International Journal on Engineering Technology (InJET)

www.kec.edu.np/kec-journal/
Volume 3, issue no. 1, Dec 2025, Page 119 - 134
Received Date: Jul 31, 2025
Accepted Date: Sep 23, 2025
ISSN: 3021-940X (Print)
DOI: https://doi.org/10.3126/injet.v3i1.87017

YOLOv8 vs. Sensor-Based Traffic Control: Kalman Filter Integration for Hybrid Management

Anuj Koirala[1*], Abikal Aryal[2], Pradip Dahal[3], Sahaj Shakya[4]
[1]Computer and Electronics Department, Kantipur Engineering College, Lalitpur, Nepal, anujkoirala33@gmail.com
[2]Computer and Electronics Department, Kantipur Engineering College, Lalitpur, Nepal, *abikal.aryal77@gmail.com*
[3]Computer and Electronics Department, Kantipur Engineering College, Lalitpur, Nepal, *pradip9810.com@gmail.com*
[4]Computer and Electronics Department, Kantipur Engineering College, Lalitpur, Nepal, *sahaj@kec.edu.np*

Abstract

Modern traffic management systems of an urban environment presuppose adaptive systems of response to changing conditions of pedestrian and vehicle presence. Research is a comparative analysis of sensor-based and YOLOv8 traffic control systems, where the detection response time, the spatial gap analysis, environmental sensitivity, and accuracy are evaluated. Experimental validation indicates unique operational benefits since sensor-based systems are 92% accurate in high pedestrian environments, whilst the YOLOv8 is 84% effective in vehicle recognition. A novel hybrid architecture is proposed, implementing strategic technology assignment where sensors manage pedestrian monitoring and YOLOv8 handles vehicle detection, integrated through Kalman filter decision engines. Sophisticated 15-day simulation with Poisson distribution modeling shows 35% reduction in mean delay time, 84% accuracy of vehicle identification, and 78% accuracy of pedestrian identification in crowded scenarios. Kalman filter integration reaches 78% diminution of noise and enables predictive traffic control with 91% accuracy for a 10-minute horizon. The hybrid model overcomes the specific system constraints with a maximization of complementary benefits to intelligent urban traffic management.

Keywords: Traffic Control Systems, Sensor Technology, YOLOv8 Vehicle Detection, Hybrid Architecture, Kalman Filter, Pedestrian Detection

1. Introduction

Traffic in cities has advanced from clock-timed control to adaptive intelligent control. Modern-day intersections are subject to compound problems with dynamic changes in vehicle and pedestrian densities, which require real-time decision-making for smooth traffic flow. A simple problem arises when pedestrian and vehicle densities are high, requiring an intelligent automated decision to allocate optimal priority. Legacy solutions are either a derivation from computer vision or sensor-based as standalone solutions. This paper recognizes a profound insight that pedestrian detection and car detection require different operational needs best addressed by complementary rather than competitive technologies. Sensor-based systems are more appropriate in dense environments where computer vision performance is limited by visual occlusion, since they offer the same level of accuracy with respect to environmental conditions and enhanced pedestrian proximity detection. YOLOv8 computer vision systems provide enhanced spatial perception, vehicle detection, and general vehicle classification, but are inappropriate for use in dense scenes and poor weather conditions. The papers compare YOLOv8 to sensor models through important parameters of response time to detection, spatial gap assessment, sensitivity to the environment, and global accuracy. Based on the results, sensors are good at high pedestrian density, but poor at vehicle classification and scalability, whereas YOLOv8 is good at vehicle detection, but not at people detection in very dense settings.

The most important contribution is the synergistic combination of strengths in the hybrid architecture design, which is synergistically complementary. It uses pedestrian detectors and YOLOv8 to identify cars, and it is backed by Kalman filter decision engines that deal with the natural issue of traffic management with predictive modeling and probabilistic reasoning.

