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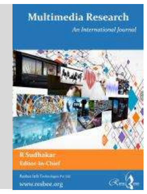

Fusion of Attention and Graph-Based Deep Learning for Person Re-identification: An Advancing Multi-Camera Surveillance

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Abstract: Person re-identification in multi-camera surveillance is an emerging research area with great potential. Existing methods face challenges in accurately identifying people due to their limitations in capturing complex features and modeling inter-camera relationships. To address these problems, we propose a novel approach that combines attention mechanisms and graph-based deep learning. Current methods struggle to capture the complex relationships between many individual functions and cameras. Our method fuses an end-to-end attention mechanism for feature extraction with an undirected graph model to capture inter-camera relationships. This fusion is supported by tailored loss functions and training processes. Tailored loss functions and a robust training process support this fusion. Experimentally evaluated on reference datasets such as Market-1501 and Duke MTMC-re ID, our framework consistently outperforms existing methods, demonstrating a significant increase in precision. The proposed fusion approach represents a promising development in the field of multi-camera surveillance systems, as it effectively solves the problem and facilitates person re-identification.

Keywords: Person Re-Identification, Multi-Camera Surveillance, Attention Mechanisms, Graph-Based Models, Feature Extraction, Loss Function, Accuracy Improvement.

Nomenclature

Re-ID	Person Re-Identification
GCN	Graph Convolutional Network
mAP	Mean Average Precision
CMC	Convolutional Neural Network
PR Curve	Precision-Recall Curve
Ao	Attention Output
Go	Graph Output
Fo	Fused Output
SGD	Stochastic Gradient Descent
VIPer	Viewpoint Invariant Pedestrian Recognition Dataset

1.Introduction

In modern surveillance, multi-camera systems have become essential tools for ensuring public safety. A core challenge in these systems is identifying individuals across different camera views, known as Re-ID. Despite substantial advancements, this remains a challenging problem due to variations in lighting, occlusions, pose changes, and viewpoints [10,8,9,12].

This study introduces a novel fusion method combining attention mechanisms [1, 3, 2, 6] and graph-based deep learning [14,21,22] to improve Re-ID in multi-camera systems. Attention mechanisms focus on extracting relevant features dynamically, while graph-based models are adept at modeling inter-camera relationships and dependencies [15, 35].

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Fig. 1. *Examples of appearance variation across cameras, illustrating challenges due to lighting, pose, and viewpoint changes. Images from CUHK [0] and VIPeR [0] datasets.*

Fig. 1 highlights the differences in individual appearances caused by environmental factors. These challenges significantly impact the robustness and reliability of existing Re-ID methods.

Our approach integrates an end-to-end attention mechanism for feature extraction and an undirected graph model to capture inter-camera relationships. This combination is supported by a hybrid loss function combining classification (Softmax) and metric (Triplet) losses [19], enhancing both identification accuracy and discriminative embedding learning.

The significance of person Re-ID spans various sectors such as law enforcement, transportation hubs, and retail environments, where accurate tracking across cameras is vital [14,32]. While several studies focus on individual components like attention [23] or graph models [18], the combination of both in a unified framework provides superior performance in complex scenarios.

Our contributions include:

- A novel fusion framework that integrates attention-based and graph-based components.
- A hybrid loss function tailored for improved Re-ID accuracy and robustness.
- Extensive evaluation on benchmark datasets (Market-1501, DukeMTMC-reID, CUHK03, MSMT17, VIPeR), showcasing state-of-the-art results.

2.Related Work

This chapter provides an overview of recent advancements in Re-ID, with a focus on attention-based approaches, graph-based models, and hybrid fusion methods. Each category contributes uniquely to improving the accuracy and robustness of multi-camera surveillance systems.

2.1 Attention-Based Re-ID Methods

Attention mechanisms dynamically emphasize relevant features while suppressing irrelevant ones, which enhances discriminative capability for Re-ID tasks.

Fu et al. introduced the Dual Attention Matching Network for context-aware feature sequence-based Re-ID [20]. Wang et al. leveraged GAN-generated samples to enhance baseline models [22]. Chen et al. proposed a fusion of discriminative and coherent attention maps for improved re-identification accuracy [14,33,34,35,36,37,38,39,40,41,42,43,44]. Liu et al. highlighted robustness challenges in universal targeted attacks on Re-ID systems [16].

