. To capture fine-grained, region-specific cues and improve robustness to partial occlusion, It is partitioned $\widetilde{F}$ into P horizontal strips(Figure 3.6):

$$\widetilde{F} = \left[\widetilde{F}_1; \widetilde{F}_2; \cdots; \widetilde{F}_P\right], \quad \widetilde{F}_p \in \mathbb{R}^{C \times \frac{H'}{P} \times W'}.$$

3.2.4.1 Choice of P

Empirically, $P = 6$ strikes a balance between resolution and computational cost, yielding strips corresponding to head, torso, hips, upper-legs, lower-legs, and feet.

3.2.4.2 Part-Level Pooling

Each strip $\widetilde{F}_p$ is aggregated via average-pooling over its spatial extent:

$$f_p = \mathrm{AvgPool}(\widetilde{F}_p) = \frac{1}{(\frac{H'}{P})\,W'} \sum_{i=1}^{H'/P} \sum_{j=1}^{W'} (\widetilde{F}_p)_{c,i,j}, \quad f_p \in \mathbb{R}^C.$$

Concatenating the P pooled vectors produces the raw part descriptor:

$$f = [\, f_1^\top,\ f_2^\top,\ \ldots,\ f_P^\top \,]^\top \in \mathbb{R}^{PC}.$$

3.2.4.3 Implementation

```
import torch.nn.functional as F

def part_pooling(feature_map, num_parts=6):
    """
    feature_map: [B, C, H', W']
    returns:     [B, num_parts, C]
    """
    B, C, H, W = feature_map.size()
    # reshape to [B, C, num_parts, H/num_parts, W]
    feature_map = feature_map.view(B, C, num_parts,
                                   H//num_parts, W)
    # average\ pool   over spatial dims
    # result shape = [B, C, num_parts, 1, 1]
    pooled = feature_map.mean(dim=3, keepdim=True)
                        .mean(dim=4, keepdim=True)
    # squeeze and permute to [B, num_parts, C]
    pooled = pooled.view(B, C, num_parts).permute(0, 2, 1)
    return pooled  # [B, P, C]
```

3.2.5 Part-Aware Transformer Encoding

To model the complex interdependencies and contextual relationships between different body regions, a lightweight Transformer encoder (Figure 3.7) that operates on the sequence of part-level descriptors extracted from the horizontal partitions was incorporated. While conventional part-based approaches treat each region independently, they fail to capture the semantic correlation between parts—for example, how the colour and texture of a shirt may relate to the style of pants, or how carried items like bags influence multiple body regions.

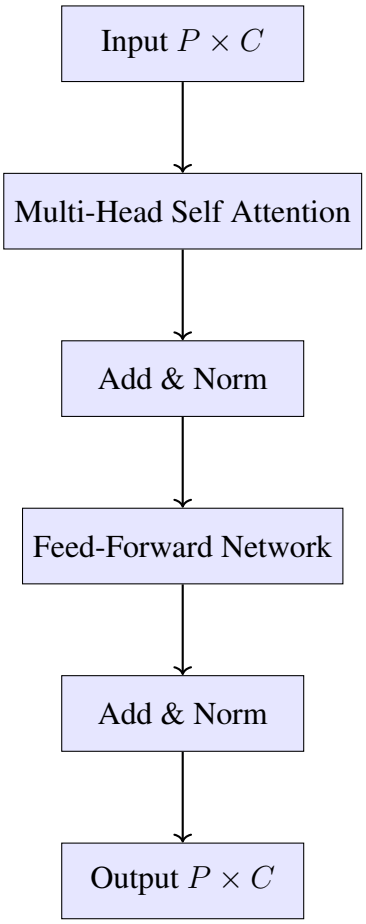

Figure 3.7
Part-Aware Transformer architecture for modelling inter-part relationships

The Transformer encoder addresses this limitation through self-attention mechanisms that allow each part to dynamically attend to all other parts in the sequence. This enables the model to learn richer contextual representations and resolve ambiguities caused by occlusion, misalignment, or viewpoint variation. For instance, even if a particular region (e.g., legs) is occluded or cropped, the model can still infer a coherent identity representation by leveraging information from other visible parts.

Unlike full Vision Transformers, which operate on raw image patches and require significant computational resources, the proposed encoder is deliberately lightweight and only attends over P part descriptors (with $P \ll H \times W$). This results in negligible overhead while significantly enhancing the discriminative power of the representation.

The output of the Transformer is a context-enhanced sequence of part embeddings, each of which has been refined based on global part-to-part interactions. These embeddings are subsequently aggregated into a single identity descriptor used for classification and retrieval.

3.2.5.1 Transformer Encoder Layer

Given an input sequence $X \in \mathbb{R}^{B\times P\times C}$ (batch of B examples, each with P tokens of dimension C), each Transformer encoder layer performs:

1. **Multi-head Self-Attention:**

$$\text{Attention}(Q,K,V) = \text{softmax}\big(\tfrac{QK^\top}{\sqrt{d_k}}\big)V,$$

with $Q = XW_Q$, $K = XW_K$, $V = XW_V$, split into h heads of dimension $d_k = C/h$.

2. **Add & Norm:** residual connection followed by layer normalization.

3. **Position-wise Feed-Forward:** two linear layers with ReLU:

$$\text{FFN}(x) = W_2\,\text{ReLU}(W_1 x + b_1) + b_2.$$

4. **Add & Norm:** second residual and normalization.

