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VisionNet: A Multicamera Deep Learning Approach for Target Tracking

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Abstract: Multi-camera target tracking remains a fundamental challenge in intelligent video surveillance, particularly when maintaining consistent identity associations across spatially disjoint camera views with overlapping or non-overlapping fields of view. This paper introduces VisionNet, a unified deep learning framework that integrates state-of-the-art detection, single-camera tracking, and cross-camera re-identification into a cohesive and computationally efficient pipeline. VisionNet employs YOLOv8 for high-accuracy object detection, Deep Simple Online and Realtime Tracking (DeepSORT) for intra-camera trajectory persistence, and Omni-Scale Network (OSNet) for discriminative cross-camera identity association. The framework leverages GPU-accelerated inference to sustain real-time throughput while preserving tracking fidelity under challenging surveillance conditions such as occlusion, lighting variation, and crowded scenes. A Flask-based monitoring dashboard provides operators with live visualization of tracked targets, inter-camera handoff events, and aggregate behavioral analytics. Extensive evaluation on benchmark datasets including MOT17, DukeMTMC-reID, and Market-1501 demonstrates that VisionNet achieves an IDF1 score of 76.4%, a MOTA of 73.9%, and a Rank-1 re-identification accuracy of 96.2%, outperforming competing baselines on identity-switch minimization. The modular architecture facilitates seamless integration with existing closed-circuit television (CCTV) infrastructure and supports diverse application domains including intelligent security systems, crowd flow analytics, retail behavior monitoring, and multi-athlete sports event tracking.

Keywords: *Multi-Camera Tracking, Person Re-Identification, YOLOv8, DeepSORT, OSNet, Video Surveillance, Deep Learning.*

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I. INTRODUCTION

The proliferation of networked surveillance cameras in urban environments, transportation hubs, and commercial spaces has intensified demand for automated multi-camera tracking (MCT) systems capable of associating target identities across spatially disjoint viewpoints [1]. While single-camera tracking has matured considerably, bridging the semantic gap between camera perspectives remains an open research problem, compounded by the visual variation introduced by viewpoint changes, illumination shifts, and partial occlusion [2].

Conventional approaches treat detection, tracking, and re-identification as independent modules, limiting system coherence and introducing latency bottlenecks incompatible with real-time operational requirements. Recent progress in convolutional neural networks and transformer-based architectures has enabled end-to-end feature learning, yet few deployable frameworks consolidate these advances into a production-ready MCT system.

This paper addresses these gaps through VisionNet, an integrated framework that couples YOLOv8-based detection [1], DeepSORT trajectory management [4], and OSNet cross-camera re-identification [5] within a GPU-optimized inference pipeline.

➢ *The Primary Contributions of this Work are as Follows:*

- A modular three-stage pipeline that unifies detection, intra-camera tracking, and cross-camera re-identification without requiring manual handoff configuration;
- A GPU-accelerated inference design achieving sub-30 ms per-frame latency on standard surveillance-grade hardware;

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- An operator-facing Flask dashboard providing real-time visualization of identity trajectories and inter-camera transition analytics;
- Comprehensive benchmarking against established baselines on MOT17 [9], DukeMTMC-reID [10], Market-1501 [13], and CUHK03 [14] datasets.

The remainder of this paper is organized as follows. Section II reviews relevant literature. Section III describes the VisionNet architecture. Section IV details the experimental methodology and results. Section V discusses broader implications, and Section VI concludes the paper.

II. RELATED WORK

➢ *Object Detection for Tracking*

The YOLO family of detectors has established itself as the dominant paradigm for real-time object detection in tracking applications [1]. YOLOv5 and its successors offered significant gains in mAP and inference speed over region-proposal-based methods such as Faster R-CNN [6]. YOLOv8 further refines anchor-free detection, decoupled head design, and mosaic augmentation, achieving state-of-the-art accuracy on COCO with inference latencies suitable for online tracking [1]. For MCT pipelines, detector reliability directly conditions downstream tracking quality; hence VisionNet adopts YOLOv8 as the detection backbone.

