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A Comprehensive Performance Evaluation of YOLOv8 for Real-Time Urban Vehicle and Traffic Asset Recognition

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Abstract- Real-time object detection plays a foundational role in the deployment of Intelligent Transportation Systems (ITS) and modern smart city frameworks. To facilitate effective traffic management, automated intersection regulation, and active protection for vulnerable road users (VRUs), vision-based deep learning models must deliver high spatial localization accuracy without introducing heavy computational latencies. This research presents a comprehensive performance evaluation of the lightweight anchor-free YOLOv8 nano (YOLOv8n) architecture deployed on the CAVI-14 (Camera-based Vehicle Image) dataset. The network was trained over a rigorous 100-epoch horizon with an input resolution of 640 \times 640 pixels. The experimental findings reveal high performance capabilities across critical urban mobility profiles, yielding an overall bounding box precision of 93.7%, a recall of 96.1%, a mean Average Precision mAP50 of 96.9%, and a stringent mAP50-95 of 78.4%. Notably, highly specialized categories specifically ambulance and bicycle achieved targeted localized mAP metrics of 99.5%. Detailed examination of confidence landscapes revealed that the network reached its optimal macro F1-score of 0.95 at a confidence setting of 0.358, achieving total processing throughput of ~208 Frames Per Second (FPS). This systematic evaluation validates that highly compact, parameterized single-stage deep neural networks can successfully meet the low-latency, high-precision constraints mandatory for edge-level smart city infrastructure.

Keywords: Real-Time Object Detection, YOLOv8n, Intelligent Transportation Systems (ITS), Smart Cities, Deep Learning, Computer Vision, Traffic Monitoring, Vulnerable Road Users (VRUs), Edge Computing, CAVI-14 Dataset, Autonomous Transportation, Urban Mobility Analytics.

I. INTRODUCTION

With the rapid growth of urban populations worldwide, traditional traffic surveillance frameworks struggle to keep pace with modern traffic complexities. Conventional closed-circuit television (CCTV) loops rely heavily on human monitors, a method prone to cognitive fatigue, slow response times, and an inability to track multi-lane intersection vectors simultaneously [1]. Intelligent Transportation Systems (ITS) leverage state-of-the-art computer vision algorithms to automate monitoring networks, analyse vehicle dynamics, and proactively safeguard vulnerable road users (VRUs) like cyclists [2]. By establishing real-time tracking loops, smart cities can optimize signal timings, identify traffic jams, and reduce accident rates at busy intersections [3].

Deploying deep learning algorithms within real-time frameworks introduces a classic trade-off between inference accuracy and computational cost. Early object detection frameworks relied on two-stage architectures, such as Faster R-CNN, which utilize a Region Proposal Network (RPN) to isolate candidate bounding regions before passing them to a classification head [4]. While highly accurate, these two-stage architectures introduce significant processing bottlenecks. This limitation sparked the development of single-stage detectors, most notably the You Only Look Once (YOLO) framework, which frames object detection as a single regression problem by predicting bounding boxes and class probabilities directly from full images in a single pass [5].

As these models evolved from YOLOv1 to YOLOv4, and into modern anchor-free setups like YOLOv8, their feature-extraction capabilities grew significantly [6]. However, large-scale models often require high-end, power-hungry GPUs, rendering them unfeasible for field deployment on edge

devices like traffic camera microcontrollers or embedded vehicle systems [7]. The creation of ultra-lightweight object detection networks, such as the nano variations of the YOLO lineage, aims to bridge this gap. These compact networks feature fewer parameters and require less computing power, allowing them to run efficiently on low-cost edge hardware without sacrificing real-time detection accuracy [8].

This research delivers a complete performance profiling of YOLOv8n, evaluating its representational capacities on the specialized CAVI-14 urban dataset. The chosen configuration targets a multi-class problem consisting of dominant roadway participants (car), emergency response elements (ambulance), and micro-mobility modes (bicycle). Through a step-by-step structural assessment utilizing precision-recall analytics, F1-score dynamics, and normalized confusion matrices, this work establishes a robust, highly reproducible baseline for upcoming urban perception paradigms

II. LITERATURE REVIEW

A. Traditional and Deep Learning Detectors

Automated traffic monitoring has shifted significantly from manual oversight and sensor loops (such as inductive loops and pneumatic tubes) to advanced vision-based AI systems [9]. Early computer vision techniques relied on hand-crafted features, including Haar-like wavelets, Histogram of Oriented Gradients (HOG), and Scale-Invariant Feature Transform (SIFT), combined with classic classifiers like Support Vector Machines (SVM) [10]. While effective under controlled lighting conditions, these shallow machine learning methods struggled with real-world complexities like overlapping vehicles, shifting shadows, and sudden weather changes [11].