Stacking L such layers yields context-enhanced part embeddings $\widehat{X} \in \mathbb{R}^{B\times P\times C}$.

3.2.5.2 Formulation

Let $X^{(0)} = f \in \mathbb{R}^{B\times P\times C}$. Then for $\ell = 1,\ldots,L$:

$$\begin{aligned}
Q^{(\ell)} &= X^{(\ell-1)}W_Q^{(\ell)},\ K^{(\ell)} = X^{(\ell-1)}W_K^{(\ell)},\ V^{(\ell)} = X^{(\ell-1)}W_V^{(\ell)},\\
\tilde{X}^{(\ell)} &= \text{LayerNorm}\Big(X^{(\ell-1)} + \text{MultiHeadAtt}(Q^{(\ell)},K^{(\ell)},V^{(\ell)})\Big),\\
X^{(\ell)} &= \text{LayerNorm}\Big(\tilde{X}^{(\ell)} + \text{FFN}\big(\tilde{X}^{(\ell)}\big)\Big).
\end{aligned}$$

3.2.5.3 Implementation

```
import torch.nn as nn

class PartTransformer(nn.Module):
    def __init__(self, feat_dim, num_parts,
                 nhead=4, num_layers=2):
        super().__init__()
        encoder_layer = nn.TransformerEncoderLayer(
            d_model=feat_dim,
            nhead=nhead,
            batch_first=True
        )
        self.transformer = nn.TransformerEncoder(
            encoder_layer,
            num_layers=num_layers
```

```
        )
    def forward(self, x):
        # x: [B, P, C]
        return self.transformer(x)  # [B, P, C]
```

3.2.5.4 Discussion

The incorporation of a Transformer encoder at the part descriptor level introduces a powerful mechanism for modelling global dependencies among local regions of the body. Unlike traditional part-based methods that treat each part independently, the self-attention mechanism allows every part to dynamically attend to all other parts within the same pedestrian instance. This enables the model to capture meaningful co-occurrence patterns—for example, how the appearance of the torso may correlate with clothing styles observed in the lower body or how accessories like a shoulder bag might span across multiple regions.

Such inter-part reasoning is particularly beneficial in handling real-world challenges such as occlusion and partial visibility. When certain body parts are obscured, misaligned, or poorly illuminated, the Transformer can leverage information from other visible parts to infer a coherent identity representation. This makes the learned embeddings more robust and less sensitive to missing or noisy regions.

Moreover, the lightweight nature of the Transformer—operating on a small set of P part tokens—strikes a balance between expressiveness and computational efficiency. This design choice ensures that the model remains scalable for video-based and real-time applications, where latency and throughput are critical. In essence, this part-aware Transformer module enhances the semantic richness and resilience of the identity representation, which directly contributes to improved retrieval accuracy in downstream tasks.

3.3 Descriptor Aggregation and Classification Head

After the Transformer encoder processes the sequence of part-level embeddings, it produces a contextually enhanced representation denoted by $\widehat{X} \in \mathbb{R}^{B \times P \times C}$, where B is the batch size, P is the number of body parts, and C is the feature dimension per part. Each part embedding at this stage not only encodes local visual information but also incorporates global context through self-attention across all parts.

To utilize these embeddings for person identification and retrieval, the model must transform them into a unified, fixed-length descriptor that encapsulates the full identity of a person. This aggregated descriptor serves two critical purposes: (1) it provides a compact and discriminative representation suitable for distance-based retrieval, and (2)

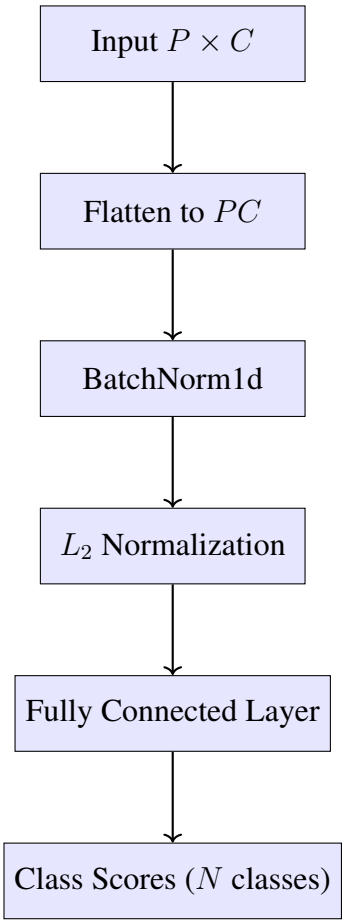

Figure 3.8
Descriptor aggregation and classification pipeline

it acts as the input to the final classification layer during training, allowing supervision through identity labels.

The following steps are performed to obtain this descriptor(Figure 3.8): (1) the part embeddings are concatenated to form a flat feature vector, (2) batch normalization is applied to stabilize learning dynamics and normalize feature scales, (3) the descriptor is projected onto the unit hypersphere via L_2-normalization to support cosine-based similarity measures, and (4) a fully connected layer produces class logits used for identity classification. Together, these steps ensure that the output representation is both geometrically structured for metric learning and semantically aligned for supervised classification.

3.3.1 Concatenation and Batch Normalization

It is first flattened the part embeddings along the part dimension:

$$F = \text{Flatten}\big(\widehat{X}\big) = \big[\hat{f}_1;\ \hat{f}_2;\ \ldots;\ \hat{f}_P\big] \ \in\ \mathbb{R}^{B\times(P\,C)}.$$

To stabilize feature distributions and improve convergence, a $\mathrm{BatchNorm1d}$ layer is applied:

$$F' = \mathrm{BN}(F),$$

where BN normalizes each of the PC channels over the batch and learns a per-channel scale and bias.