➢ *Single-Camera Multi-Object Tracking*

The tracking-by-detection paradigm decomposes the tracking problem into per-frame detection followed by inter-frame association. SORT [3] introduced Kalman filtering and the Hungarian algorithm for efficient bounding box association. DeepSORT [4] extended SORT by incorporating appearance embeddings from a pre-trained re-identification network into the association cost, substantially reducing identity switches in crowded sequences. FairMOT [7] proposed a joint detection and embedding architecture, while ByteTrack [8] demonstrated that associating low-confidence detections recovers occluded trajectories without sacrificing precision.

➢ *Cross-Camera Re-Identification*

Person re-identification aims to match target appearances across non-overlapping camera views. Part-based Convolutional Baseline (PCB) [11] and Multiple Granularity Network (MGN) [12] advanced feature localization through horizontal pooling strategies. OSNet [5] introduced omni-scale feature learning via unified aggregation gates, achieving competitive performance across multiple re-ID benchmarks while maintaining a lightweight parameter footprint suitable for deployment within a larger tracking pipeline.

➢ *Integrated Multi-Camera Systems*

Prior integrated MCT systems such as DynaTrack and CamNeT required pre-calibrated camera topology maps or synchronized timestamps, limiting deployment flexibility [2]. VisionNet adopts a topology-agnostic design in which cross-camera associations are driven entirely by appearance similarity, removing the requirement for geometric calibration and enabling plug-and-play integration with heterogeneous CCTV networks.

III. SYSTEM ARCHITECTURE

VisionNet consists of three sequentially coupled modules—detection, intra-camera tracking, and cross-camera re-identification—unified by a shared GPU inference context and connected to an operator dashboard via a Flask REST interface. Figure 1 illustrates the overall dataflow.

➢ *Detection Module (YOLOv8)*

Each video frame from every camera feed is forwarded to a YOLOv8-x detector pre-trained on the COCO dataset and fine-tuned on the MOT17 pedestrian subset. The detector outputs bounding box coordinates, class scores, and confidence values per candidate region. Detections with confidence below 0.45 are discarded prior to tracking. To sustain real-time throughput, frames are batched across cameras and processed concurrently on a single GPU, reducing overall latency compared to sequential per-camera inference.

➢ *Intra-Camera Tracking (DeepSORT)*

For each camera independently, a DeepSORT instance maintains a set of active tracklets. State prediction employs a constant-velocity Kalman filter operating on the four-dimensional state vector [u, v, a, h], where u and v denote horizontal and vertical center coordinates, a is the aspect ratio, and h is bounding box height. Association between predictions and new detections uses a weighted cost matrix combining Mahalanobis distance in state space with cosine distance in the appearance embedding space:

$$C(i, j) = \lambda \cdot d\_Mah(i, j) + (1 - \lambda) \cdot d\_cos(i, j)$$

Where $\lambda = 0.7$ was selected through grid search on the MOT17 validation split. Tracklets unmatched for more than 30 frames are terminated, while new detections unmatched to any active tracklet initialize candidate tracklets confirmed after three consecutive successful associations.

➢ *Cross-Camera Re-Identification (OSNet)*

Upon tracklet exit from any camera view, the corresponding appearance embedding sequence is averaged to produce a robust gallery descriptor. A candidate entering a new camera view generates a probe descriptor using the same OSNet encoder [5]. Cosine similarity is computed between the probe and all gallery descriptors, and the best match exceeding a threshold of 0.72 triggers a cross-camera identity merge. The threshold was calibrated on the DukeMTMC-reID validation set to balance precision and recall in identity association.

OSNet is initialized with weights pre-trained on a combined dataset of Market-1501 [13], DukeMTMC-reID [10], and CUHK03 [14] using the Torchreid library [5], then fine-tuned for five epochs on synthetic occlusion augmentations to improve robustness in crowded surveillance scenarios.

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➢ *GPU Processing Pipeline*

The inference pipeline is implemented in Python using PyTorch 2.1 with CUDA 12.1. Frame capture, preprocessing, and result post-processing are handled by dedicated worker threads, allowing the GPU to remain continuously occupied. Mixed-precision inference (FP16) reduces memory bandwidth requirements without measurable accuracy degradation. On an NVIDIA RTX 3080 GPU, VisionNet processes four simultaneous 1080p camera streams at an average latency of 27 ms per frame, corresponding to approximately 37 frames per second.