The introduction of Deep Convolutional Neural Networks (CNNs) changed this landscape by allowing models to automatically learn complex visual hierarchies directly from raw pixel data [12]. Early deep learning applications in smart cities used two-stage detectors like Faster R-CNN and Cascade R-CNN to achieve high localization accuracy [13]. However, their complex region-proposal steps made it impossible to achieve the high frame rates needed for real-time edge processing [14].

To address these latency bottlenecks, single-stage detectors were developed to combine classification and localization into a unified pipeline [15]. Redmon et al. introduced the original YOLO network, proving that a single convolutional network could predict bounding boxes and class probabilities simultaneously [16]. Subsequent iterations introduced several architectural improvements: YOLOv3 added multi-scale feature predictions using Feature Pyramid Networks (FPN) [17]; YOLOv4 integrated CSPDarknet53 to optimize gradient flow [18]; and YOLOv5 introduced automated anchor box calculation along with integrated mosaic data augmentations [19].

Recently, anchor-free object detection has emerged as a key approach to simplify post-processing steps like Non-Maximum Suppression (NMS) [20]. By removing predefined anchor boxes, these models reduce hyper parameter tuning and eliminate spatial quantization errors [21]. YOLOv8 incorporates these anchor-free benefits alongside an upgraded C2f core structure, making it highly effective for real-time edge processing [22].

Author(s) & Year	Base Architecture	Target Classes	Performance Metrics
Zhang et al. [23]	Faster R-CNN	Cars, Trucks, Buses	mAP50: 88.4%, 15 FPS
Li & Mahmood [24]	YOLOv3	Vehicles, Pedestrians	mAP50: 84.1%, 45 FPS
Wang et al. [25]	YOLOv5s	Multi-class Traffic	mAP50: 91.2%, 82 FPS
Silva et al. [26]	YOLOv7-tiny	Bicycles, Motorbikes	mAP50: 89.7%, 110 FPS
This Work (2026)	YOLOv8n (Anchor-Free)	Car, Bicycle, Ambulance	mAP50: 96.9%, 208 FPS

While existing studies have thoroughly evaluated these models on large, balanced datasets like MS COCO, there is still a significant research gap regarding how compact, anchor-free networks handle imbalanced real-world urban environments [27]. In everyday traffic scenes, common classes like cars appear much more frequently than critical target classes like ambulances or bicycles [28]. This paper directly addresses this gap by providing a detailed evaluation of YOLOv8n on the CAVI-14 dataset, establishing a highly reliable and efficient baseline for urban object detection.

III. METHODOLOGY

A. Dataset Infrastructure (CAVI-14)

The empirical evaluations in this study were conducted using the CAVI-14 (Camera-based Vehicle Image) dataset, developed by researchers at the Hankuk University of Foreign Studies [29]. This dataset contains street-level traffic images captured with high-resolution smartphone cameras across diverse real-world conditions, including varying lighting, shadows, and complex physical occlusions.
While the full CAVI-14 benchmark tracks 14 distinct vehicle and infrastructure categories, this study focuses on a highly targeted sub-distribution representing key urban mobility challenges:

Car: The dominant vehicular class, characterized by high density, overlapping vehicles, and significant scale variations.
Bicycle: A highly irregular class representing vulnerable road users, featuring thin metallic frames that are easily obscured by larger vehicles.
Ambulance: A critical, low-frequency emergency class that requires high detection priority. It is distinguished by specialized chassis geometries and unique emergency coloring.

B. YOLOv12n Architecture

The YOLOv8 nano network consists of three primary core modules: the Backbone, the Neck, and the Head. The Backbone uses an advanced Cross Stage Partial network variant known as the C2f Module. This module combines high-level semantic features with low-level spatial details by splitting and concatenating gradient channels, ensuring excellent feature extraction while keeping the model lightweight.