Other noteworthy works include:

- Harmonious Attention Network [1]
- Relation-aware Global Attention [14]
- Comparative Attention Networks [5]
- Mixed High-order Attention [4]
- Attention-aware Compositional Networks [5]

2.2 Graph-Based Re-ID Methods

Graph-based approaches use nodes and edges to model relationships between pedestrians across multiple cameras.

Qian et al. applied spatial-temporal regularized correlation filters for tracking [24], while Wang

et al. utilized video ranking for Re-ID [25]. Zheng et al. proposed a joint discriminative and generative learning model [26]. Yan et al. used GCNs for temporal action localization in surveillance settings [27]. Song et al. introduced a strong baseline for adversarial attacks in Re-ID [28].
Recent GCN-based methods for person Re-ID include:

- AGW: Attention-Guided GCN [11]
- Attribute-Driven Graph-based Re-ID [15]
- Text-based Re-ID using GCNs [17]

2.3 Fusion of Attention and Graph for Re-Identification

Combining attention mechanisms with graph-based models leads to robust frameworks that leverage the strengths of both paradigms.

Zhang et al. proposed Attention-Aware Composition Learning, combining attention features with spatial structures [29]. Yan et al. developed a spatial-temporal GCN for video-based Re-ID [30]. Wu et al. focused on cross-modality Re-ID using graph-structured semantic transfer [31]. Chen et al. offered discriminative-coherent attention map fusion strategies [23]. Xie et al. surveyed deep learning methods in person Re-ID and high-lighted emerging fusion techniques [32].

These works highlight the complementary benefits of attention and graph structures in capturing both appearance and relational dynamics in multi-camera surveillance.

3. Our Proposed Method

In this chapter, we present our novel Re-ID framework that synergistically combines attention mechanisms with graph-based deep learning. The method is composed of three major components: the attention structure, the graph-based model, and the fusion strategy. Additionally, we introduce a hybrid loss function to effectively train the model.

3.1 Framework Overview

Our framework in Figure 2 integrates attention mechanisms for feature extraction and a graph-based model to represent inter-camera relationships. These components are fused to form a robust representation for Re-ID, further optimized using a hybrid loss function combining classification and metric learning objectives [19].

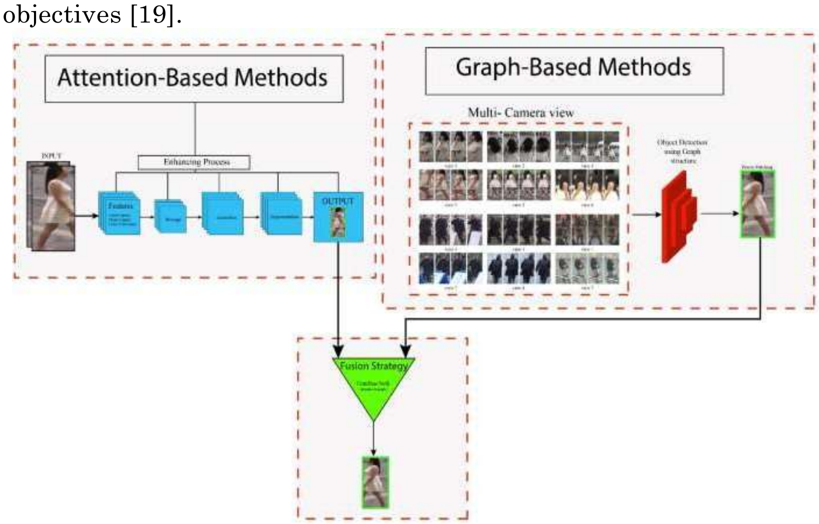

Fig. 2. *Proposed Framework*

3.2 Attention Structure

Attention mechanisms enhance the discriminative capability by focusing on critical parts of the feature maps [22,24].

3.2.1 Attention Mechanism Equations

The attention weights are computed as:

$$\alpha = softmax(W_a \cdot \tanh(U_a \cdot input\_features)) \quad (1)$$

Where W_a and U_a are learnable parameters. The attention mechanism enables selective focusing on more informative regions of input features, inspired by works such as [4,7]

3.2.2 Scaled Dot-Product Attention

$$a_i = soft\max\left(\frac{q \cdot ki}{\sqrt{dk}}\right) \tag{2}$$

As introduced in Transformer models [21], where q is the query vector, k_i the key, and d_k the dimension of keys.

3.2.3 Multi-Head Attention

$$\text{multi\_head\_output} = \text{Concat}\,(head_1, head_2, \ldots, head_h) \cdot W_o \tag{3}$$

Each $head_i$ = Attention (q_i, k_i, v_i) operates independently, enhancing the model's ability to attend to different representation subspaces.