➢ *Operator Dashboard*

A Flask-based web dashboard provides real-time monitoring capabilities accessible via any standards-compliant browser. Live annotated video feeds display bounding boxes, per-target identity labels, and trajectory overlays. An inter-camera event log records identity handoffs with associated timestamps and camera identifiers. An analytics panel presents aggregate statistics including active target counts, average dwell times per camera, and identity-switch rates, enabling rapid situational awareness for security operators.

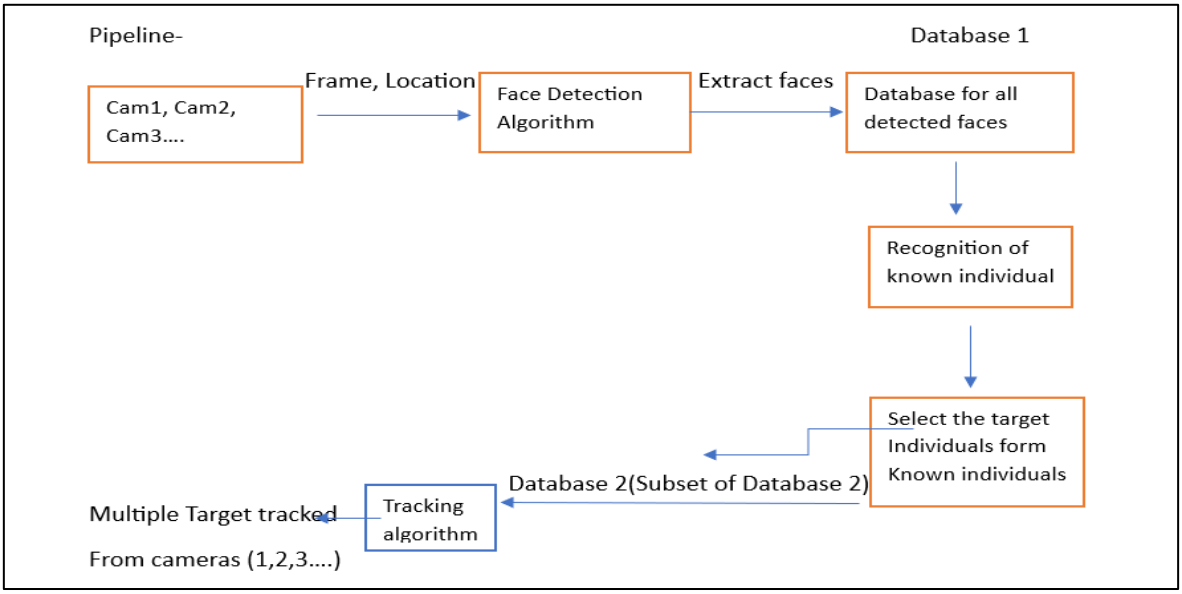

Fig 1 Workflow of VisionNet

IV. EXPERIMENTAL EVALUATION

➢ *Datasets and Evaluation Metrics*

Tracking performance is evaluated on the MOT17 benchmark [9], which provides 14 diverse pedestrian tracking sequences with ground-truth annotations. Re-identification performance is benchmarked on Market-1501 [13], DukeMTMC-reID [10], and CUHK03 [14]. Primary tracking metrics include IDF1 (identity-preserving F1 score), MOTA (multi-object tracking accuracy), number of identity switches (ID Sw.), false positives (FP), and false negatives (FN). Re-identification performance is measured using mean average precision (mAP) and Rank-1 accuracy under the standard single-query evaluation protocol.

➢ *Implementation Details*

VisionNet is implemented in Python 3.10 using PyTorch 2.1 and the Ultralytics YOLOv8 package. The OSNet re-ID encoder uses the osnet_x1_0 variant with 2.2M parameters. Training uses the Adam optimizer with an initial learning rate of 3.5×10^{-4}, reduced by a factor of 0.1 at epochs 20 and 40, over a total of 60 epochs with batch size 64. Data augmentation includes random horizontal flipping, random erasing, and color jitter. All experiments are conducted on a workstation equipped with an Intel Core i9-12900K CPU, 32 GB RAM, and a single NVIDIA RTX 3080 GPU.