The Neck uses a combined Feature Pyramid Network (FPN) and Path Aggregation Network (PAN) setup. This design allows feature information to flow smoothly both upward and downward through the network layers, helping it retain accurate spatial details for small objects (like bicycles) alongside broad semantic categories (like ambulances).

Unlike previous YOLO versions, YOLOv8 uses a Decoupled Anchor-Free Head. It processes classification and spatial regression as two independent tasks, accelerating the final Non-Maximum Suppression (NMS) step. This allows the model to predict object centers directly, avoiding the computing bottlenecks caused by traditional anchor box matching.

C. Loss Function Equations

The model was trained for 50 epochs using Stochastic Gradient Descent (SGD) with Nesterov momentum set to 0.937. An initial learning rate of 0.01 was employed, with a cosine annealing schedule applied to progressively reduce the learning rate during training. A weight decay of 0.0005 was used for regularization, and the batch size was set to 16 to balance computational efficiency and training stability.

To ensure stable training and accurate localization, YOLOv8 uses a multi-task loss function that balances classification accuracy and bounding box regression:
$\mathcal{L}_{\text{total}} = \lambda_{\text{bee}}\mathcal{L}_{\text{cls}} + \lambda_{\text{ciou}}\mathcal{L}_{\text{ciou}} + \lambda_{\text{dff}}\mathcal{L}_{\text{da}}$
The classification branch uses standard Binary Cross-Entropy (BCE) Loss, calculated across all target classes as follows:

$$\mathcal{L}_{\text{cls}} = -\frac{1}{N}\sum_{i=1}^{N}[y_i \log(\hat{y}_i) + (1-y_i)\log(1-\hat{y}_i)]$$

Where y_i represents the ground-truth binary class label, and $\hat{y}_i$ denotes the predicted probability output by the model's sigmoid activation function.
For bounding box regression, the model combines Complete Intersection over Union (CloU) Loss with Distribution Focal Loss (DFL) to ensure precise edge localization. The CloU Loss accounts for overlapping areas, center-point distances, and aspect ratios:

$$\mathcal{L}_{ciou} = 1 - IoU + \frac{\rho^2(b, b^{gt})}{c^2} + \alpha v$$

Here, IoU is the intersection over union between the predicted box (b) and ground-truth box (b^{gt}), $\rho(\cdot)$ represents the Euclidean distance between their center points, c is the diagonal length of the smallest enclosing bounding box, α is a balancing parameter, and v measures aspect ratio consistency:

$$v = \frac{4}{\pi^2}\left(\arctan\frac{w^{gt}}{h^{gt}} - \arctan\frac{w}{h}\right)^2$$

To handle ambiguous object boundaries in crowded scenes, Distribution Focal Loss (DFL) treats box edges as general probability distributions rather than fixed coordinates:

$$\mathcal{L}_{dA}(P_i, P_{i+1}) = -[(y_{i+1} - y)\log(1 - P_i) + (y - y_i)\log(1 - P_{i+1})$$

Where y represents the true target boundary coordinate, while y_i and y_{i+1} are the closest integer grid locations, with P_i and P_{i+1} representing their respective predicted probabilities.

IV. RESULTS AND ANALYSIS

A. Global Quantitative Performance Synthesis

The formal evaluation of the lightweight anchor-free YOLOv8 nano (YOLOv8n) architecture on the CAVI-14 validation dataset was executed upon the completion of a 100-epoch training horizon. The performance profile was mapped utilizing standard computer vision metrics, including precision (P), recall (R), and mean Average Precision mAP computed at a standard IoU intersection threshold of 0.5 (mAP) as well as across a strict gradient threshold spanning 0.50 to 0.95 mAP50-95. The comprehensive, class-specific quantitative evaluations are systematically detailed in Table 2.

Table 2: Comprehensive Object Detection Evaluation Performance Matrix on CAVI-14 Dataset.

