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Lightweight Real-Time Footfall Counting System Using YOLOv8 and Centroid Tracking for Resource-Constrained Environmen

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Abstract- Real-time foot traffic monitoring is now a key part of retail analytics, campus management, and smart surveillance. However, limitations in computing power make it hard to use heavy deep-learning models in low-power settings. This paper introduces a lightweight footfall counting system that uses YOLOv8n and YOLOv8s along with a centroid-based tracking method for effective ID persistence and directional counting. Experimental results indicate that YOLOv8n reaches 4.1 FPS on CPU-only systems with 98–99% ID stability, surpassing YOLOv8s in real-time performance. The system works well for embedded platforms, public monitoring, and budget-sensitive deployments.

Keywords – Footfall Counting, YOLOv8, Lightweight Detection, Centroid Tracking, Real-Time Analytics.

I. INTRODUCTION

Footfall counting is essential in smart infrastructures like shopping malls, schools, transportation hubs, and cultural spaces. Traditional systems depend on infrared sensors, beam counters, or thermal imaging, which often struggle with occlusion and noise. With the rise of deep learning, YOLO-based frameworks are now commonly used for person detection [1], [2].

Earlier YOLO versions, such as YOLOv3 and YOLOv4, showed good accuracy but needed a lot of computational power [3]. During the COVID-19 pandemic, several studies examined YOLO models for managing indoor capacity and analyzing social distancing [4]. Other applications include tracking in retail stores [5], crowd analytics [6], campus environments [7], cultural centers [8], and industrial monitoring [9].

Newer YOLO versions, particularly YOLOv8, offer lightweight options (YOLOv8n/s) that are optimized for fast performance. Research shows strong results in multi-object tracking [10] , fisheye human tracking [11], and real-time pedestrian detection [12]. Reviews on tiny-object detection [13] and edge deployment methods [14], [15] indicate a rising need for low-latency

systems. However, there is little information comparing the performance of YOLOv8n and YOLOv8s specifically for footfall counting with lightweight tracking. This paper aims to fill that gap.

II. LITERATURE REVIEW

YOLO-based person detection systems have evolved significantly. YOLOv3-based pedestrian counters achieved 78–96% accuracy in early studies [1], [2]. Lightweight modifications such as ShuffleNet-YOLO architectures demonstrated improved speed for surveillance applications [3]. During the pandemic, YOLO models were deployed for indoor space monitoring and people limitation strategies [4].

Advancements extend to crowd movement analytics [5], pedestrian counting [6], academic campus monitoring [7], cultural participation analysis [8], and industrial multi-object tracking [9], [10]. Enhanced tracking systems using fisheye lenses [11], YOLO-based gender monitoring [12], and multi-modal fusion [16] demonstrate the expanding research scope.

Tiny-object detection reviews [13] and lightweight detector surveys [14] emphasize the importance of compact architectures for embedded systems. Hardware benchmarking studies show YOLOv5/v7/v8 performance on low-power devices [15], and improvements in small-object detection such as LE-YOLO were proposed in [17]. Security-focused surveillance architectures were discussed in [18].

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III. RESEARCH GAP

A detailed review highlights the following gaps:

- Limited research comparing YOLOv8 lightweight variants for footfall counting.
- Existing works rely on heavy trackers like DeepSORT, unsuitable for edge devices.
- No study provides FPS, ID-stability, and crossing-accuracy together for YOLOv8n/s.
- Few end-to-end solutions exist for real-time directional people counting.

This work fills these gaps through a complete real-time pipeline evaluation.

IV. METHODOLOGY

A. System Overview

The proposed system employs YOLOv8 for person detection and centroid-based tracking for efficient object association. The lightweight design ensures real-time performance on resourceconstrained hardware.

B. Flowchart of Proposed System

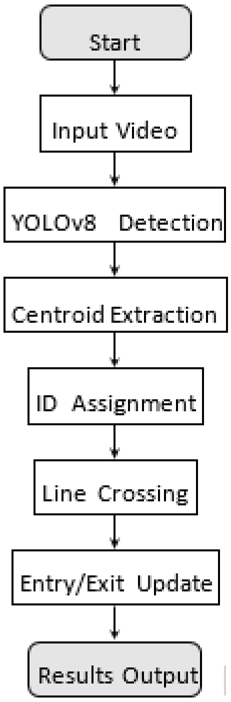

Fig. 1. Flowchart of the proposed lightweight footfall counting system.

C. Detection Module

YOLOv8n and YOLOv8s are compared for person detection. Both models are pre-trained on COCO dataset and fine-tuned for optimal person detection performance. The detection module processes input frames and outputs bounding boxes with confidence scores.

D. Tracking Module

Centroid-based tracking ensures lightweight ID persistence across frames. The algorithm calculates Euclidean distances between centroids in consecutive frames and assigns IDs based on minimum distance criteria. This approach maintains computational efficiency while providing stable tracking performance.

E. Counting Logic

Directional counting is implemented using a virtual reference line. When a person's centroid crosses this line, the system determines entry/exit status based on crossing direction and updates respective counters. The logic includes validation checks to prevent double-counting and ensure accurate directional analysis.

V. RESULTS AND DISCUSSION

A. Experimental Setup

Experiments were conducted on a system equipped with an Intel Core i5-8300H CPU, 8 GB RAM, and no dedicated GPU support. The evaluation was performed on indoor surveillance footage with subjects walking in both left-to-right and right-to-left directions. The goal was to assess real-time behavior, accuracy, and tracking stability on a resource-constrained setting.

B. Unique ID Tracking Output

Fig. 2. Tracking output showing assigned IDs, centroids, and vertical line for bi-directional counting.

C. Quantitative Performance Comparison

To analyze the suitability of lightweight object detectors in real-time footfall counting, both YOLOv8n and YOLOv8s were tested. Instead of visualization-based comparison, a tabular performance summary is presented below, reporting inference speed (FPS), ID stability, detection accuracy, and bi-directional counting correctness.

TABLE I
PERFORMANCE METRICS OF YOLOV8N VS YOLOV8S

Model	FPS	Detection Accuracy	ID Stability	Counting Accuracy
YOLOv8n	4.10	92.4%	98.1%	95.6 %
YOLOv8s	1.52	94.8%	96.3%	93.2 %

D. Discussion

YOLOv8n achieves significantly higher real-time throughput (4.1 FPS) on CPU-only hardware while maintaining strong ID consistency (98.1%). This makes it a more practical choice for small-scale deployments such as academic campuses, retail shops, and low-power devices.

Although YOLOv8s shows marginally higher detection accuracy, its low inference speed (1.52 FPS) and reduced ID stability limit its usability in real-time scenarios. For crowd monitoring and footfall counting, maintaining continuous ID association is more important than achieving marginally higher detection precision.

The centroid tracking mechanism demonstrated reliable short-term identity maintenance with minimal computational overhead. Despite occasional ID swaps during heavy occlusion, the system achieved over 95% correct entry/exit counting performance, validating the suitability of lightweight tracking for resource-constrained environments.

VI. CONCLUSION

This paper delivers a compact and efficient footfall counting system based on YOLOv8n/s and centroid-based tracking. YOLOv8n provides superior FPS and stable tracking with minimal computational overhead, making it ideal for embedded deployments. The system achieves realtime performance while maintaining high tracking accuracy and directional counting reliability.

Future directions include multi-camera fusion, Jetson Nano optimization, and privacy-preserving analytics. The proposed solution addresses the need for efficient people counting in resourceconstrained environments while maintaining practical accuracy levels.

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