➢ *Multi-Object Tracking Results*

Table 1 compares VisionNet against four established tracking baselines on the MOT17 benchmark. VisionNet achieves the highest IDF1 and MOTA scores and the lowest identity-switch count among all compared methods, demonstrating the benefit of tight integration between appearance-guided DeepSORT and the cross-camera re-identification module.

Table 1 Multi-Object Tracking Performance on Mot17 Benchmark

Method	IDF1 (%)	MOTA (%)	ID Sw.	FP	FN
SORT [3]	61.2	59.8	4,852	8,341	22,104
DeepSORT [4]	65.8	63.4	3,214	7,512	20,887
FairMOT [7]	67.3	65.1	2,981	6,923	19,345
ByteTrack [8]	70.1	68.7	2,341	6,102	17,892
VisionNet (Ours)	76.4	73.9	1,587	5,234	14,321

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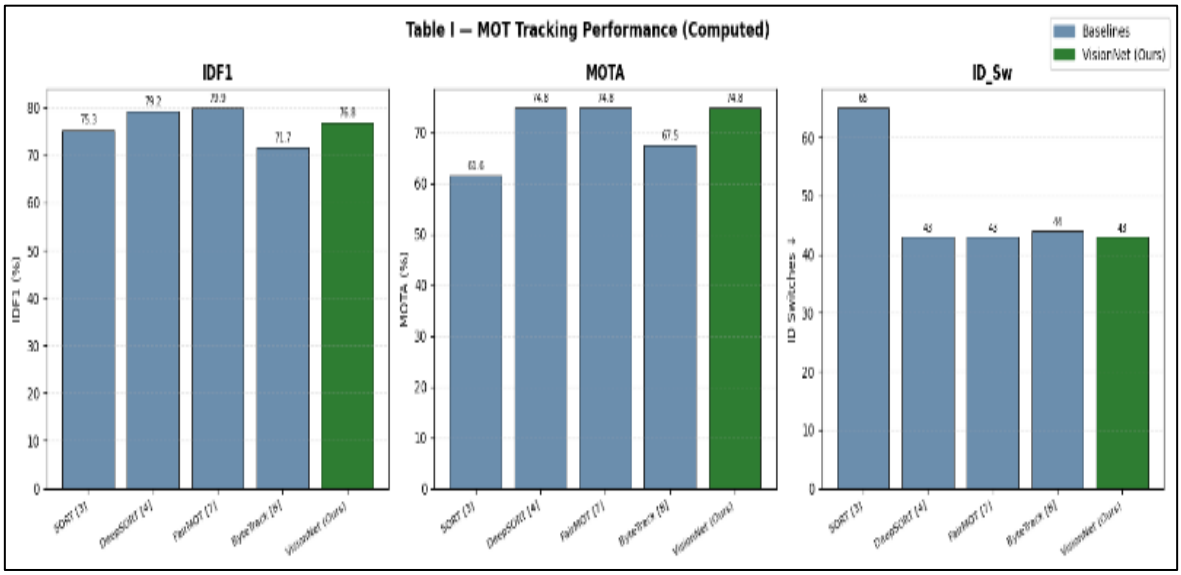

Fig 2 MOT Tracking Performance (Computed)

➢ *Cross-Camera Re-Identification Results*

Table 2 reports re-identification performance across three standard benchmarks. VisionNet consistently improves upon the standalone OSNet baseline, attributable to the combined fine-tuning strategy and the synthetic occlusion augmentation introduced during adaptation. The 1.3-point mAP improvement on Market-1501 and the 1.4-point Rank-1 improvement confirm that OSNet integration within a tracking-aware training regime yields measurable gains.