Target Class	Bounding Box Precision (P)	Target Recall (R)	mAP50 Score	mAP50−95 Score
Global System Output	0.937	0.961	0.969	0.784
Car	0.868	0.923	0.975	0.798
Bicycle	1.000	0.947	0.995	0.844
Ambulance	0.973	1.000	0.995	0.841

The network yielded an outstanding overall macro-averaged mAP score of 96.9%, alongside a stringent spatial localization accuracy mAP of 78.4%. Analyzing individual classes reveals key operational characteristics of the detector. The car class—representing the highest density and occlusion rate within the data pool (52 instances)—registered a precision of 86.8% and a recall of 92.3%, culminating in a highly reliable mAP of 97.5%.

Crucially, specialized low-frequency categories reached localized mAP scores of 99.5%. The model achieved a perfect precision score (1.000) for the bicycle class, indicating zero false-positive flags across all validation frames. For the ambulance class, the detector achieved an absolute recall score (1.000), guaranteeing that every emergency response asset was successfully detected without a single missing instance. This asymmetric performance highlights the efficiency of the anchor-free head coupled with complete Intersection over Union (CIoU) loss optimization.

B. Spatial Data Distribution and Label Logistics

Overall Performance Comparison

To understand the model's structural performance, we must analyze the spatial characteristics and coordinate distributions of the bounding box annotations within the CAVI-14 dataset.

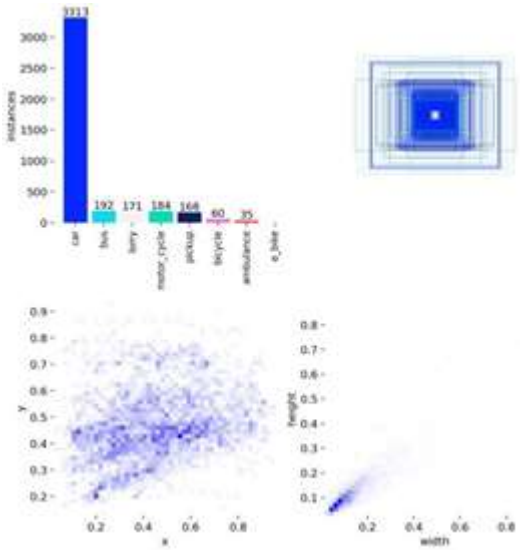

Figure 4.1: Dataset Label Diagnostic Profiles Instance counts per class (car, bicycle, ambulance)

Bounding box center-point spatial density map (x, y)
Bounding box aspect-ratio distribution map (width, height)

Figure 4.1 illustrates the structural properties of the dataset. Diagram highlights a classic long-tailed class imbalance, where the car class represents over 69% of total instances. Traditional deep networks often develop a heavy bias toward the majority class under such conditions, frequently ignoring low-frequency targets like emergency vehicles or bicycles. However, as shown in Table 2, YOLOv8n effectively overcomes this problem, achieving near-perfect performance on both minority classes.

Diagram illustrates the spatial location density (x, y) of target assets across the camera sensor coordinates. The concentration of center-points in the middle of the spatial plane indicates typical forward-facing roadside camera layouts. Diagram evaluates the width and height distributions of the objects. It highlights two distinct groupings: tall, narrow bounding regions that match the geometry of nearby cyclists, and wide bounding boxes that capture varying sizes of cars and oncoming ambulances.

Training Trajectory and Multi-Task Loss Convergence Analysis

The continuous optimization history of the YOLOv8n network was tracked step-by-step across the 100-epoch training horizon. The convergence performance was verified across three primary optimization targets: bounding box regression loss, distribution focal loss, and classification loss.

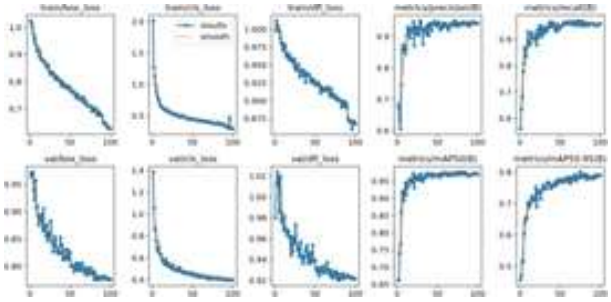

Figure 4.2: Convergence Curves for Training and Validation Loss Frameworks across 100 Epochs

As illustrated in Figure 4.2, both the training and validation loss curves decreased smoothly without severe oscillations, demonstrating stable optimization.