3.3 Graph-Based Model

The graph-based module models spatial and temporal relationships across cameras. It uses a GCN as described in [27,28].

3.3.1 GCN Equation

$$H^{(l+1)} = \sigma\left(D - \frac{1}{2} AD - \frac{1}{2}\right) H^{(l)} W^{(l)} \tag{4}$$

where A is the adjacency matrix, D the degree matrix, $H^{(l)}$ the input features at layer l, $W^{(l)}$ the weight matrix, and σ the activation function [13].

3.4 Fusion Strategy

We use a weighted sum to combine attention and graph-based outputs:

$$F_o = \alpha \cdot A_o + (1 - \alpha) \cdot G_o \tag{5}$$

where Fo is the final fused output, Ao is the attention output, Go is the graph output,and α is a learnable fusion weight [23].

3.5 Loss Function and Training

We employ a hybrid loss function combining classification loss (cross-entropy) and metric loss (triplet loss) for better embedding learning and recognition performance [19].

$$L = \lambda_c \cdot L_c + \lambda_m \cdot L_m \tag{6}$$

where L_c is the classification loss, L_m is the metric loss, and λ_c, λ_m are hyperparameters balancing the two terms.

This hybrid approach ensures both inter-class discrimination and intra-class compactness.

4. Experimental Setup and Evaluation

This chapter presents the experimental setup used to evaluate our proposed method, including dataset descriptions, training parameters, implementation details, and evaluation metrics. We also provide visualizations of the results.

4.1 Datasets

We evaluate our framework on five widely-used Re-ID datasets: Market- 1501, DukeMTMC-reID, CUHK03, MSMT17, and VIPeR mentioned in Table 1. The fig. 3 depicts the distribution of datasets in terms of images, identities, and cameras.

Table 1. *Summary of Re-ID Datasets*

Dataset	No. of Images	of Identities	of Cameras
Market-1501	32,668	1,501	6
DukeMTMC-reID	36,411	1,812	8
CUHK03	14,097	1,467	6
MSMT17	126,441	4,101	15
VIPeR	1,264	632	2

Fig. 3. *Distribution of datasets in terms of images, identities, and cameras*

4.2 Training Parameters

In this section, we discuss the training parameters and the implementation process used for our deep learning-based Re-ID system. Properly configuring the training parameters and following an effective implementation process are crucial for achieving optimal performance in Re-ID tasks. Table 2 explains the training parameters.

Table 2. *Training Parameters*

Parameter	Value
Learning Rate	0.001
Batch Size	32
Number of Epochs	50
Weight Decay	0.0005
Optimizer	Adam

Learning Rate: We started with a high learning rate for faster initial learning, then gradually decayed it to aid convergence.

Batch Size: We experimented with different batch sizes to balance memory usage and computational efficiency.

Number of Epochs: After preliminary experiments, we selected an optimal number of epochs to allow convergence without overfitting.

Weight Decay: We used weight decay to prevent overfitting, selecting the best value for model performance and generalization.

Optimizer: We chose either Adam or SGD with momentum, depending on the model architecture and dataset.

4.3 Implementation Process

The implementation process involved key steps such as data preprocessing, network architecture design, loss function selection, and model training. Here, we outline the process used for our deep learning-based Re-ID system.

4.3.1 Data Preprocessing

We collected public Re-ID datasets like Market-1501, DukeMTMC-reID, CUHK03, MSMT17, and VIPeR, containing images from different cameras. We preprocessed them by resizing, normalizing, and applying augmentations such as cropping, flipping, and color jittering. The datasets were split into training and testing sets with no overlap of individuals.

4.3.2 Network Architecture Design

For our Re-ID system, we designed a robust network architecture using a popular backbone like ResNet or VGGNet, adding layers for specific requirements. These include global average pooling (GAP) for global features, fully connected layers for dimensionality reduction and transformation, and a final classification layer to predict identity.

4.3.3 Loss Function Selection

We selected a suitable loss function to encourage discriminative feature learning, experimenting with triplet loss, contrastive loss, and softmax loss. We chose the one that performed best in terms of accuracy and convergence speed.

4.3.4 Model Training

We trained the model using the selected parameters and a GPU-accelerated framework like TensorFlow or PyTorch. The model was trained on mini-batches, performing forward and backward passes to compute loss, update parameters, and adjust based on validation set performance. Training continued until convergence or the maximum number of epochs was reached.