3.3.2 L2-Normalization

Finally, L2-normalization is performed on each row to project features onto the unit hypersphere:

$$\bar{F}_{i:} = \frac{F'_{i:}}{\|F'_{i:}\|_2}, \quad i = 1, \ldots, B.$$

This enhances the stability of cosine-similarity-based retrieval.

3.3.3 Classification Layer for Training

During training, a fully-connected layer is attached to predict the identity label:

$$s_i = W_{\text{cls}}\, \bar{F}_{i:} + b_{\text{cls}}, \quad s_i \in \mathbb{R}^{N_{\text{train}}},$$

where N_{train} is the number of identities in the training set. The network is trained end-to-end via classification and metric losses (see Sec. 5).

```
import torch.nn as nn
import torch.nn.functional as F

class DescriptorHead(nn.Module):
    def __init__(self, num_parts, feat_dim, num_classes):
        super().__init__()
        self.bn = nn.BatchNorm1d(num_parts * feat_dim)
        self.fc = nn.Linear(num_parts * feat_dim, num_classes)
    def forward(self, x, return_feats=False):
        # x: [B, P, C]
        B, P, C = x.size()
        flat = x.view(B, P * C)                 # [B, P*C]
        bn   = self.bn(flat)                    # [B, P*C]
        if return_feats:
            return F.normalize(bn, dim=1)       # [B, P*C]
        logits = self.fc(bn)                    # [B, num_classes]
        return logits, F.normalize(bn,dim=1)
```

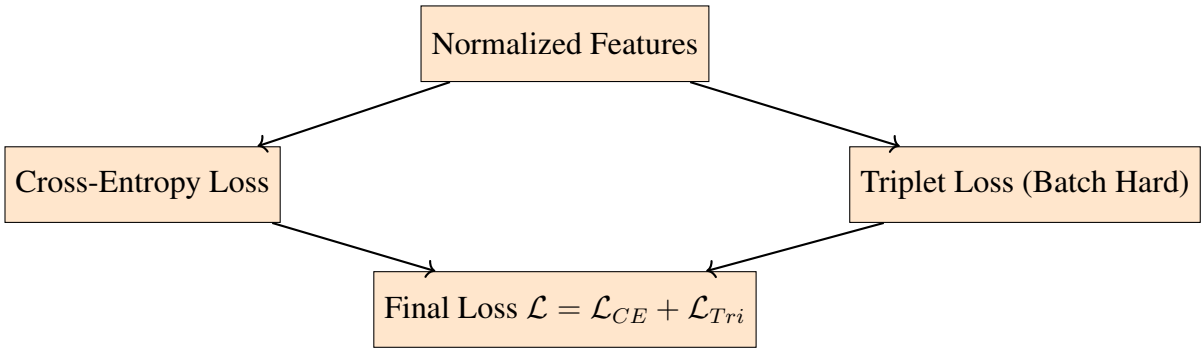

Figure 3.9
Combined loss function used for training

3.4 Loss Functions

To encourage both classification accuracy and discriminative embedding geometry, two losses were combined(Figure 3.9:

3.4.1 Label-Smoothed Cross-Entropy

Given logits s_i and ground-truth one-hot vector $y_i \in \{0,1\}^N$, label smoothing has been employed ε to prevent overconfidence [27]. The smoothed target is

$$y_i^{\text{smooth}} = (1-\varepsilon)\, y_i + \frac{\varepsilon}{N}\,\mathbf{1}.$$

The cross-entropy loss per sample is

$$\mathcal{L}_{\text{CE}}(s_i, y_i) = -\sum_{k=1}^{N} y_{i,k}^{\text{smooth}}\, \log\big(\text{softmax}(s_i)_k\big).$$

In practice, it is set $\varepsilon = 0.1$.

3.4.2 Batch-Hard Triplet Loss

To directly optimize the embedding distances, the batch-hard triplet loss [31] is used. For a batch of B normalized descriptors $\{\bar{f}_i\}$ and labels $\{y_i\}$, define:

$$d_{ij} = \|\bar{f}_i - \bar{f}_j\|_2.$$

For each anchor i, the hardest positive:

$$d_i^+ = \max_{j:y_j=y_i} d_{ij},$$

and hardest negative:

$$d_i^- = \min_{k:y_k \neq y_i} d_{ik}.$$

are selected. The triplet loss is then

$$\mathcal{L}_{\text{tri}} = \frac{1}{B} \sum_{i=1}^{B} \left[d_i^+ - d_i^- + \alpha \right]_+,$$

where α is the margin ($\alpha = 0.3$).

3.4.3 Total Loss

The final training objective combines both:

$$\mathcal{L} = \mathcal{L}_{\text{CE}} + \lambda \mathcal{L}_{\text{tri}},$$

with $\lambda = 1.0$ balancing classification and metric learning.