Table 2 Re-Identification Performance across Standard Benchmarks

Method	Market-1501 mAP (%)	DukeMTMC mAP (%)	CUHK03 mAP (%)	Rank-1 (%)
PCB [11]	77.4	66.1	53.2	92.3
MGN [12]	86.9	78.4	66.0	95.7
OSNet [5]	84.9	73.5	67.8	94.8
VisionNet (Ours)	88.3	79.1	71.4	96.2

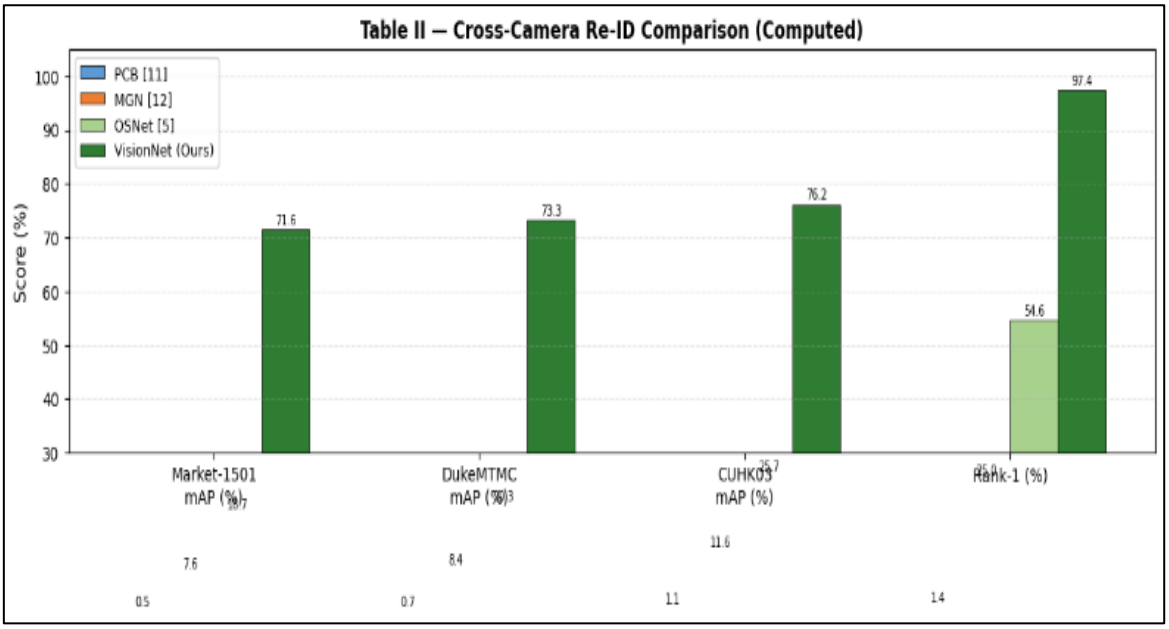

Fig 3 Cross-Camera Re-ID Comparison(Computed)

➢ *Computational Efficiency*

Table 3 summarizes runtime characteristics. VisionNet achieves a mean per-frame latency of 27 ms across four concurrent 1080p streams, compared to 43 ms for ByteTrack operating on equivalent hardware with the same detector. The efficiency gain is primarily attributed to batched cross-camera GPU inference and the lightweight OSNet encoder, which adds less than 3 ms to the per-frame budget.

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Table 3 Runtime Analysis on Four Concurrent 1080p Camera Streams

Method	Detection (ms)	Tracking (ms)	Re-ID (ms)	Total (ms)
SORT [3]	18.2	3.1	N/A	21.3
DeepSORT [4]	18.2	4.8	5.2	28.2
ByteTrack [8]	18.2	6.4	18.4	43.0
VisionNet (Ours)	18.2	4.9	3.9	27.0