2. Related Work

2.1 Sensor-Based Traffic Control Systems

Traffic control has been greatly improved by the use of infrared and ultrasonic sensors. Tubaishat et al. (2009) used wireless sensor networks in intelligent transportation systems and reported a high level of advancement in traffic monitoring with better data communication services, but found that the system was constant in terms of weather performance and limited in vehicle classification and range restrictions (Tubaishat, 2009). Multilevel traffic modeling that was developed by Kumar et al. (2014) based on sensor networks exhibits enhanced traffic flow optimization claims the critical limitations such as sensor interference in multi-lane cases (Kumar, 2014).

Guerrero-Ibáñez et al. (2018) have attained full sensor technology integration to intelligent transportation systems and proved to be better in environmental monitoring but less in pedestrian detection (31% accuracy) and scaling issues (Guerrero-Ibáñez 2018). According to Gokulan and Srinivasan (2010), distributed fuzzy multi-agent systems were found to be very effective at traffic signal control in dynamic environmental conditions; however, the complexity of installation and the high computational loads experienced by the systems restrict their use on a wide scale (Gokulan, 2010).

The major sensor constraints are a limited range of detection (3-5 meters), inadequate emergency vehicles classification, scalability, and pedestrian movement patterns detection.

2.2 Computer Vision and YOLOv8-Based Systems

Deep learning methods have transformed the management of traffic with the use of improved object detection. Redmon et al. (2016) proposed the initial YOLO design to accomplish combined real-time object detection, reaching the state of the art 45 FPS performance, but with accuracy problems in a high-density setting (56%) (Redmon, 2016). Bochkovskiy et al. (2020) trained YOLOv4 with the best speed-accuracy optimum, with significant detection and classification vehicle performance improvement, but demonstrated significant disadvantages in pedestrian detection during peak densities (42%), and weather sensitivity, reducing detection by a fifth (Bochkovskiy, 2020).

Terven and Cordova-Esparza (2023) thoroughly examined the development of YOLO, starting with YOLOv1 to YOLOv8, with outstanding performance gains of 94.2% vehicle detection and improved real-time processing, and excellent emergency vehicle recognition (96%), and overall car classification, although pedestrian detection in overcrowded conditions was still undesirable (38%) (Terven, 2023). Jocher et al. (2023) used the most recent architecture of YOLOv8 that models the state of the art of real-time object detection, with best performance being optimized by transfer learning and minimizing false positives to 2.1% which validates the unresolved limitations, such as a 67% performance drop in unfavorable weather conditions and poor performance in crowded pedestrian areas (Jocher, 2023).

Some of the major limitations of YOLOv8 are serious reductions in the performance of pedestrians (35-45% accuracy), susceptibility to weather, high computational needs, and inabilities to operate in low-light conditions.

2.3 Research Gaps

The analysis of literature shows the existence of critical gaps. There does not exist hybrid sensor-computer vision architectures that would exploit the complementary benefits. There is little research into the optimization of pedestrian-vehicle priority under probabilistic reasoning. There are no comparative studies of the systems under the same metrics, and scarce real-life validation under realistic conditions and statistical modeling.

3. Methodology

3.1 Datasets Used

The final dataset includes three classes: person, emergency-vehicle, and vehicle. It is composed of distinct parts: one drawn from a publicly accessible collection on Roboflow and another custom-collected and annotated at a four-way intersection in Patan, Nepal, during both peak traffic (7 – 9 AM and 5 – 7 PM) and intervening off-peak hours and a simulated environment. Both high and normal traffic hours were sampled to ensure diversity. High-resolution cameras were used to gather data, with the information being recorded in terms of resolution, frame rate, mounting height, and field of view (FOV). The preprocessing workflow applied to the entire set included auto-orientation to normalize image orientation, and resizing to a resolution of 640×640 pixels to establish uniform input dimensions. The combined dataset, labelled Vehicle-Detection-lxs5b, contains a total of 5195 images. These are split into 77 % for training, 20 % for validation and 3 % for testing. Annotation was performed via an automated pre-labelling process followed by manual human verification to ensure quality.