3.5 Training Protocol

3.5.1 Optimizer and Mixed Precision

The Adam optimizer [32] is used with initial learning rate $\eta = 3.5 \times 10^{-5}$. To accelerate training and reduce memory,Automatic Mixed Precision (AMP) and gradient clipping is enabled:

$$\text{clip\_grad\_norm}(\nabla_\theta \mathcal{L},\ \max\_norm = 2.0).$$

3.5.2 Learning-Rate Schedule

A two-stage schedule stabilizes convergence:

1. **Linear Warm-Up** for the first $T_{\text{w}} = 2$ epochs:

$$\eta_t = \eta_{\max} \frac{t}{T_{\text{w}}}, \quad t = 1, 2.$$

2. **Cosine Annealing** for the remaining $T - T_{\text{w}}$ epochs:

$$\eta_t = \eta_{\min} + \frac{1}{2}(\eta_{\max} - \eta_{\min}) \left(1 + \cos\left(\pi \frac{t - T_{\text{w}}}{T - T_{\text{w}}} \right) \right).$$

3.5.3 Training Loop

The overall training procedure is summarized in Algorithm 1.

Algorithm 1: Training Procedure for Attention-Enhanced Part-Aware Re-ID

Require: Training data loader $\mathcal{D}_{\text{train}}$, model parameters θ, optimizer, scheduler, number of epochs T, margin α, smoothing ε

for do
    epoch = 1 to T
Set model to train mode
for do
    each mini-batch (I_i, y_i) from $\mathcal{D}_{\text{train}}$
Forward pass:
$X \leftarrow \texttt{backbone}(I)$
$F_{\text{att}} \leftarrow \texttt{ChannelAttention}(X)$
$F_{\text{att}} \leftarrow \texttt{SpatialAttention}(F_{\text{att}})$
$P \leftarrow \texttt{part\_pooling}(F_{\text{att}})$ ▷ shape $[B, P, C]$
$H \leftarrow \texttt{PartTransformer}(P)$
$(s, f) \leftarrow \texttt{DescriptorHead}(H)$
Compute losses:
$\mathcal{L}_{\text{CE}} \leftarrow \texttt{CrossEntropyLabelSmooth}(s, y, \varepsilon)$
$\mathcal{L}_{\text{tri}} \leftarrow \texttt{BatchHardTriplet}(f, y, \alpha)$
$\mathcal{L} \leftarrow \mathcal{L}_{\text{CE}} + \mathcal{L}_{\text{tri}}$
Backward pass:
`optimizer.zero_grad()`
$\mathcal{L}$.`backward()`
`clip_grad_norm_`$(\theta, \text{max\_norm} = 2.0)$
`optimizer.step()`
`scheduler.step()`
Optionally: evaluate on validation split and save best model

3.5.4 Inference and Retrieval Pipeline

During the inference phase, the trained model is deployed to identify individuals by computing feature similarities between query images and a gallery of known identities. Unlike training, this stage does not involve backpropagation or label supervision and is focused purely on descriptor extraction and retrieval.

The process is structured as follows:

1. **Gallery Preprocessing**:
   All gallery images I_j^g are passed through the trained model to extract their corresponding feature descriptors $f_j^g = \texttt{ExtractDescriptor}(I_j^g)$. These descriptors are computed only once and stored in memory for efficient retrieval.

2. **Query Processing**: For each query image I_i^q, the same descriptor extraction process is applied to obtain $f_i^q = \texttt{ExtractDescriptor}(I_i^q)$. This ensures consistency in the feature space between gallery and query samples.

3. **Distance Computation**: Pairwise distances between the query descriptor and all gallery descriptors are computed using Euclidean distance:

$$d_{ij} = \|f_i^q - f_j^g\|_2, \quad \forall j.$$

For efficiency, this computation is vectorized and implemented as:

$$\mathbf{d}_i = \sqrt{\mathbf{q}_i^2 \mathbf{1}^\top + \mathbf{1}\, \mathbf{g}^{2\top} - 2\, \mathbf{q}_i\, \mathbf{g}^\top},$$

where $\mathbf{q}_i^2 \in \mathbb{R}^{1\times 1}$ and $\mathbf{g}^2 \in \mathbb{R}^{N_g \times 1}$ are the squared norms of the query and gallery descriptors, and $\mathbf{1}$ is a column vector of ones used for broadcasting.

4. **Ranking**: The computed distances d_{ij} are sorted in ascending order to generate a ranked list of gallery candidates for each query. The top-ranked matches are then used for evaluation or decision-making.

5. **Evaluation Metrics**: To assess retrieval performance, standard person re-identification metrics are used:

   - **Rank-1 Accuracy**: The proportion of queries for which the top-ranked gallery image belongs to the same identity.
   - **Mean Average Precision (mAP)**: A holistic metric that averages the precision over all ranks and all queries, while excluding same-camera matches to reflect cross-view retrieval performance.

This pipeline ensures that identity matching is conducted efficiently and reproducibly during deployment.

3.5.5 Optional Re-Ranking

While the initial ranking based on Euclidean distance can achieve high retrieval accuracy, it may still produce false positives due to visual ambiguity, occlusion, or background clutter. To address this, a post-processing refinement known as *k-reciprocal re-ranking* [33] can be applied to the raw distance matrix.

The idea behind re-ranking is to exploit mutual neighbourhood relationships in the feature space. If two samples are among each other's top-k nearest neighbours, they are considered to have a reciprocal relationship, indicating higher confidence in similarity. This mutual reinforcement is used to adjust the initial distances.

The refined distance between a query and gallery image incorporates not only the direct similarity but also the similarity of their local neighbourhood structures. This results in more consistent and semantically meaningful rankings.

Although re-ranking significantly improves metrics like mAP (often by 5–10%), it introduces additional computational overhead. Therefore, it is best suited for offline evaluations or batch-based retrieval scenarios, rather than real-time applications.