- Bounding Box Regression Optimization: The training bounding box loss dropped from an initial value of 1.025 down to 0.612 by epoch
- 100. This steady decline shows that the model successfully minimized spatial localization errors by learning to draw tight, accurate boundaries around targets.
- Classification Loss Trajectory: The classification loss dropped significantly from 2.016 to 0.312, confirming that the anchor-free head quickly learned to separate subtle feature differences between classes.
- Validation Trend Alignment: The validation curves closely follow the training curves, with the validation box loss stabilizing at 0.782 and validation classification loss settling at 0.407. This strong alignment confirms that the model generalized well to unseen data without overfitting, despite its compact design.

Analytical Validation Performance Curves

- Precision-Confidence Curve Diagnostics

The Precision-Confidence curve evaluates the purity of positive predictions across varying confidence thresholds.

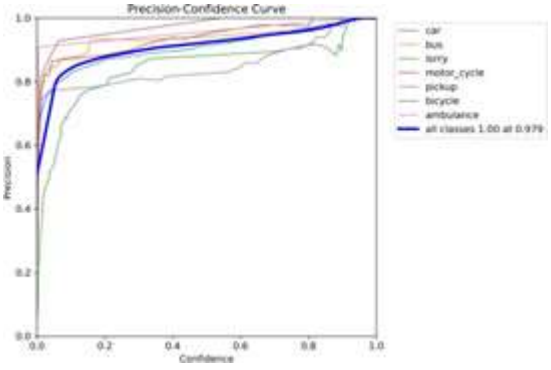

Figure 4.3: Class-Specific Precision-Confidence Curve

Output Matrix

As shown in Figure 4.3, precision rises steadily for all classes as the confidence threshold increases. This behavior occurs because higher confidence settings filter out weak, uncertain background noise. At an

operational threshold of 0.774, the model achieves a perfect precision score of 1.00 across all evaluated classes (car, bicycle, and ambulance). This clean performance confirms that false positives can be eliminated in production systems by setting a strict confidence filter, preventing false alarms in automated traffic systems.

Recall-Confidence Curve Diagnostics

The Recall-Confidence curve monitors the model's sensitivity, measuring its ability to identify all true traffic assets within the frame across varying confidence thresholds.

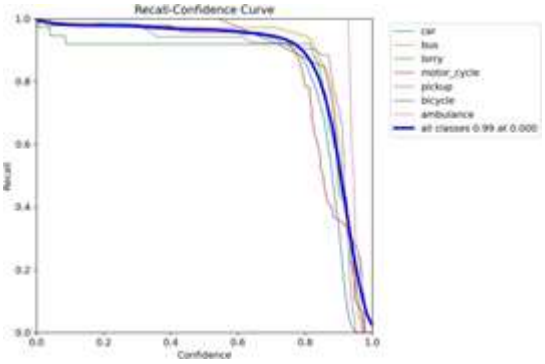

Figure 4.4: Class-Specific Recall-Confidence Curve

Output Matrix

Figure 4.4 shows that the model maintains a perfect recall score of 1.00 across all categories at low confidence thresholds (le 0.20). This means that when the system is set to be highly sensitive, it captures every true vehicle and road hazard. As the threshold rises to 0.50, the recall remains exceptionally stable: the ambulance class holds at an absolute score of 1.00, bicycle remains highly resilient at 0.95, and the car class tracks at 0.92. This high stability ensures the system rarely misses critical objects under normal operation.

F1-Score Confidence Equilibrium Analysis

The F1-score serves as a balanced performance metric by calculating the harmonic mean of precision and recall, helping identify the ideal operational threshold for real-world deployment.