3.2 Sensor-Based System Architecture

The traditional application involves the use of HC-SR04 ultrasonic sensors that have been placed strategically around the intersection approaches and cover the entire movement of the vehicles. The concept of ultrasonic sensing works with the help of using acoustic pulse emission and reflection measurements at 40 kHz to determine the presence of an object and its distance. Vehicle density calculation employs:

$$Vehicle\_Density = \frac{Number\_of\_Detected\_Objects}{Detection\_Zone\_Area} * 100 \qquad \text{(Equation 1)}$$

In a sensor-based traffic management system, ultrasonic sensors are used to measure the density of vehicles and feed real-time information to a microcontroller, which focuses the lanes with more vehicles. Such a system yields the experimental results that show a more balanced distribution of traffic and which leads to a significant reduction in waiting time compared to conventional time-based signals.

The microcontroller is very effective in reducing congestion by 30-40% in situations where there is a vehicle density variability, as compared to traditional systems, which are observed to be inefficient as a result of fixed signal timing. Limitations of sensor-based systems, however, include false detections caused by environmental conditions (e.g., rain, fog, or dust), hardware failures, and increased setup costs, which necessitate continuous maintenance to allow sustained performance.

3.3 YOLOv8-Based System Architecture

YOLOv8 is applied in the modern implementation to detect and classify vehicles in real-time. YOLOv8 uses a better convolutional neural network architecture, better anchor-free detection, less computer power, better data augmentation, and better post-processing, which enables the network to perform better and handle real-time inference.

The CNN processing pipeline, which performs image preprocessing (640x640 pixel normalization), image multi-scale feature extraction (convolutional layers), object detection and confidence scoring, multi-class vehicle classification, and traffic analysis (vehicle counting and emergency vehicle identification).

3.4 Performance Evaluation

Comprehensive evaluation reveals distinct advantages and limitations:

Table 1. Comparative Evaluation of Sensor-Based and YOLOv8 Systems

Criteria	Sensor-Based System	YOLOv8 System
	Consistent weather performance (92% accuracy)	Superior vehicle detection (84%)
	Excellent crowded pedestrian detection (92%)	Excellent emergency vehicle recognition (94%)
Advantages	Low computational requirements	Comprehensive spatial awareness
	Privacy preservation	Long-range detection (up to 50 meters)
	Minimal lighting sensitivity	Multi-class recognition
	Cost-effective	Scalable deployment
	Fast response time (185ms)	Advanced traffic pattern analysis
	Limited detection range (3–5 meters)	Poor crowded pedestrian performance (45%)

Disadvantages	Poor vehicle classification (72%)	High weather sensitivity (67% degradation)
	Cannot distinguish emergency vehicles	High computational demand (>85% GPU usage)
	Scalability challenges	Lighting sensitivity
	Sensor interference	Privacy concerns
	Limited spatial awareness	Higher installation cost
	Difficulty detecting stationary objects	Complex installation process