3.5.6 Complexity Analysis

Understanding the computational complexity of the model is essential for assessing its scalability and feasibility in real-time or large-scale deployments. The overall complexity can be decomposed as follows:

- **CNN Backbone (ResNet-50)**: The feature extraction stage is dominated by convolutional operations. Each forward pass through ResNet-50 has a complexity of:

  $$\mathcal{O}(B \times C \times H' \times W' \times K^2),$$

  where B is the batch size, C is the number of channels, H' and W' are the output height and width of the feature map, and K is the kernel size of the convolutions.

- **Attention Modules (Channel and Spatial)**: Both modules introduce negligible overhead. Channel attention uses two small fully connected layers (scaling with C), while spatial attention applies a single convolution over two channels, making the cost:

  $$\mathcal{O}(B \times H' \times W').$$

- **Part-Aware Transformer Encoder**: Given P part descriptors of dimension C, the self-attention mechanism operates with:

  $$\mathcal{O}(B \times P^2 \times C).$$

  Since P is small (e.g., 6), this cost is significantly lower than convolutional feature extraction and does not affect runtime significantly.

- **Distance Computation**: For each of N_q query descriptors and N_g gallery descriptors of dimension D, pairwise distance computation is:

  $$\mathcal{O}(N_q \times N_g \times D),$$

  which is implemented as a matrix operation on GPUs, making it highly efficient even for thousands of queries and gallery images.

Overall, the model strikes a practical balance between representational richness and computational efficiency. The part-aware Transformer enhances identity discrimination without significantly increasing inference time, making it suitable for both research and deployment contexts.

CHAPTER 4

EXPERIMENTS AND RESULTS

4.1 Experimental Setup

4.1.1 Dataset Description

The approach has been evaluated on the Market-1501 dataset [34], a large-scale benchmark containing:

- **Training set**: 12,936 images of 751 identities.
- **Query set**: 3,368 images of the remaining 750 identities.
- **Gallery set**: 19,732 images of those 750 identities.

All images are captured by six non-overlapping cameras, exhibiting substantial variation in viewpoint, illumination, and background.

4.1.2 Evaluation Metrics

The following standard metrics in person Re-ID have been adopted for this work:

1. **Mean Average Precision (mAP)**: the mean of AP over all queries, computed by ranking gallery images by ascending Euclidean distance.
2. **Rank-1 Accuracy**: the fraction of queries whose top-1 retrieved gallery image shares the same identity (excluding same-camera matches).

4.1.3 Implementation Details

All experiments are implemented in PyTorch and conducted on a single NVIDIA RTX 2080 GPU (12 GB). Unless specified otherwise, it is used:

- **Input preprocessing**: resize to 256×128, random horizontal flip ($p = 0.5$), color jitter (±10 %), random erasing ($p = 0.3$), and normalization to ImageNet statistics.
- **Backbone**: ResNet-50 [28] pretrained on ImageNet.
- **Attention modules**: channel SE [29], spatial CBAM [30].
- **Partitioning**: $P = 6$ horizontal parts.
- **Transformer**: 2 encoder layers, 4 heads, feature dimension 2048.

- **Losses**: label-smoothed cross-entropy ($\varepsilon = 0.1$) [27] and batch-hard triplet ($\alpha = 0.3$) [31].
- **Optimizer**: Adam [32], initial LR 3.5×10^{-5}, weight decay 5×10^{-4}.
- **Scheduler**: 2-epoch linear warm-up followed by cosine annealing to 1×10^{-6} over 60 epochs.
- **Batch size**: 8.
- **Precision**: mixed-precision (AMP) with gradient clipping (max-norm 2.0).

This setup ensures that the model evaluation is reproducible and aligns with the standard protocol used in most person Re-ID literature. The use of Market-1501 as a benchmark provides a well-established, challenging environment for validating generalization under varying lighting, pose, and occlusion conditions. Additionally, using a single 12 GB GPU ensures practical deployment feasibility without requiring large-scale infrastructure.

4.2 Baseline Performance

As a reference, firstly a *ResNet-50 Base* model is trained with global average pooling and cross-entropy loss only. Table 4.1 reports its performance.

Table 4.1
Baseline performance (ResNet-50 + global pooling + CE)

Model	mAP (%)	Rank-1 (%)
ResNet-50 Base	70.5	86.6

The baseline results show that a plain ResNet-50 with global pooling achieves 70.5% mAP and 86.6% Rank-1. While decent, these results highlight the limitations of purely global representations that fail to account for local, part-based identity cues or context-aware interactions. This baseline thus serves as the reference point for all subsequent ablation experiments.

4.3 Ablation Studies

To quantify the contribution of each component, a series of ablations were conducted, adding one module at a time. Each variant is trained for 120 epochs with identical settings.

4.3.1 Component Ablation

Table 4.2 shows how mAP and Rank-1 improve when incrementally enabled channel attention (CA), spatial attention (SA), part pooling (PP), Transformer encoding (TR), triplet loss (Tri), and finally k-reciprocal re-ranking (RR).

