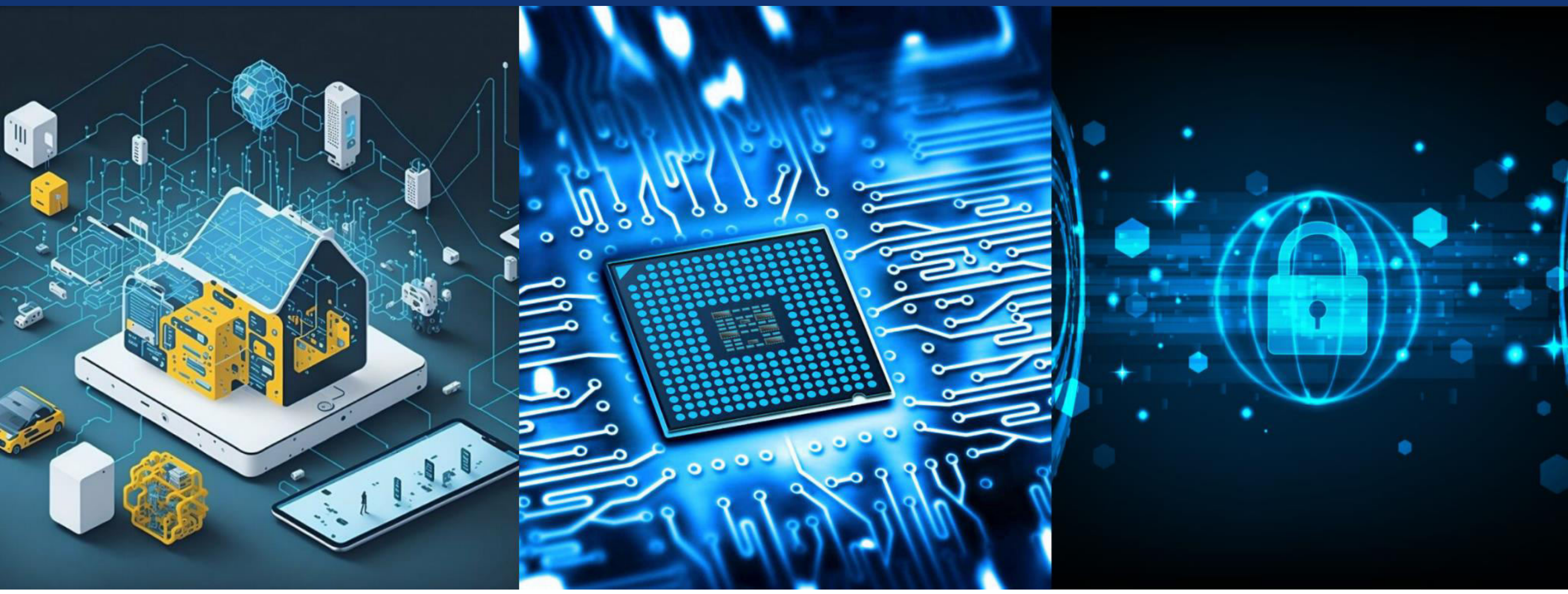
ISSN(O): 2320-9801
ISSN(P): 2320-9798



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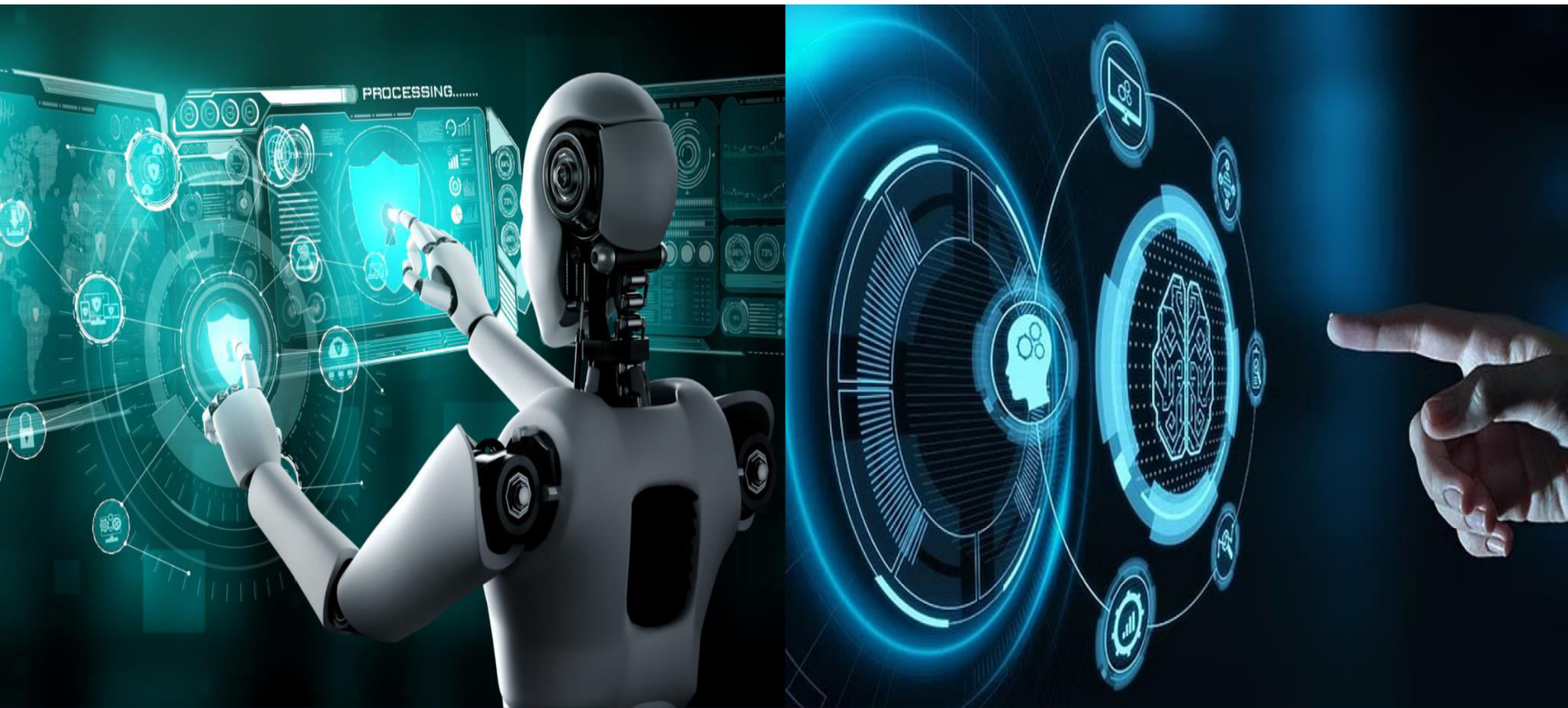

Impact Factor: 8.625

Volume 13, Issue 1, January 2025

© 2025 IJIRCCE | Volume 13, Issue 1, January 2025| DOI: 10.15680/IJIRCCE.2025.1301147

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International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

Person Re-identification using Unsupervised Learning and ResNets in Surveillance Systems: A Progressive Clustering-based Learning Approach

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ABSTRACT: Unsupervised re-identification of individuals is centered around the extraction of unique features without labeled data, which holds significant importance for implementations in surveillance. In the present study, we introduce Progressive Clustering-Based Learning (PCBL), an advanced framework derived from Progressive Unsupervised Learning (PUL) that enhances clustering and feature acquisition through a confidence-oriented sample selection methodology. Leveraging the architecture of ResNet-50, PCBL employs deep residual learning to facilitate robust feature extraction. In contrast to conventional approaches, PCBL identifies dependable samples predicated on model confidence, thereby mitigating noise and augmenting feature learning. The framework engages in an iterative process encompassing clustering, sample selection, and fine-tuning to optimize performance. Empirical evaluations conducted on three extensive re-ID datasets reveal that PCBL surpasses existing methodologies, attaining state-of-the-art performance metrics. Specifically, it realizes an enhancement in rank-1 accuracy of +5.6% and an increase in mAP of +4.2% on the Market-1501 dataset when compared to the original PUL framework. These findings underscore the efficacy of confidence-based selection in the amplification of feature learning pertinent to real-world surveillance systems.

KEYWORDS: Person re-identification; unsupervised learning; Progressive Clustering-Based Learning; Confidence-Based Sample Selection; ResNet-50.