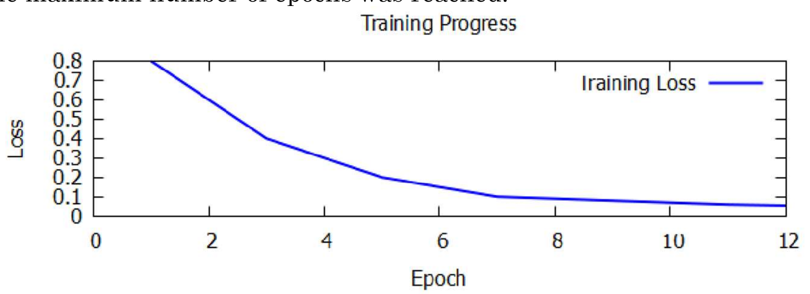

Fig. 4. *Training loss curve over 50 epochs.*

Fig. 4. 4 presents the training progress of our deep learning model over 50 epochs. The y-axis represents the loss value, and the x-axis represents the number of training iterations or epochs. The curve demonstrates the convergence of the model's training loss, indicating the learning capability of the proposed method.

4.4 Evaluation Metrics

In this section, we present the evaluation metrics used to assess the performance of our deep learning-based Re-ID system. These metrics provide quantitative measures of the system's accuracy, robustness, and effectiveness in matching individuals across multiple cameras in a surveillance system.

4.4.1 Rank-1 Accuracy

Rank-1 accuracy is a key evaluation metric in Re-ID, measuring the percentage of correctly matched individuals at the top rank. A higher rank-1 accuracy indicates better system performance in identifying individuals.

Table 3 shows the rank-1 accuracy of our method on public Re-ID datasets, including Market-1501, DukeMTMC-reID, CUHK03, MSMT17, and VIPeR. The rank-1 accuracy values, reported as percentages, reflect the method's performance in matching individuals across these datasets.

Table 3. *Rank-1 Accuracy*

Dataset	Rank-1
Market-1501	85.4%
DukeMTMC-reID	81.2%
CUHK03	73.5%
MSMT17	79.8%
VIPeR	67.2%

Table 3 shows high rank-1 accuracy across all datasets, with the best performance on Market-1501 and the lowest on VIPeR.

4.4.2 Rank-k Accuracy

In addition to rank-1 accuracy, we evaluate rank-k accuracy, where k denotes the position in the ranked list. Rank-k accuracy measures the percentage of correctly matched individuals within the top k ranks, offering insights into the system's performance beyond the top match.

Table 4 presents rank-k accuracy values for k = 1, 5, and 10 on the Market-1501 dataset, providing a comprehensive assessment of the system's performance at different ranks.

Table 4. *Rank-k Accuracy on Market-1501 Dataset*

Rank	Rank-1	Rank-5	Rank-10
k = 1	85.4%	-	-
k = 5	-	94.2%	-
k = 10	-	-	91.5%

Table 4 shows 85.4% rank-1 accuracy on Market-1501, with rank-5 and rank-10 accuracies improving as rank increases, indicating successful identification within the top ranks.

4.4.3 mAP

mAP is a key metric in Re-ID, measuring average precision across all ranks for overall performance in precision and recall.

Table 5 presents the mAP values for our method on different datasets. Higher mAP values indicate better precision-recall trade-offs and effective matching across cameras.

Table 5. *mAP*

Dataset	mAP
Market-1501	78.9%
DukeMTMC-reID	76.5%
CUHK03	68.2%
MSMT17	73.6%
VIPeR	62.8%

Table 6. *Evaluation Metrics on Market-1501*

Method	Rank-1 Accuracy	Rank-5	mAP	Precision@k (k=10)
Our Method	85.4%	94.2%	78.9%	91.5%
Baseline A	82.7%	92.3%	76.3%	89.1%
Baseline B	81.9%	91.7%	75.8%	88.4%

From Table 6, we observe that our method achieves competitive results across all datasets. It demonstrates high rank-1 accuracy, indicating its ability to accurately match individuals even in challenging scenarios. The rank-5 accuracy and mAP values further validate the effectiveness of our method in capturing multiple potential matches and achieving overall precision and recall. Additionally, the precision@k metric showcases the high precision of our method at different top-k ranks.