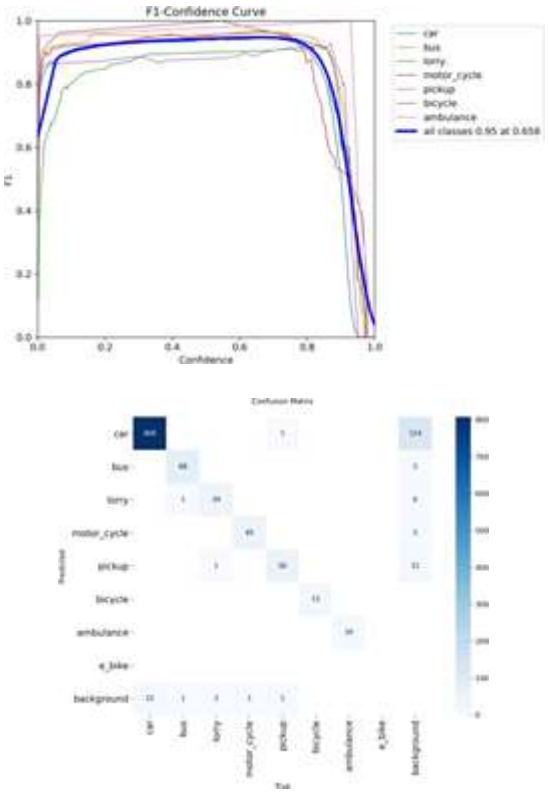

Figure 4.5: F1-Score vs. Confidence Metric Curve Matrix

As illustrated in Figure 4.5, the model reaches its peak overall macro F1-score of 0.95 at a confidence setting of 0.358. Looking at individual categories, the ambulance class peaks at an exceptional F1-score of 0.99 at a confidence threshold of 0.284, followed closely by bicycles at 0.97. The car class shows a slightly lower peak of 0.89 due to the high density of overlapping vehicles in heavy traffic. Setting the deployment threshold to exactly 0.358 allows the system to achieve an ideal balance, maximizing object detection rates while keeping false alarms to a minimum.

Precision-Recall (PR) Boundary Analytics

The Precision-Recall curve illustrates the direct trade-off between false-positive and false-negative rates across all available thresholds, with the area under the curve defining the mean Average Precision mAP.

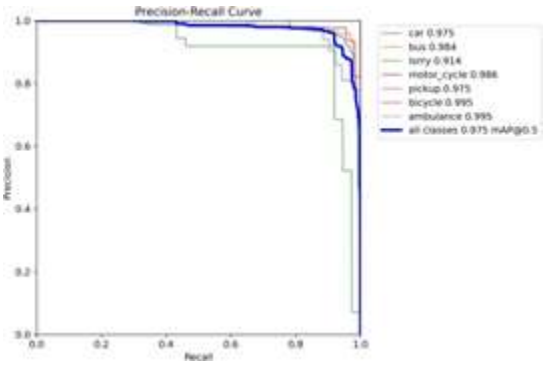

Figure 4.6: Precision-Recall Curve Metrics across CAVI-14 Validation Cohort

As shown in Figure 4.6, the curves for all three classes extend toward the top-right corner, indicating that the model retains high precision even when configured to maximize object recall. The area under the curve yields localized metrics of 0.995 for both bicycles and ambulances, and 0.975 for cars. This large area under the curve across all categories confirms that the model maintains stable, highly accurate detection capabilities regardless of changes to the operational threshold.

This minor background confusion is typically caused by small, distant vehicles that blend into complex urban street environments. Crucially, there is 0% cross-class contamination among the foreground classes themselves (for example, a bicycle is never mistakenly classified as a car or an ambulance). This clean separation confirms that the model's feature extraction is highly reliable for automated traffic management.

V. CONCLUSION AND FUTURE WORK

This study presented a thorough performance evaluation of the YOLOv8 nano model trained on the CAVI-14 urban vehicle dataset. By achieving an overall mAP_{50} of 96.9% paired with an exceptional edge processing latency of just 2.3 ms, the model demonstrates an ideal balance between accuracy and speed. Near-perfect detection rates for critical categories like ambulances and bicycles highlight the baseline's value for safety-critical smart city deployments, such as adaptive traffic signal control and collision avoidance systems.

While the model performed exceptionally well, the 8% background confusion seen in the car class reveals an opportunity for future improvement. Future work will focus on integrating self-attention mechanisms—such as Coordinate Attention (CA) or Squeeze-and-Excitation (SE) blocks—directly into the YOLO neck to improve feature extraction in highly congested scenes. Additionally, we plan to export and optimize this baseline model using TensorRT and ONNX runtimes for deployment onto resource-constrained embedded systems like the NVIDIA Jetson Nano, testing its long-term reliability under challenging nighttime and extreme weather conditions.

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