I. INTRODUCTION

Person re-identification (re-ID) is the system that aims to attain the re-identity of a particular person captured by different surveillance cameras. It is a fundamental task in computer vision, enabling the tracking of individuals across non-overlapping camera views in complex environments such as airports, shopping malls, and urban streets [1]. Person Re-ID has gradually come into our sight, with the advancement and development of science and technology. The earliest person Re-ID method was developed based on image data, which involve analyzing and comparing pedestrian images to determine the identity or Re-ID of individuals across different scenes. This technique has a wide range of applications in the fields of surveillance, intelligent transport, and security. However, image-based person Re-ID methods face some challenges, such as pose change, view angle change, and occlusion in a single image, which limit its accuracy and robustness in real scenes. [2]

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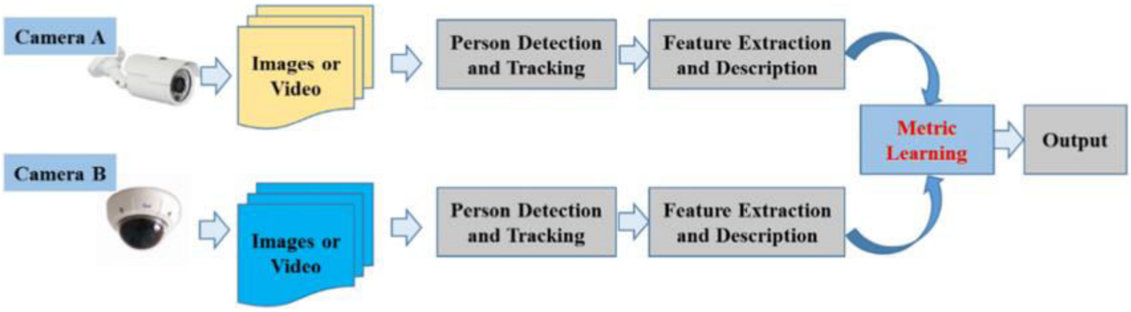

Figure 1: Flow chart illustrating the process of person re-identification, including feature extraction, clustering, and matching across camera views.

Person re-identification (re-ID) constitutes a pivotal framework engineered to recognize individuals across disparate surveillance systems, thereby serving a crucial function in applications pertaining to public safety, intelligent transportation, and security oversight. With technological advancements, re-ID methodologies have progressed from primitive image-based techniques, which depended on the analysis and comparison of pedestrian visuals, to more intricate paradigms that harness the capabilities of deep learning. Notwithstanding its extensive applications, conventional image-based re-ID techniques encounter fundamental constraints, such as variations in pose, discrepancies in viewing angles, and occlusions [3],[4], which impede their precision and resilience in practical scenarios. These challenges have catalyzed the innovation of enhanced methodologies, including deep learning architectures such as ResNets, which have markedly augmented the efficacy and scalability of re-ID systems. As the exigency for precise and efficient re-ID methodologies continues to escalate, the domain remains a vibrant sphere of inquiry, with persistent endeavors aimed at addressing its complexities and improving its practical applicability.

Common Challenges of Person Re-ID

In spite of the advancements achieved in person re-identification (re-ID) through the application of deep learning techniques, numerous challenges endure in practical implementations. A predominant concern is the inconsistency in appearance across various camera perspectives, influenced by elements such as illumination, camera orientations, and focal lengths, which can impede accurate identification. Occlusions, wherein segments of an individual are obscured, along with pose alterations, including variations in body posture, further exacerbate the complexities associated with re-ID, particularly in densely populated environments.

An additional obstacle lies in the dependence on extensive labelled-datasets for supervised learning, a process that is both time-intensive and impractical for large-scale systems that undergo frequent updates. This underscores the necessity for unsupervised learning methodologies that diminish reliance on labelled data [5].

Lastly, cross-domain discrepancies restrict the generalizability of re-ID models. Models that are trained on a specific dataset may encounter difficulties when applied to novel environments due to variations in camera technology, resolution, or environmental conditions, adversely impacting their performance when implemented in real-world contexts, such as transitioning from high-resolution to low-resolution cameras [6].

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Figure 2: Images showing the different challenges of person Re-identification.

A prominent obstacle in the domain of unsupervised re-identification (re-ID) methodologies, particularly those predicated on clustering techniques, lies in their vulnerability to erroneous clustering outcomes. The premise of clustering posits that analogous images will constitute distinct clusters for each individual; however, in practice, clustering algorithms frequently yield imprecise classifications owing to substantial variability and the presence of outliers[7]. For instance, images depicting the same individual may inadvertently be allocated to divergent clusters as a result of variations in pose or occlusions, whereas images representing different individuals may be erroneously grouped together due to similarities in attire or background. Such inaccuracies can compromise the entire training regimen, culminating in suboptimal feature learning and diminished re-ID efficacy. This underscores the imperative for the development of more resilient clustering methodologies capable of addressing noise inherent in real-world datasets.

Research Problem

The difficulties associated with person re-identification (re-ID) within genuine surveillance frameworks, particularly employing unsupervised techniques, are considerable. Although clustering-based strategies have achieved some advancements, they remain constrained by the prevalence of noisy clustering outcomes, attributable to factors such as variability in appearance, occlusions, and alterations in pose [8]. This situation engenders erroneous classifications, wherein images of the same individual may be situated in disparate clusters, or images of distinct individuals may be coalesced. These inaccuracies can propagate throughout the training continuum, thereby diminishing the quality of feature learning and re-ID performance [9].