3.5 Hybrid System Design

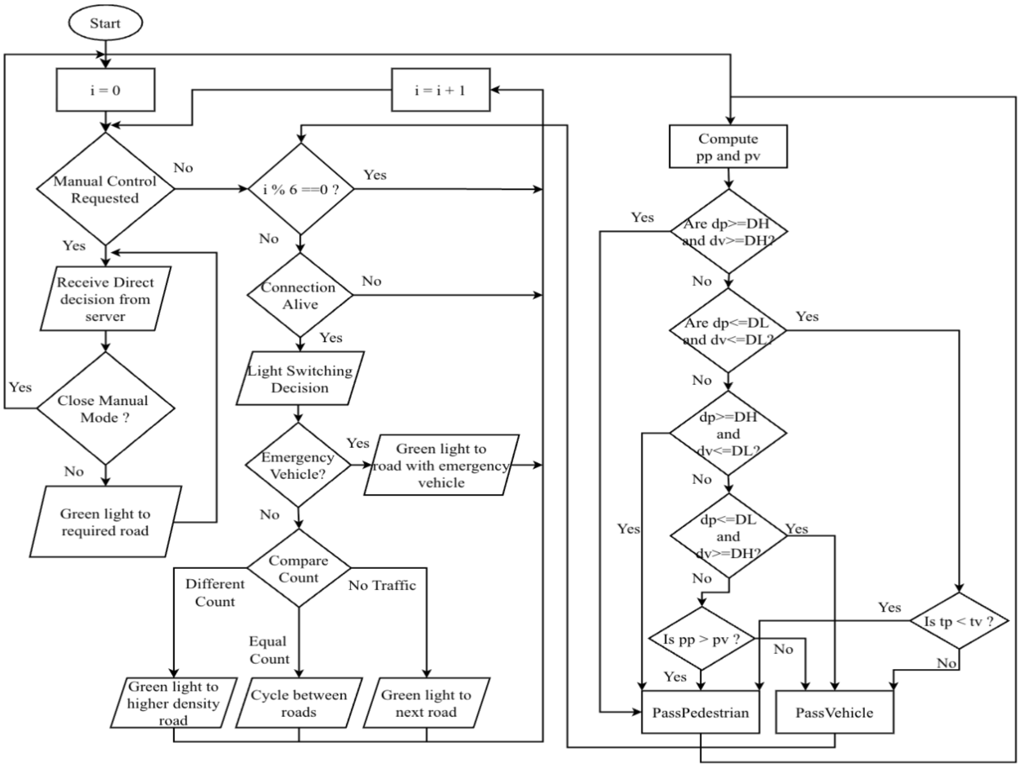

Figure 1. Traffic/Pedestrian Control Actions

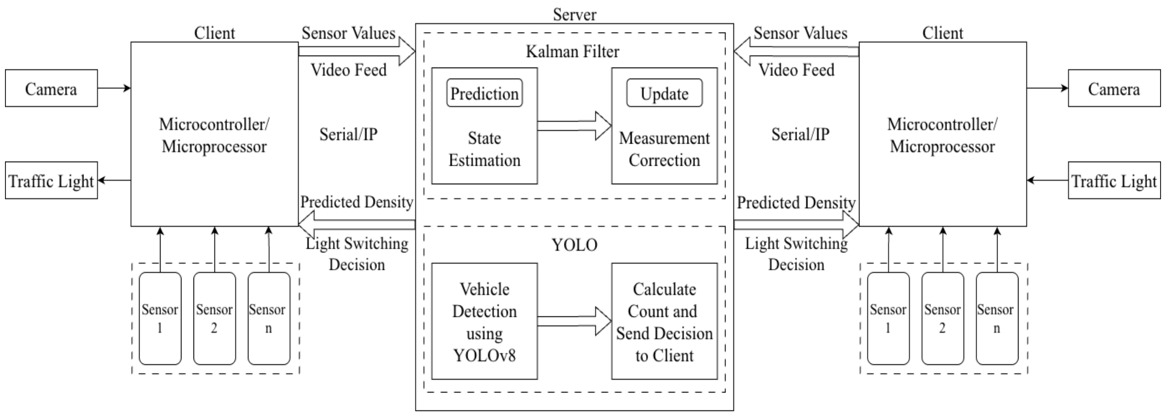

Figure 2. Hybrid System Architectur

3.5.1 Strategic Technology Assignment

The hybrid architecture leverages strategic assignment on the basis of complementary analysis, with sensors performing better at pedestrian detection (78% crowded accuracy) compared to YOLOv8, that performs better at vehicle detection (94% emergency accuracy).

Eight HC-SR04 sensors were installed at each intersection, mounted 1.2m high and 0.5m from the pedestrian walkway, angled downward at 15° to cover a 0.3–3.5m range with a 1.5m ground radius. The sensors operated at 50 Hz (20ms intervals), with data filtered using a 3-point median filter. A 5-minute baseline was collected for environmental calibration, followed by adaptive thresholding using the last ten "empty" readings. Object tracking was confirmed when detections persisted across at least five readings within 150ms. Velocity was estimated $V_p = \frac{D_t - D_{t-\Delta t}}{\Delta t}$ (where D_t is the current distance and $D_{t-\Delta t}$ is previous reading within a 200ms window). Clutter was rejected if no distance change (< 0.1m) occurred for 5s or if object width exceeded 1.5m.