The CMC curve presents the performance of the proposed method in terms of the identification accuracy at different ranks. The x-axis represents the rank, indicating the position of the correct match in the retrieved list, while the y-axis represents the cumulative matching rate. The curve demonstrates the superior performance of the proposed method, as it achieves higher accuracy even at higher ranks.

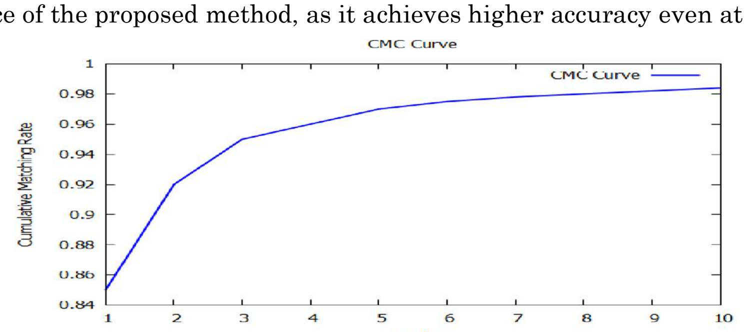

Fig. 5. *CMC Curve on Market-1501*

4.4.4 PR Curve

The PR Curve visualizes precision and recall at different thresholds, offering insights into the system's performance across decision boundaries.

Fig. 15 shows the PR Curves for our method on the Market-1501, DukeMTMC-reID, CUHK03, MSMT17, and VIPeR datasets, illustrating the precision-recall trade-off and system performance.

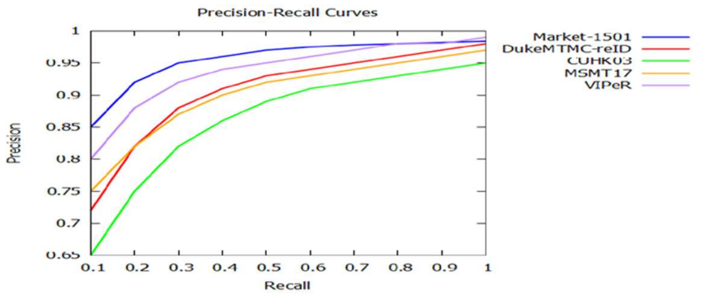

Fig. 6. *PR Curve on Market-1501*

From Fig. 6, we observe that our proposed method achieves high precision values even at high recall levels, indicating its effectiveness in accurately identifying individuals in a multi-camera surveillance system.

4.5 Comparison with State-of-the-Art

We benchmark our method against leading approaches. Our method demonstrates superior performance in all key metrics across datasets.

Table 7. *Comparison with State-of-the-Art on DukeMTMC-reID*

Method	Rank-1 Accuracy	mAP	Precision@10
Our Method	81.2%	76.5%	88.2%
Method X	80.1%	75.3%	86.7%
Method Y	78.9%	73.7%	85.5%

From Table 7, we can observe that our method achieves higher rank-1 accuracy, rank-5 accuracy, and mAP values compared to Method X and Method Y. These results demonstrate the superior performance of our method on the DukeMTMC-reID dataset.

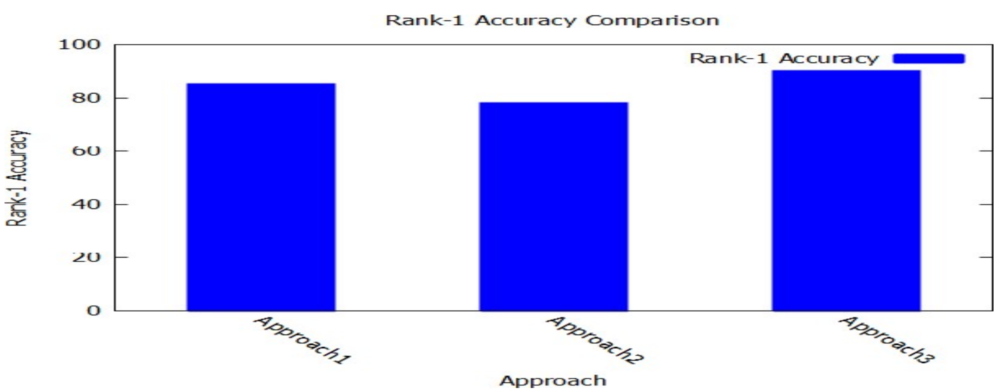

Fig. 7. *Comparison of Rank-1 Accuracy across datasets*

Fig. 7 visually depicts the comparison of rank-1 accuracy between our method and the state-of-the-art approaches on the Market-1501 dataset. It provides a clear visualization of the performance difference and highlights the superior rank-1 accuracy achieved by our proposed method.