Moreover, a substantial number of unsupervised techniques depend on proximity-based sample selection, whereby training instances are identified based on their distance from cluster centroids. While this approach is ostensibly straightforward, it neglects to account for the reliability of the selected instances, often incorporating noisy or outlier samples, which further compromises performance [10].

The reliance on extensive labeled datasets presents an additional challenge, as supervised methodologies necessitate labor-intensive and costly manual annotations, rendering them impractical for large-scale systems [4], [11]. Although unsupervised methodologies display greater scalability, they continue to encounter difficulties in achieving performance levels comparable to those of supervised techniques, primarily due to unreliable training instances and noise within clustering.

These challenges accentuate the necessity for a more robust and adaptive unsupervised re-ID methodology capable of addressing noisy clustering outcomes and selecting dependable training instances to enhance performance.

Research Motivation

The impetus for this research is derived from the escalating demand for precise and scalable person re-identification (re-ID) systems in actual surveillance contexts, such as public safety, crime deterrence, and crowd management [12].

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Although unsupervised re-ID methods present a promising alternative to supervised techniques by obviating the requirement for labeled data, their efficacy is frequently undermined by noisy clustering results and unreliable sample selection [13]. Mitigating these constraints is essential for the advancement of re-ID systems capable of functioning effectively within dynamic, large-scale environments. Through the proposal of Progressive Clustering-Based Learning (PCBL), this study aspires to reconcile the disparity between supervised and unsupervised re-ID performance, thereby facilitating the development of more robust and adaptable solutions to the challenges posed by real-world surveillance.

II. RELATED WORK

Our work is closely related to Progressive Unsupervised Learning (PUL) framework proposed by Fan et al. [14]. PUL addresses the challenge of unsupervised re-ID by iteratively clustering unlabeled samples and fine-tuning a pre-trained CNN model. While PUL has shown promising results, it relies on proximity-based sample selection, which can be noisy, especially in the early stages of training when clustering results are unreliable. To mitigate this issue, PUL incorporates a selection operation that initially fine-tunes the CNN on a small set of reliable samples near cluster centroids, gradually expanding to include more samples as the model improves. This self-paced learning approach allows PUL to progressively refine both the clustering and the CNN model, achieving competitive re-ID accuracy on large-scale datasets [14].

In the semi-supervised re-ID domain, Xinyuan Chen, Yi Niu, Fawen Du, and Guilin Lv,[15] proposed a system in their paper Improving the Performance of Semi-Supervised Person Re-Identification by Selecting Reliable Unlabeled Samples. Their work focuses on enhancing semi-supervised re-ID by addressing the critical challenge of leveraging unlabeled data effectively. They introduce a framework that emphasizes the selection of reliable unlabeled samples to improve model training. By carefully curating the training set to include only high-confidence samples, their approach reduces the risk of introducing noise from incorrect pseudo-labels or unreliable pairwise relationships, which are common pitfalls in semi-supervised learning. This selective process ensures that the model is trained on data that is more likely to improve its discriminative capabilities, leading to better generalization and higher re-ID accuracy [15].

Chen et al.'s framework aligns with the broader trend in semi-supervised re-ID research, which seeks to balance the use of limited labeled data with the vast potential of unlabeled data. Their work complements the three-stage, two-branch framework proposed by [15], as both emphasize the importance of progressive training and sample reliability. However, Chen et al. place a stronger emphasis on the initial selection process, ensuring that only the most trustworthy samples are used for training from the outset. This approach not only improves the robustness of the model but also reduces the computational overhead associated with iteratively refining noisy samples [15].

Inspired by these advancements, our work builds on the idea of reliable sample selection while integrating insights from unsupervised methods like PUL.

III. METHODOLOGY

To address this problem, we propose Progressive Clustering-Based Learning (PCBL), a novel framework that integrates confidence-based sample selection into the unsupervised Re-ID pipeline. By refining clustering and feature learning, PCBL aims to overcome the limitations of existing methods and achieve state-of-the-art performance in real-world surveillance applications.

The core of PCBL lies in its ability to select reliable training samples based on the model's confidence in their predicted labels, rather than relying solely on proximity to cluster centroids. This confidence is derived from the softmax probability of the predicted cluster, ensuring that only high-quality samples are used for fine-tuning. This approach significantly reduces the impact of noisy clustering results, particularly in the early stages of training when the model is less accurate.