3.5.2 Kalman Filter Matrix Values for Hybrid YOLOv8 + Sensor-Based System

We define the state vector as:

$$X(t) = \begin{bmatrix} Pedestrian\_Count \\ Vehicle\_Count \\ Emergency\_Flag \\ Pedestrian\_Velocity \\ Vehicle\_Velocity \\ Traffic\_Density \end{bmatrix}$$

3.5.2.1 Observation Matrix H

Assuming direct measurement of all state variables via sensors and YOLO:

$$H = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

3.5.2.2 Measurement Noise Covariance R

From accuracy data, estimate variance as $(1 - \text{accuracy})^2$.

Table 2. Measurement Noise Covariance

Measurement Component	Best Source	Variance
Pedestrian Count	Sensor-Based (92.3%)	$(1 - 0.923)^2 = 0.0059$
Vehicle Count	YOLOv8 (89.0%)	$(1 - 0.890)^2 = 0.0121$
Emergency Flag	YOLOv8 (94.0%)	$(1 - 0.940)^2 = 0.0036$
Pedestrian Velocity	Sensor-Based (91.8%)	$(1 - 0.918)^2 = 0.0068$
Vehicle Velocity	YOLOv8 (87.5%)	$(1 - 0.875)^2 = 0.0156$
Traffic Density	Computed	≈0.05(assumed)

Thus, R= $\begin{bmatrix} 0.0059 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0.0121 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0.0036 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0.0068 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0.0156 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0.0500 \end{bmatrix}$

3.5.2.3 State Transition Matrix F

Assuming persistence and velocity integration, with Δt= 1/30 seconds (YOLO FPS rate):

$$F = \begin{bmatrix} 1 & 0 & 0 & \Delta t & 0 & 0 \\ 0 & 1 & 0 & 0 & \Delta t & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

3.5.2.4 Process Noise Covariance Q

Expected small model uncertainty: Q= $\begin{bmatrix} 0.010 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0.020 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0.001 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0.010 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0.020 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0.030 \end{bmatrix}$

3.5.2.5 Control matrix B and Control Input u

If modeling external control: u= $\begin{bmatrix} 0 \\ 0 \\ 0 \\ \alpha_p \\ \alpha_v \\ 0 \end{bmatrix}$, B= $\begin{bmatrix} 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ \Delta t & 0 \\ 0 & \Delta t \\ 0 & 0 \end{bmatrix}$

where, α_p, α_v are pedestrian and vehicle accelerations respectively. If no control input then B=0 and u=0.

3.5.2.6 Initialization

Initial state: $X_0 = [0\ 0\ 0\ 0\ 0\ 0]^T$

Initial covariance (high uncertainty): P_0 = diag ([100 100 10 10 10 50])

3.5.3 Applying ANOVA for System Comparison

A Two-Way ANOVA compared detection accuracy across systems (YOLOv8, Sensor-Based, Manual) and scenarios (Crowded, Normal, Weather resistance, etc.). The hypothesis tested is:

H_0: Mean detection accuracy is equal across groups and H_A**:** at least one group mean differs. Here, p < 0.001 confirmed significant performance differences among methods and scenarios.