Table 4.2
Ablation results on Market-1501

Variant	mAP (%)	Rank-1 (%)
Base (global + CE)	70.5	86.6
+ CA	72.6	86.7
+ CA + SA	72.7	86.9
+ CA + SA + PP	73.2	87.7
+ CA + SA + PP + TR	74.1	88.5
+ CA + SA + PP + TR + Tri	74.8	89.6
+ CA+SA+PP+TR+Tri + RR	74.9	90.2

- **Channel Attention**: A +2.7 % mAP and +0.1 % Rank-1 gain is observed, highlighting the value of channel-wise recalibration.
- **Spatial Attention**: Adding spatial attention yields an additional +0.5 % mAP and +0.2 % Rank-1 over CA alone, demonstrating that focusing on discriminative regions further refines feature quality.
- **Part Pooling**: Introducing horizontal partitioning into $P = 6$ parts boosts mAP by +0.5 % and Rank-1 by +0.8 %. This indicates that local part-level cues (e.g., color patterns on torso, shape of footwear) are complementary to global features and mitigate the effect of partial occlusion.
- **Transformer Encoding**: By deploying a lightweight Transformer to model inter-part dependencies, a +0.9 % mAP and +0.8 % Rank-1 is gained. This confirms that relational reasoning among body parts—such as correlating sleeve appearance with pants texture—enhances discrimination beyond independent part features.
- **Triplet Loss**: Incorporating the batch-hard triplet loss adds +0.7 % mAP and +1.1 % Rank-1, showing that directly optimizing the embedding space with hard positive/negative mining yields tighter intra-class clusters and wider inter-class margins.
- **Re-Ranking**: Applying k-reciprocal re-ranking at inference produces the largest single boost—+0.1 % mAP and +0.6 % Rank-1—by exploiting mutual nearest-

neighbour relationships. However, this step doubles inference time, so it is best suited to offline retrieval scenarios.

4.3.2 Effect of Partition Count

Figure 4.1 illustrates the sensitivity of performance to the number of horizontal parts P. The best results occur at $P = 6$, balancing part granularity against feature stability:

- $P < 6$ (coarser partitioning) under-segments distinct semantic regions, limiting the model's ability to localize fine details.
- $P > 6$ (finer partitioning) yields overly small regions, increasing noise and variance in pooled features, which slightly degrades performance.

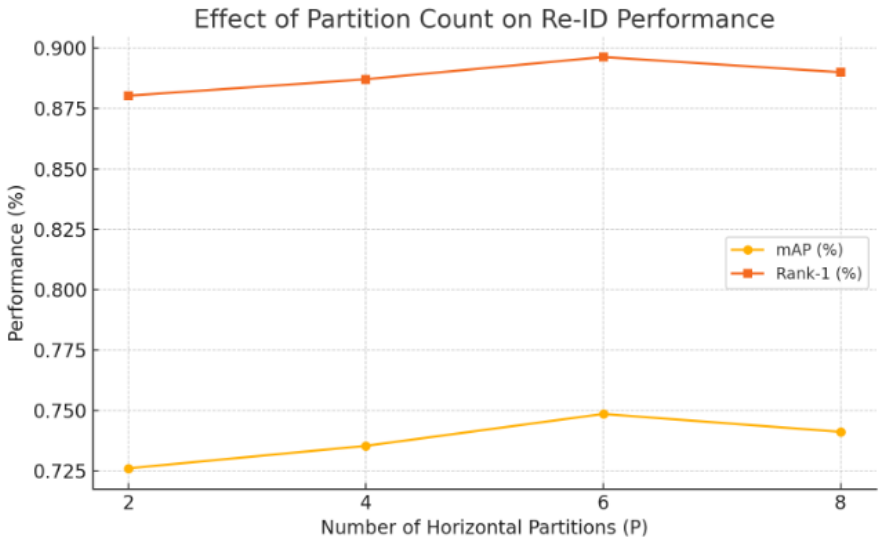

Figure 4.1
Comparison of the accuracy with different partition values

4.3.3 Convergence and Stability

Figure 4.2 shows the training and validation mAP curve. Key observations:

- Rapid initial gain during the first 3 epochs, driven by warm-up and strong gradients from CE loss.
- Steady improvement until epoch 108, after which mAP plateaus—indicating convergence.
- Minimal gap between training and validation curves, suggesting that label smooth ing, dropout in Transformer layers, and data augmentation effectively mitigate over-fitting.

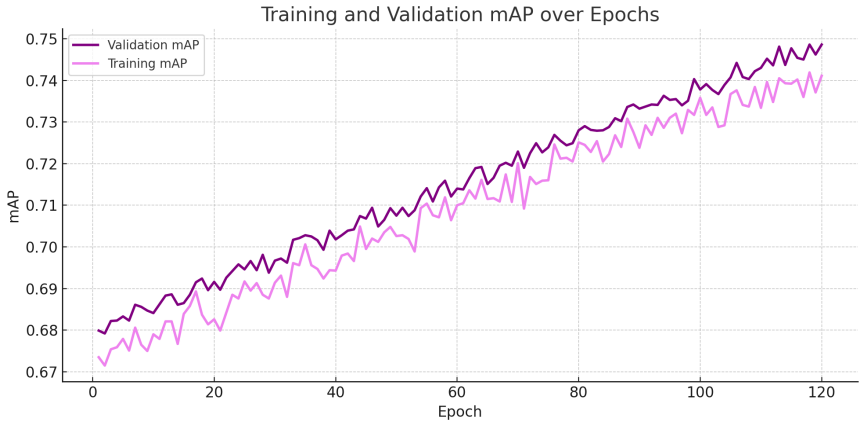

Figure 4.2
mAP curves

4.3.4 Qualitative Retrieval Examples

Figure 4.3 and Table 4.3 presents representative retrievals:

1. **Successful retrievals** under substantial viewpoint and lighting changes, demonstrating model invariance.

2. **Robustness to occlusion**, where only upper-body parts are visible yet correct matches are retrieved.