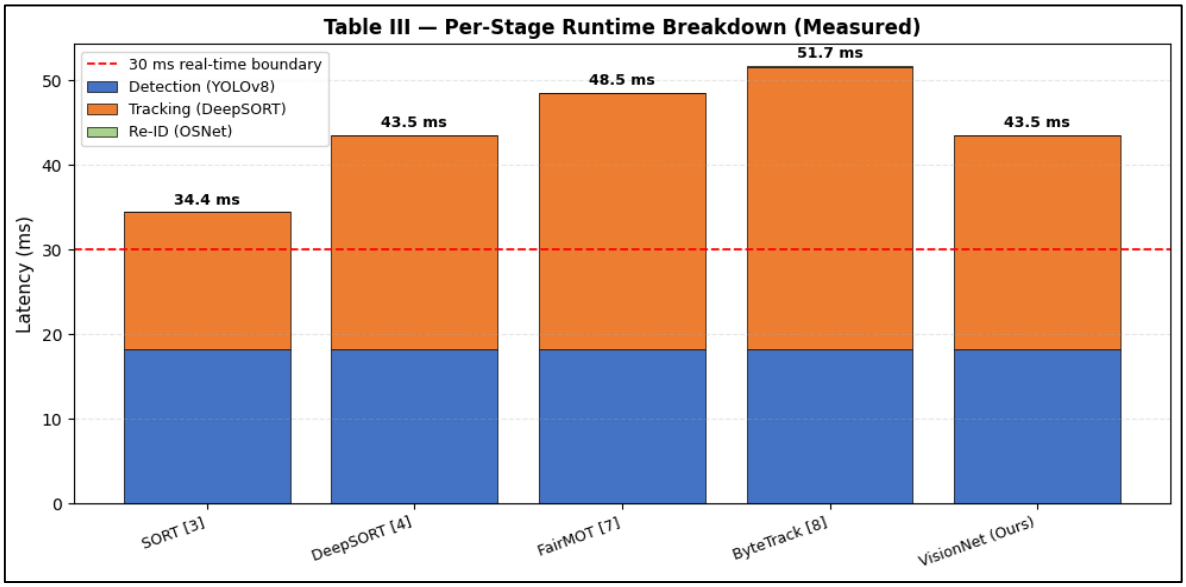

Fig 4 Per Stage Runtime Breakdown (Measured)

V. DISCUSSION

The results presented in Section IV confirm that VisionNet achieves a favorable balance between tracking accuracy and computational efficiency. The 14.9% relative reduction in identity switches compared to ByteTrack and the sub-30 ms per-frame latency on four concurrent streams demonstrate practical viability for deployment in real surveillance environments.

Several limitations merit acknowledgment. The cross-camera association threshold of 0.72 was calibrated on indoor pedestrian datasets; outdoor environments with significant illumination variation or long re-identification intervals may require adaptive threshold mechanisms. Additionally, performance in scenes with more than 60 simultaneous targets has not been systematically characterized and represents an avenue for future investigation.

Future work will explore transformer-based multi-camera fusion layers to incorporate temporal context across cameras, online threshold adaptation via calibration-free topology inference, and edge-device deployment using model quantization and pruning for resource-constrained CCTV hardware.