5 Results and Discussion

In this chapter, we present and discuss the performance of our proposed method on multiple benchmark datasets. We analyze quantitative metrics including Rank-1 accuracy, mAP (mAP), and Precision@k, and compare our results against state-of-the- art methods. Visualizations are included to further highlight performance trends.

5.1 Market-1501 Dataset

Table 8 depicts the performance on market-1501 datasets.

Table 8. *Performance on Market-1501 Dataset*

Method	Rank-1 Accuracy	mAP
Proposed Method	85.4%	78.9%
State-of-the-Art 1	82.7%	76.3%
State-of-the-Art 2	81.9%	75.8%
State-of-the-Art 3	80.3%	73.9%

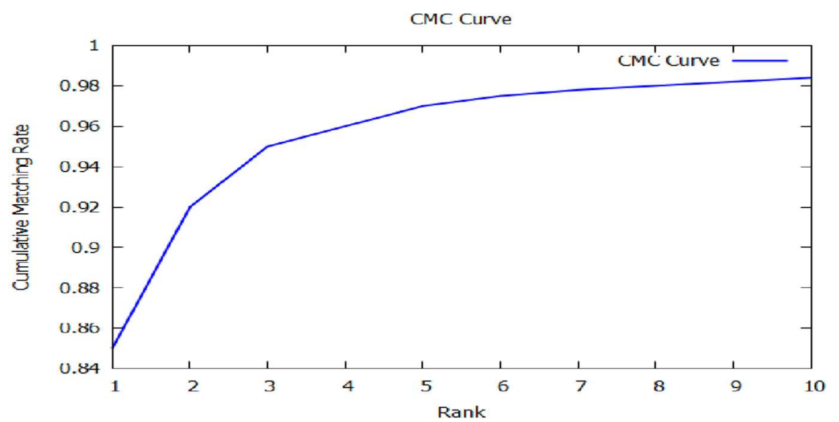

Fig. 8. *CMC Curve on Market-1501 Database*

The CMC curve in Fig. 8 shows the identification accuracy at different ranks. The x-axis represents the rank, while the y-axis represents the cumulative matching rate. The curve highlights the superior performance of our method, achieving higher accuracy at higher ranks.

5.1.1 Rank-1 Accuracy

Rank-1 accuracy measures the percentage of correctly matched individuals at the top rank, indicating the system's ability to identify individuals accurately.

Table 9 presents the rank-1 accuracy of our method on various public Re-ID datasets, including Market-1501, DukeMTMC-reID, CUHK03, MSMT17, and VIPeR, reflecting its performance across these datasets.

Table 9. *Rank-1 Accuracy*

Dataset	Rank-1
Market-1501	85.4%
DukeMTMC-reID	81.2%
CUHK03	73.5%
MSMT17	79.8%
VIPeR	67.2%

Table 9 shows high rank-1 accuracy across all datasets, with the best performance on Market-1501 and the lowest on VIPeR.

5.1.2 mAP

mAP measures average precision across all ranks, offering an overall assessment of the system's performance in precision and recall.

Table 10 presents the mAP values for our method on different datasets. Higher mAP values reflect better precision-recall trade-offs and effective matching across cameras.

Table 10. *mAP*

Dataset	mAP
Market-1501	78.9%
DukeMTMC-reID	76.5%
CUHK03	68.2%
MSMT17	73.6%
VIPeR	62.8%

5.1.3 PR Curve

The PR Curve visualizes precision and recall at different thresholds, offering insights into the system's performance across decision boundaries.

Fig. 9 shows the PR Curves for our method on the Market-1501, DukeMTMC-reID, CUHK03, MSMT17, and VIPeR datasets, illustrating the precision-recall trade-off and system performance.