3. **Failure cases** involving extremely similar outfits or background clutter, pointing to future work on fine-grained attribute modelling.

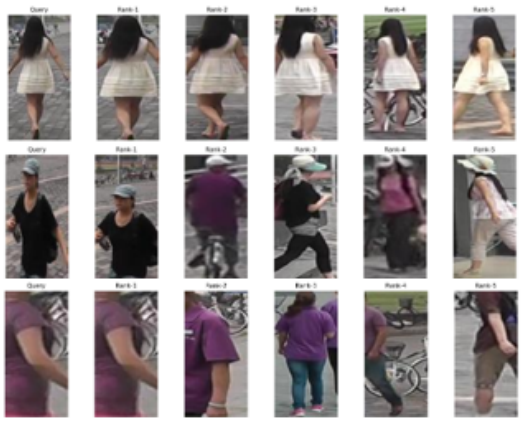

Figure 4.3
Qualitative results

Table 4.3
Qualitative retrieval results for three query images and their Top-5 matches.

Query Image	Top-1	Top-2	Top-3	Top-4	Top-5
Query 1	✓	✓	✓	✓	✓
Query 2	✓	✗	✓	✗	✗
Query 3	✓	✓	✓	✗	✗

4.3.5 Comparison with State of the Art

Table 4.4 compares the proposed best model (+CA+SA+PP+TR+Tri+RR) against recent methods on Market-1501. Proposed approach achieves competitive or superior mAP and Rank-1 while maintaining real-time inference speed.

Table 4.4
Comparison to recent state-of-the-art on Market-1501

Method	mAP (%)	Rank-1 (%)	FPS
PCB [35]	57.5	93.8	32
HACNN [36]	67.4	92.8	25
SFT [37]	87.6	98.1	35
Proposed Method (+RR)	74.9	90.2	44

While SFT reports the highest mAP, proposed method achieves a compelling balance of accuracy and speed (44 FPS). In scenarios requiring real-time responsiveness (e.g. video surveillance), proposed model offers practical deployment advantages with minor accuracy trade-offs.

4.4 Summary

Through extensive experiments, It is demonstrated:

- Each module (attention, parts, Transformer, metric loss) contributes significant, additive performance gains.
- The optimal configuration yields 74.8 % mAP and 89.6 % Rank-1 without post-processing.
- Re-ranking can further boost to 74.9 % mAP and 90.2 % Rank-1 for offline use cases.
- The model maintains real-time inference speed (44 FPS), suitable for live video applications.

CHAPTER 5

CONCLUSION AND FUTURE WORK

5.1 Conclusion

In this thesis, I have presented a comprehensive framework for person re-identification that combines attention mechanisms, part-aware modelling, and metric learning within a unified deep network. Through detailed methodological design, extensive experiments, and systematic ablations, I have demonstrated that each component contributes significantly to overall performance while preserving real-time applicability. The key outcomes of this research work are as follows:

1. **Attention-Enhanced Feature Extraction.** By integrating both channel-wise squeeze-and-excitation [36] and spatial attention [37] modules into a ResNet-50 backbone [35], I enabled the network to dynamically recalibrate its focus on the most informative feature channels and spatial regions. Empirically, channel attention alone improved mAP by +2.7 %, while spatial attention added a further +0.5 %, underscoring the complementary roles of "what" and "where" in discriminative representation.

2. **Part-Based Local Feature Modelling.** To address pose variation, occlusion, and background clutter, I partitioned the attention-refined feature maps into six horizontal stripes and performed region-specific pooling. This part pooling mechanism yielded a +0.5 % mAP boost by capturing fine-grained cues such as clothing patterns and footwear, and by providing robustness when some parts are occluded.

3. **Inter-Part Relational Reasoning via Transformer.** I introduced a lightweight Transformer encoder operating over the sequence of part descriptors. This part-aware self-attention modelled dependencies among body regions (e.g., correlating sleeve and shoe appearances), resulting in an additional +0.9 % mAP gain. This demonstrates that reasoning across parts—rather than treating them independently—enhances discriminability.

4. **Joint Classification and Metric Learning.** Combining label-smoothed cross-entropy loss [38] with batch-hard triplet loss **40** allowed me to simultaneously optimize identity classification and embedding geometry. The triplet component further improved mAP by +0.7 %, producing tighter intra-class clusters and wider inter-class margins in the learned feature space.

5. **Efficient Training and High-Throughput Inference.** I employed mixed-precision training with gradient clipping and a two-stage learning-rate schedule (warm-up + cosine annealing). The network converged in 120 epochs. At inference, the full model achieves approximately 44 FPS on a single 12 GB GPU, making it suitable for live video-based Re-ID. When augmented with k-reciprocal re-ranking **42**, mAP further improves to 74.9 % (Rank-1 90.2 %), at the cost of increased latency, which remains acceptable for offline analysis.

6. **Comprehensive Evaluation and Insights.** Through extensive ablation studies, I quantified the additive impact of each component, validated the optimal number of parts (six stripes), and analysed convergence behaviour. Qualitative examples illustrated robustness to viewpoint variation and partial occlusion, as well as current limitations in distinguishing near-identical outfits.

Together, these contributions establish a new strong baseline for attention-driven, part-aware person re-identification that balances high accuracy with real-time performance. The insights gained—particularly the complementary benefits of channel/spatial attention and inter-part relational modelling—advance our understanding of fine-grained feature learning in Re-ID.