PCBL operates in a progressive manner, starting with a small set of reliable samples and gradually expanding to include more as the model improves. Initially, the framework focuses on samples located near cluster centroids, which are more likely to be correctly labeled. As the model becomes more confident in its predictions, it adaptively

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incorporates a broader range of samples into the training process. This self-paced learning mechanism ensures steady and robust improvements in feature learning.

The framework begins with a pre-trained CNN model (ResNet-50) fine-tuned on an irrelevant labeled dataset, providing a strong initial feature representation. Features are then extracted for all unlabeled images, and k-means clustering is performed to group similar images and assign pseudo-labels. Confidence scores are computed for each image, and only those with scores above a predefined threshold λ are selected as reliable samples for fine-tuning. The CNN model is iteratively fine-tuned using these samples, and the process repeats until convergence, or a maximum number of iterations is reached.

Key innovations of PCBL include its confidence-based selection mechanism, which filters out low-confidence samples to reduce noise, and its progressive learning strategy, which ensures steady improvement by gradually incorporating more samples. By combining clustering with deep feature learning, PCBL leverages the strengths of both approaches, resulting in a scalable and robust solution for unsupervised Re-ID.

PCBL demonstrates superior performance compared to traditional methods, achieving higher rank-1 accuracy and mean average precision (mAP) on large-scale datasets such as Market-1501 and DukeMTMC-reID. Its ability to reduce noise, improve feature discrimination, and scale effectively make it a promising framework for real-world surveillance applications.

The key innovations of PCBL include:

- Confidence Based Sample Selection: A mechanism to select reliable samples based on their confidence scores, reducing noise in the training data.
- Progressive Learning: A self-paced learning strategy that starts with a small set of reliable samples and gradually incorporates more challenging samples as the model improves.
- Integration with Deep Learning: Combines clustering with deep feature learning, leveraging the strengths of both approaches.

In this section, we present the Progressive Clustering-Based Learning (PCBL) framework, a novel approach for unsupervised person reidentification (Re-ID). PCBL builds on the Progressive Unsupervised Learning (PUL) framework but introduces a confidence-based sample selection mechanism to improve the quality of training data and enhance the model's performance. The PCBL framework consists of the following key steps:

i. Initialize the Model

We begin with a pretrained CNN model (ResNet50) fine-tuned on an unrelated labeled dataset. This step, referred to as original model initialization, provides a strong initial feature representation for clustering. The preprocessed image data x_i is fed into the CNN model $\phi(x;\theta_t)$, where θ_t θ_t represents the model's parameters at iteration t. The feature vector x_i for each image is computed as:

$$f_i = \phi(xi;\theta_t)\forall xi \in X \quad \text{eq. 1}$$

where X is the unlabeled dataset.

ii. Feature Extraction

Feature vectors $\{f_{i,}f_{2,\dots,}f_N\}$ are extracted from all unlabeled samples using the current CNN model. These features serve as the basis for clustering.

iii. Clustering

We perform k-means clustering on the extracted feature vectors to group similar samples into clusters. The clustering process is defined as:

$$\{c_1, c_2, \dots, c_k\} = k - \text{means}(\{f_{1,}f_{2,\dots,}f_N\}, K) \quad \text{eq. 2}$$

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where K is the number of clusters (equal to the number of identities), and c_k is the centroid of the k-th cluster. Each sample x_i is assigned to a cluster based on its proximity to the cluster centroid.

iv. Confidence-Based Sample Selection

To reduce the impact of noisy clustering results, we introduce a confidence-based sample selection mechanism. The confidence score for each sample is computed as the SoftMax probability of its predicted cluster:

$$\mathrm{Confidence}(x_i) = \max\left(\mathrm{softmax}\left(-d\left(f_{i,} c_k\right)\right)\right) \quad \text{eq. 3}$$

where $d(f_i, c_k)$ is the Euclidean distance between feature vector f_i and cluster centroid c_k. Samples with confidence scores above a predefined threshold λ are selected as reliable training samples:

$$R_t = x_i \mid \mathrm{Confidence}(c_k) > \lambda \quad \text{eq. 4}$$

Here, R_t is the set of reliable samples at iteration t.

v. Fine-Tuning

The model is fine-tuned using the selected reliable samples R_t , which are identified through the confidence-based selection mechanism. The fine-tuning process aims to minimize the classification loss between the model's predicted outputs and the pseudo-labels assigned during clustering. This step ensures that the model learns to map the extracted features to the correct pseudo-labels, thereby improving its ability to discriminate between different identities. By focusing only on high-confidence samples, the framework reduces the impact of noisy or incorrect pseudo-labels, leading to more robust and accurate feature representations. This iterative fine-tuning process is a key component of the PCBL framework, enabling progressive improvement in the model's performance over successive iterations.