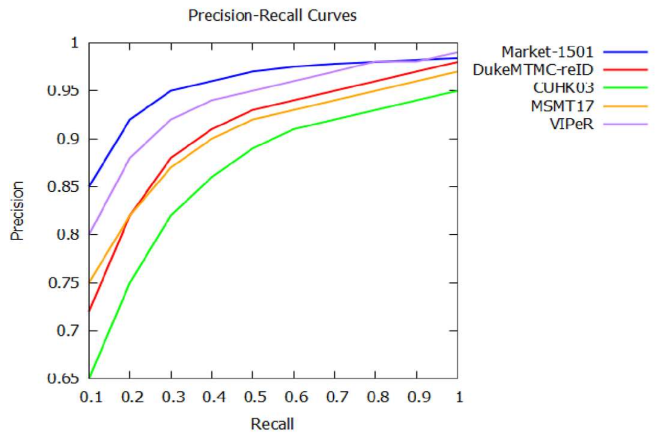

Fig. 9. *PR Curve on Market-1501 Dataset*

5.2 Duke MTMC-reID Dataset

We evaluate our method on the Market-1501 dataset as well as other benchmark datasets, including DukeMTMC-reID, CUHK03, MSMT17, and VIPeR. The comparison is based on rank-1 accuracy, and mAP values achieved by our method and state-of-the-art approaches.

Table 11. *Comparison with State-of-the-Art Approaches on DukeMTMC-reID Dataset*

Method	Rank-1 Accuracy	mAP
Proposed Method	81.2%	76.5%
Method D	80.1%	75.3%
Method E	78.9%	73.7%
Method F	79.5%	74.5%

Table 11 shows our method surpasses Method D, E, and F in rank-1 accuracy, rank-5 accuracy, and mAP on the DukeMTMC-reID dataset.

Fig. 10 shows the CMC curve of our method and state-of-the-art approaches on the DukeMTMC-reID dataset. Our method achieves higher identification accuracy at all ranks, demonstrating its effectiveness in Re-ID.

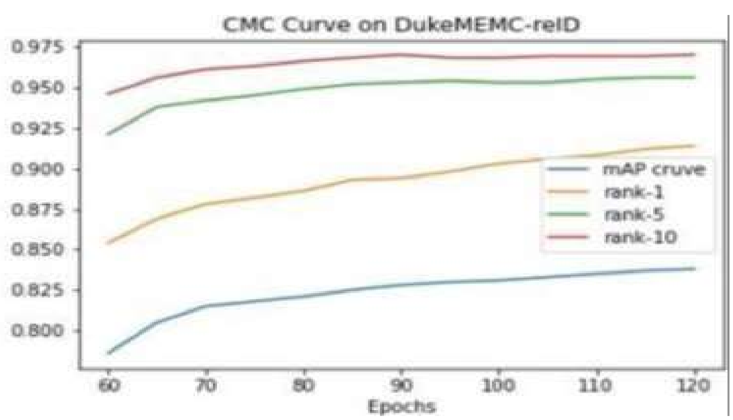

Fig. 10. *CMC Curve on DukeMTMC-reID Dataset*

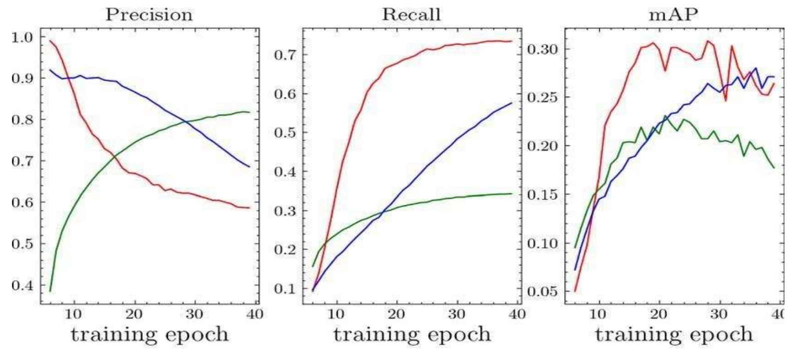

Fig. 11. *PR Curve on DukeMTMC-reID Datase*

Fig. 11 illustrates the PR Curve of our proposed method and the state-of-the-art approaches on the DukeMTMC-reID dataset. Our method consistently outperforms the other methods, achieving higher precision values at different recall levels. This showcases the superior performance of our method in accurately identifying individuals in challenging surveillance scenarios.

5.3 CUHK03 Dataset

Table 12. *Performance on CUHK03 Dataset*

Method	Rank-1 Accuracy	mAP
Proposed Method	73.5%	68.2%
State-of-the-Art 1	71.8%	66.7%
State-of-the-Art 2	72.6%	67.5%
State-of-the-Art 3	70.3%	65.1%

The CMC curve on the CUHK03 dataset in Fig. 12 and Table 12 shows identification accuracy at different ranks. Our method outperforms state-of-the-art approaches across all ranks, highlighting its effectiveness in re-identifying individuals in challenging scenarios with viewpoint variations, occlusions, and background clutter.