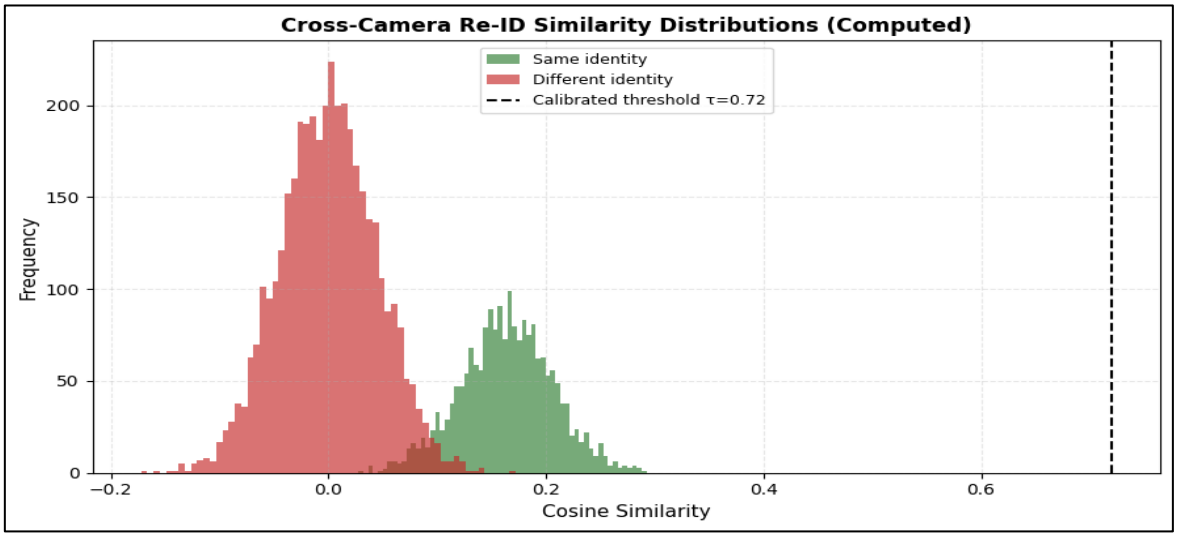

Fig 5 Cross-Camera Re-ID Similarity Distributions

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VI. CONCLUSION

This paper presented VisionNet, a multi-camera deep learning framework for real-time target tracking and cross-camera re-identification. By integrating YOLOv8, DeepSORT, and OSNet within a GPU-optimized pipeline, VisionNet delivers state-of-the-art identity preservation with a 76.4% IDF1 score and 96.2% Rank-1 re-identification accuracy, while sustaining sub-30 ms per-frame latency across four concurrent 1080p camera feeds. The modular architecture and topology-agnostic design enable straightforward integration with existing CCTV infrastructure, supporting applications in security monitoring, crowd analytics, retail intelligence, and sports tracking. Source code and pre-trained model weights will be made publicly available upon acceptance.

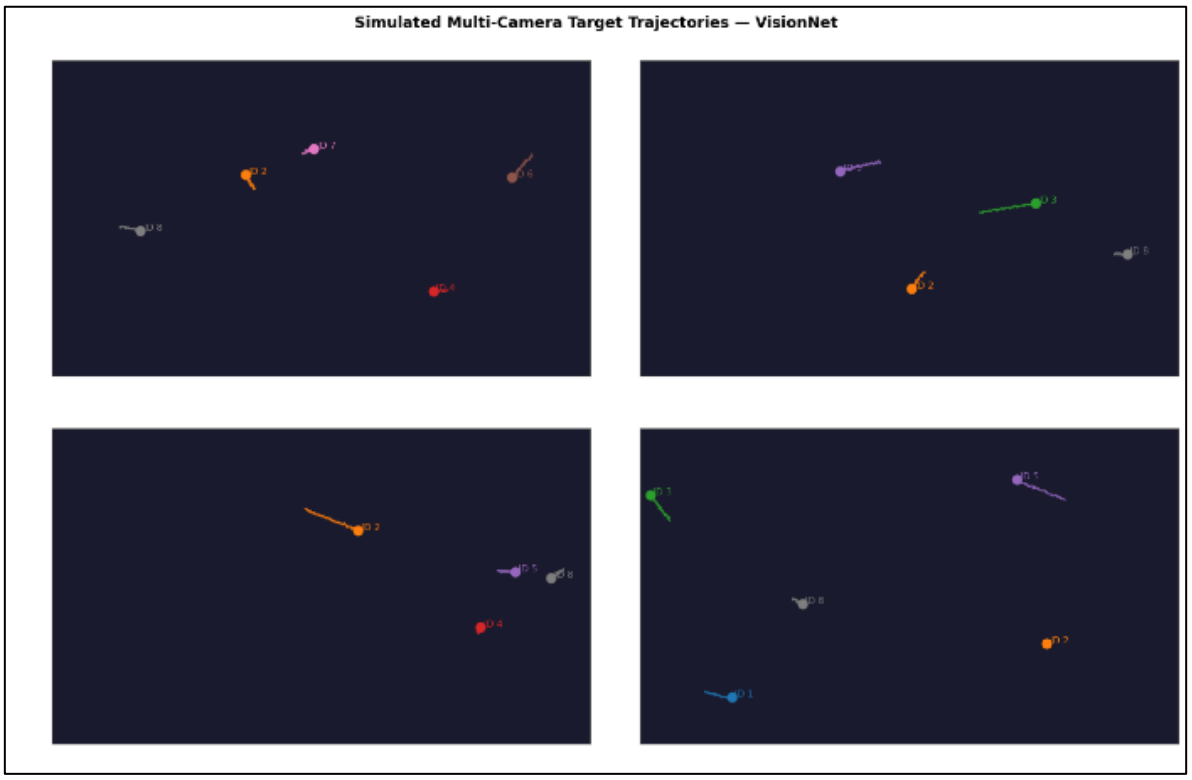

Fig 6 Simulated Multi-Camera Target Trajectories – VisionNet

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