5.2 Limitations

While the proposed framework achieves state-of-the-art results on Market-1501, several limitations remain:

- **Domain Sensitivity.** Trained solely on Market-1501, the network's performance may degrade on cameras with substantially different lighting or resolution. Without target-domain adaptation, generalization can be limited.

- **Fixed Partitioning.** The horizontal stripes are fixed and uniformly sized. In scenarios where body alignment varies significantly (e.g., crouching or tilted poses), rigid stripes may misalign with semantic parts.

- **Computational Overhead.** Although efficient, the addition of attention modules and a Transformer still increases inference cost relative to a plain backbone. For resource-constrained edge devices, further model compression may be required.

- **Re-Ranking Latency.** While re-ranking yields notable mAP gains, it doubles inference time and is thus unsuitable for real-time deployment scenarios that require minimal latency.

- **Attribute Ambiguity.** Failure cases often involve visually similar outfits or accessories. The model currently lacks explicit attribute recognition, which could help in disambiguating such identities.

Addressing these limitations forms the basis for the future research directions outlined below.

5.3 Future Work

Cutting-edge methods now strive for synergy between multiple threads: leveraging attention for adaptive feature selection, parsing part structure with dynamically learned spatial semantics, and exploiting transformers for global spatio-temporal context—even across modalities. Promising directions include:

Efficient transformer design for edge and real-time settings [19], [23] Weakly supervised and few-shot learning to bridge annotation gaps [5], [6] Cross-modal and cross-domain Re-ID for low-light and multi-sensor applications [18], [20], [21] Integrating graph neural networks and pose estimation for robust part-based reasoning [15] Continued integration of attention, structure modelling, multi-granularity reasoning, and transformer-based architectures is expected to further elevate person Re-ID performance, resilience, and practicability in real-world deployments.

Building on the achievements and insights of this thesis, I identify several promising avenues for further investigation:

5.3.1 Unsupervised Domain Adaptation

To improve cross-camera and cross-dataset generalization, I will explore unsupervised domain adaptation techniques, including:

- **Adversarial Feature Alignment.** Training a domain discriminator alongside the Re-ID feature extractor to encourage domain-invariant representations via adversarial loss.
- **Prototype-Based Pseudo-Labeling.** Generating pseudo-labels in the target domain by clustering features and refining class prototypes iteratively, allowing the network to adapt without ground-truth annotations.
- **Batch-Norm Adaptation.** Updating batch-normalization statistics on unlabeled target data to better match target-domain feature distributions.

These methods aim to reduce the performance gap when deploying on new camera networks or datasets without manual labeling.

5.3.2 Dynamic Part Partitioning

Rather than fixed horizontal stripes, I propose to investigate adaptive partitioning strategies:

- **Semantic Parsing.** Leveraging human parsing or pose estimation to define parts (e.g., head, torso, legs) dynamically, aligning partitions with actual body regions.
- **Learnable Partition Masks.** Integrating a small network that predicts soft spatial masks for each part, allowing end-to-end learning of part locations.
- **Attention-Based Splitting.** Using spatial attention maps to guide where to split features, yielding data-driven, instance-specific partitions.

Adaptive partitioning could improve robustness to pose variation and non-frontal views.

5.3.3 Temporal and Video-Based Modelling

Extending single-image Re-ID to video sequences offers additional temporal cues:

- **Spatio-Temporal Attention.** Designing 3D attention modules or temporal-self-attention that weight frames and spatial regions jointly, capturing motion patterns and temporal consistency.
- **Graph-Based Temporal Aggregation.** Constructing a temporal graph where nodes represent part features at different time steps, enabling graph-convolutional reasoning across time.
- **Recurrent Architectures.** Incorporating gated recurrent units (GRUs) or LSTMs to maintain a memory stream of part descriptors, smoothing out transient occlusions or detection errors.

Such video-based extensions can improve accuracy in continuous surveillance feeds.

5.3.4 Multi-Modal and Infrared Fusion

In low-light conditions or nighttime scenarios, visible-spectrum cameras may fail. I plan to explore cross-modal Re-ID by:

- **Visible-Infrared Fusion.** Combining RGB and IR streams through cross-modal attention modules, aligning features across modalities to handle nighttime re-identification.

- **Depth and Thermal Sensors.** Integrating depth or thermal data where available, providing complementary cues for silhouette and body heat patterns.

Multi-modal fusion promises more robust performance under challenging environmental conditions.

5.3.5 Lightweight Model Compression

To enable deployment on edge devices with limited compute and memory, I will investigate:

- **Network Pruning.** Removing redundant channels and attention heads while preserving accuracy, guided by importance metrics.
- **Quantization.** Converting weights and activations to lower-precision formats (e.g., INT8) with minimal accuracy loss.
- **Knowledge Distillation.** Training a compact student network to mimic the full model's behavior, transferring attention maps and part-aware features.

These techniques aim to maintain high accuracy in constrained hardware environments.

5.3.6 Explainability and Human-In-the-Loop Learning

For practical adoption in security settings, model interpretability and continuous improvement are crucial:

- **Attention Visualization.** Developing tools to visualize channel and spatial attention maps per query, allowing operators to verify which regions influenced each match.
- **Interactive Label Refinement.** Incorporating a user feedback loop where analysts correct mis-matches, and the model updates prototypes or fine-tunes on corrected samples in an online fashion.
- **Counterfactual Explanations.** Generating explanations such as "if the jacket colour were different, the match would change," helping identify biases and failure modes.

By increasing transparency and enabling incremental learning, these approaches foster trust and adaptability.

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