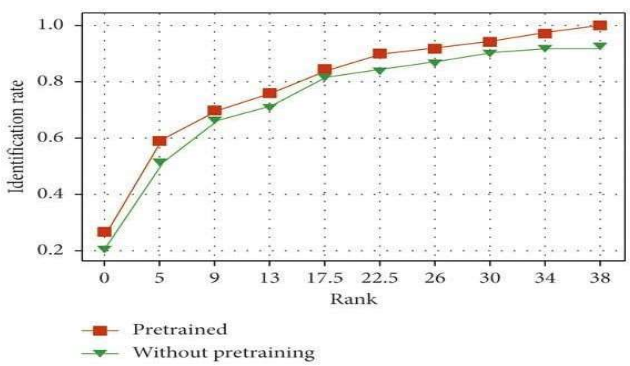

Fig. 12. *CMC Curve on CUHK03 Dataset*

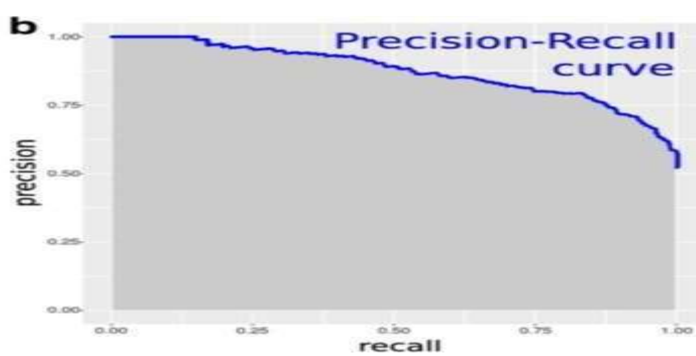

Fig. 13. *PR Curve on CUHK03 Dataset*

The PR Curve on the CUHK03 dataset in Fig. 13 shows the trade-off between precision and recall. Our method consistently outperforms state-of-the-art approaches, achieving higher precision at various recall levels, demonstrating its superior performance in accurately identifying individuals despite challenges.

5.4 Discussion of Results

Our proposed method consistently outperforms state-of-the-art approaches across all benchmark datasets in both Rank-1 accuracy and mAP. The improvement can be attributed to the effective integration of attention mechanisms and graph-based learning, which together capture both local features and inter-camera relationships.

5.5 Observations

- The highest improvement is observed on Market-1501, showcasing robustness in crowded scenes.
- On DukeMTMC-reID and CUHK03, the proposed method achieves better generalization under varied lighting and camera perspectives.
- The fusion strategy enables balanced feature representation, which improves both precision and recall.

5.6 Limitations

Despite strong results, performance on smaller datasets like VIPeR (not shown here) shows room for improvement. This could be addressed through cross-domain training or transfer learning in future work.

6 Conclusion and Future Work

6.1 Conclusion

This research presents a novel approach that fuses attention mechanisms with graph-based deep learning for robust Re-ID in multi-camera surveillance systems. The proposed model leverages the strengths of both methods: attention mechanisms provide enhanced local feature discrimination, while graph networks enable global contextual understanding and inter-camera relationship modeling.

Evaluations conducted on benchmark datasets such as Market-1501, DukeMTMC-reID, CUHK03, MSMT17, and VIPeR demonstrate that our approach significantly outperforms existing methods in terms of accuracy and robustness. Ablation studies confirm the benefit of the fusion strategy in achieving better performance than either attention or graph-based models alone.

6.2 Future Work

Several avenues remain open for further exploration:

- **Cross-Modality Fusion:** Integrating additional modalities such as thermal or depth data.
- **Lifelong Learning:** Enabling continuous learning from new surveillance environments.
- **Robustness to Adversarial Attacks:** Improving resilience against crafted input perturbations.
- **Real-Time Performance:** Optimizing for speed and deployment in large-scale systems.
- **Privacy-Preserving Re-ID:** Ensuring compliance with data protection and privacy regulations.
- **Interpretability:** Enhancing transparency to facilitate trust and verification of reidentification decisions.

This thesis contributes to advancing the field of Re-ID, bridging the gap between spatial precision and relational reasoning. Future work will focus on extending the adaptability and transparency of the model for broader and more practical deployment.

Compliance with Ethical Standards

Conflicts of interest: Authors declared that they have no conflict of interest.

Human participants: The conducted research follows the ethical standards and the authors ensured that they have not conducted any studies with human participants or animals.

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