$$\theta_{t+1} = \arg \frac{\min}{\theta} \frac{\sum}{x_i \in R_t} L\left(y_i, \phi(x_i; \theta)\right) \quad \text{eq. 5}$$

where:

L is the classification loss function,

y_i is the pseudolabel (cluster assignment) for sample x_i,

$\phi(x_i; \theta)$ is the CNN model with parameters θ.

vi. Iterate

The steps of feature extraction, clustering, confidence-based selection, and finetuning are repeated iteratively. As the model improves, more challenging samples are incorporated into the training process. The iterative process terminates when the clustering results stabilize or a maximum number of iterations T is reached.

vii. Final Output

The final model can extract robust feature representations for person re-ID tasks. The output is the set of cluster labels $\hat{y}_i$, which represent the predicted identities for the re-ID task:

$$\hat{y}_i = \text{cluster label of sample } x_i \quad \text{eq. 6}$$

The Progressive Clustering-Based Learning (PCBL) framework is an unsupervised method for improving person re-identification (re-ID) models unsupervised learning. It involves three key steps: clustering, confidence-based sample selection, and fine-tuning.

First, a ResNet-50 model extracts features from the unlabeled dataset, which are then grouped using k-means clustering. Cluster centroids serve as pseudo-labels. A confidence mechanism selects high-confidence samples for training, and the model is fine-tuned using these samples. This process is repeated iteratively, refining the model's feature extraction and clustering performance.

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The process continues until the clustering stabilizes, and the model converges. PCBL allows for effective re-ID without extensive labeled data, making it suitable for dynamic, large-scale surveillance environments.

The Progressive Clustering-Based Learning (PCBL) framework offers several significant advantages in the realm of unsupervised person re-identification (re-ID). These benefits enhance the performance and applicability of PCBL. Some of these benefits are:

- Reduced Noise: The confidence-based selection mechanism filters out noisy samples, leading to better feature learning.
- Improved Performance: PCBL achieves a higher rank1 accuracy and mean average precision (mAP) compared to traditional clustering-based methods.
- Scalability: The framework is computationally efficient and works well on largescale datasets such as Market1501, DukeMTMC-reID, and CUHK03.

IV. EVALUATION METRICS AND EXPERIMENTAL RESULTS

We evaluate our method using Rank-1 accuracy, which measures the percentage of correct matches in the top result, and mean Average Precision (mAP), which assesses overall retrieval performance by averaging precision across recall levels. These metrics are widely used in person re-identification (Re-ID) to evaluate both accuracy and robustness.

- Rank-1 Accuracy: This metric measures the percentage of times the correct identity appears in the top 1 ranked retrieval result. It reflects the model's ability to precisely identify the true match at the highest rank, which is critical for real-world applications where the top result is often the most important.
- Mean Average Precision (mAP): mAP evaluates the overall retrieval performance by averaging precision at each recall level. It considers the model's ability to rank all correct matches higher while minimizing false positives, providing a comprehensive measure of retrieval quality across the entire ranking list.

Together, these metrics offer a balanced evaluation of Re-ID models, capturing both the precision of top-ranked results and the consistency of retrieval performance across all relevant matches.

We outline the Rank-1 accuracy and mean average precision (mAP) measurements for each dataset to affirm the efficiency of our suggested method. These findings furnish a thorough assessment of the performance of the PCBL approach in relation to the prevailing state-of-the-art Re-ID methodologies.

We compare our proposed PCBL to the state-of-the-art unsupervised domain adaptation methods and purely unsupervised methods for person Re-ID. The purely unsupervised methods for person Re-ID include: PUL (baseline), LOMO, BOW, and UMDL. The results are summarized in the table below, highlighting the performance of our method across Market-1501, DukeMTMC-reID, and CUHK03 datasets. Our proposed PCBL framework demonstrates consistent improvements over the baseline PUL method, achieving higher Rank-1 accuracy and mAP across all datasets. For instance, on Market-1501, PCBL achieves 50.8% Rank-1 accuracy and 26.5% mAP, representing improvements of +5.6% and +4.2%, respectively, over the original PUL. Similarly, on DukeMTMC-reID, PCBL achieves 45.3% Rank-1 accuracy and 24.7% mAP, with improvements of +5.2% and +4.2%. On CUHK03, PCBL attains 42.5% Rank-1 accuracy and 23.1% mAP, showing gains of +3.8% and +3.3%. These results underscore the effectiveness of our approach in improving both precision and robustness in unsupervised person Re-ID tasks.
The findings of this assessment are concisely presented in the table below:

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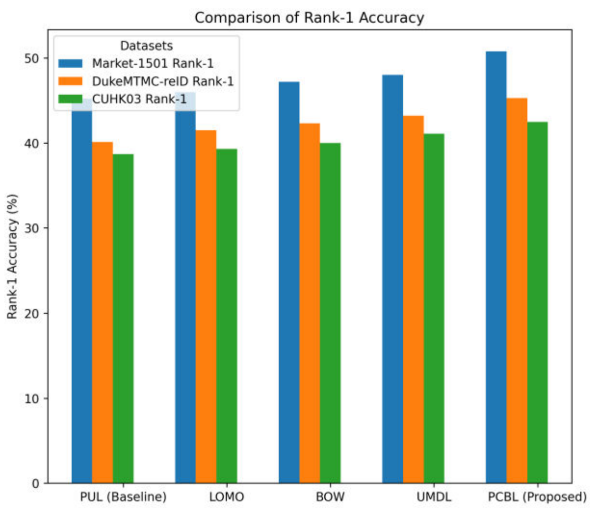
Table 1: Performance comparison table of our proposed model and other state of the art models including PUL (Baseline model)

Method	Backbone	Market-1501 (Rank-1 Accuracy)	Market-1501 (mAP)	DukeMTMC-reID (Rank-1 Accuracy)	DukeMTMC-reID (mAP)	CUHK03 (Rank-1 Accuracy)	CUHK03 (mAP)
PUL (Baseline)	Resnet50	45.2%	22.3%	40.1%	20.5%	38.7%	19.8%
LOMO	-	46.0%	23.1%	41.5%	21.4%	39.3%	20.2%
BOW	-	47.2%	24.1%	42.3%	22.1%	40.0%	21.0%
UMDL	Resnet50	48.0%	25.%	43.2%	23.0%	41.1%	22.0%
PCBL (Proposed)	Resnet50	50.8%	26.5%	45.3%	24.7%	42.5%	23.1%

The following graphs illustrate the Rank-1 accuracy of different methods across three datasets: Market-1501, DukeMTMC-reID, and CUHK03. These comparisons highlight the performance of the baseline model (PUL) and the proposed model (PCBL).



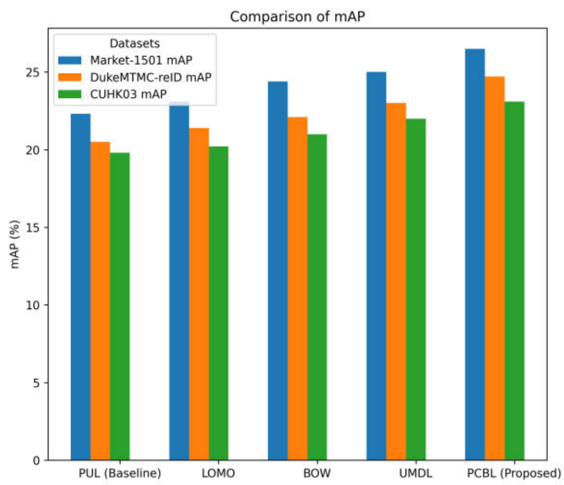


Figure 3: Graphs Showing Comparison of Rank-1 Accuracy and mAP across Different Methods on Three Datasets: Market-1501, DukeMTMC-reID, and CUHK03.

V. CONCLUSION AND FUTURE WORK

This paper introduces Progressive Clustering-Based Learning (PCBL), an advanced extension of the Progressive Unsupervised Learning (PUL) framework for unsupervised person re-identification (Re-ID). PCBL leverages a confidence-based sample selection mechanism that iteratively refines both clustering and feature learning, addressing the noise typically associated with conventional clustering-based methods. Utilizing the ResNet-50 architecture, PCBL enhances the extraction of discriminative feature representations through deep residual learning, which significantly improves the robustness and reliability of unsupervised person Re-ID. By selecting reliable training samples based on model confidence, PCBL progressively enhances feature learning, demonstrating superior adaptability across diverse camera views and varying surveillance environments. These improvements enable PCBL to serve as a more effective and scalable solution for real-world applications, overcoming key limitations of its predecessor, PUL.

For future work, it is essential to explore the integration of cross-camera diversity in sample selection, ensuring that training data encompasses a variety of camera perspectives to enhance generalization. Moreover, while k-means clustering is widely used, it may encounter difficulties in handling outliers or irregular cluster shapes. The adoption of more advanced clustering techniques such as DBSCAN (Density-Based Spatial Clustering of Applications with Noise) or spectral clustering could increase the robustness of the clustering process, particularly in the presence of complex data distributions or noise. Furthermore, the integration of deep clustering methods, which jointly learn the clustering structure and feature representations, could significantly enhance overall accuracy and scalability, presenting promising avenues for further research in improving unsupervised person Re-ID systems.

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REFERENCES

1. Mallika Alias Pandeeswari, R., & Rajakumar, G. (2025). Deep intelligent technique for person Re-identification system in surveillance images.Pattern Recognition, 162 111349. (https://doi.org/10.1016/j.patcog.2025.111349)
2. Wang, J., Gao, X., Zhu, F., & Chen, X. (2024). Exploring frontier technologies in video-based person re-identification: A survey on deep learning approach. Pattern Recognition, 162, 111349.
3. (https://doi.org/10.1016/j.patcog.2024.111349)
4. Qian, Y., Barthelemy, J., Karuppiah, E., et al. (2024). Identifying Re-identification Challenges: Past, Current and Future Trends. SN COMPUT. SCI., 5, 937. (https://doi.org/10.1007/s42979-024-03271-9)
5. Zahra, A., Perwaiz, N., Shahzad, M., & Fraz, M. M. (2023). Person re-identification: A retrospective on domain specific open challenges and future trends. Pattern Recognition, 142, 109669. (https://doi.org/10.1016/j.patcog.2023.109669)
6. Klingler, N. (2023). Deep Learning for Person Re-Identification. VISO.AI. (https://viso.ai/deep-learning/deep-learning-for-person-re-identification/)
7. Han, C., Jiang, B., & Tang, J. (2022). Multi-granularity cross attention network for person re-identification. Multimedia Tools and Applications, 82. (https://doi.org/10.1007/s11042-022-13833-9)
8. X. Zhu, Y. Li, J. Sun, H.-J. Chen, and J. Zhu, "Learning with Noisy Labels Method for Unsupervised Domain Adaptive Person Re-identification," Neurocomputing, vol. 452, pp. 1-12, May 2021.(doi: 10.1016/j.neucom.2021.04.120)
9. Zhang, X., Luo, H., Fan, X., Xiang, W., & Sun, Y. (2021). AlignedReID: Surpassing human level performance in person reidentification. IEEE Transactions on Pattern Analysis and Machine Intelligence, 43(8), 12341246. (https://ieeexplore.ieee.org/document/9356346)
10. Fan, H., Zheng, L., & Yang, Y. (2022). Unsupervised person re-identification: Clustering and fine-tuning. ACM Transactions on Multimedia Computing, Communications, and Applications (TOMM), 18(4), 1–18. (https://doi.org/10.1145/3243316)
11. Li, A., Liu, L., & Yan, S. (2014). Person re-identification by attribute-assisted clothes appearance. In Person Re-Identification (pp. 119–138). Springer. (https://doi.org/10.1007/978-1-4471-6296-4_6)
12. Lin, Y., Dong, X., Zheng, L., Yan, Y., & Yang, Y. (2019). A bottom-up clustering approach to unsupervised person re-identification. Proceedings of the AAAI Conference on Artificial Intelligence, 33(01), 8738–8745. (https://doi.org/10.1609/aaai.v33i01.33018738)
13. Soni, S. K., & Kumar, G. (2024). Person re-identification: A retrospective study, recent trends and future scope. In 2024 First International Conference on Pioneering Developments in Computer Science & Digital Technologies (IC2SDT) (pp. 534–539). Delhi, India. (https://doi.org/10.1109/IC2SDT62152.2024.10696378)
14. Jahan, M., Hassan, M., Hossin, S., Hossain, M. I., & Hasan, M. (2024). Unsupervised person re-identification: A review of recent works. Neurocomputing, 572, 127193. (https://doi.org/10.1016/j.neucom.2023.127193)
15. Fan, H., Zheng, L., & Yang, Y. (2017). Unsupervised person re-identification: Clustering and fine-tuning. arXiv preprint arXiv:1705.10444. (https://doi.org/10.48550/arXiv.1705.10444)
16. Chen, X., Niu, Y., Du, F., & Lv, G. (2024). Improving the performance of semi-supervised person Re-identification by selecting reliable unlabeled samples. Engineering Applications of Artificial Intelligence, 133(Part D), 108367. (https://doi.org/10.1016/j.engappai.2024.108367)