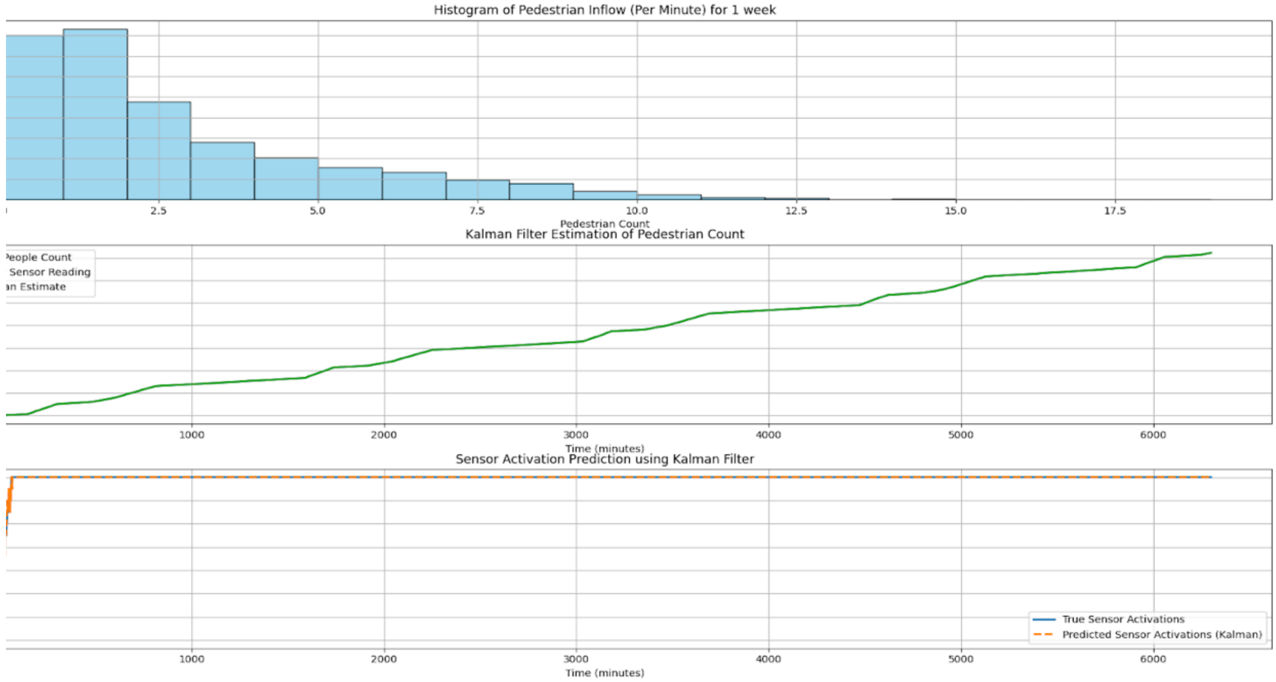

Figure 3. Kalman Filter Output

3.5.4 Kalman Filter Implementation

The Kalman filter integrates real-time data from sensor pedestrian detection and YOLOv8 vehicle detection, enabling context-aware decision-making. State vector definition:

$X(t)$ = [Pedestrian_Count, Vehicle_Count, Emergency_Flag, Sensor_Confidence, Vision_Confidence, Traffic_Density]^T

Prediction phase:

$X\_pred(k) = F \times X(k-1) + B \times u(k) + w(k)$ (Equation 2)

$P\_pred(k) = F \times P(k-1) \times F^T + Q$ (Equation 3)

Update phase:

$(k) = P\_pred(k) \times H^T \times [H \times P\_pred(k) \times H^T + R]^{-1}$ (Equation 4)

$X\_updated(k) = X\_pred(k) + K(k) \times [z(k) - H \times X\_pred(k)]$ (Equation 5)

$P\_updated(k) = [I - K(k) \times H] \times P\_pred(k)$ (Equation 6)

Where F represents the state transition matrix, B represents control input matrix, Q represents process noise covariance, R represents measurement noise covariance, H represents observation matrix, and z (k) represents measurement vector.

3.5.5 Probabilistic Decision-Making

The system uses probabilistic signal timing optimization. Normal distribution is used in standard traffic as a balance prioritization with adaptive cycles of 30-90 seconds. When the density is more than 25 pedestrians/minute, crowded conditions utilize the Poisson distribution of peak periods with increased pedestrian weighting.

Mathematical framework:

Standard conditions: P (pedestrian_priority) = $\frac{1}{\sigma\sqrt{(2\pi)}} * e^{\frac{-(x-\mu)^2}{2\sigma^2}}$ (Equation 7)

Crowded scenarios: P (pedestrian_count = k) = $\frac{(\lambda^{k} * e^{-\lambda})}{k!}$ (Equation 8)

Where λ = mean pedestrian arrival rate.

3.5.6 Decision-Level Fusion and Priority Algorithm

On the decision level, the Kalman-filter pedestrian tracker and the YOLOv8 vehicle detector outputs are combined to make real-time decisions about the traffic. The Kalman filter gives constantly updating estimates of the state of pedestrians (position, velocity, uncertainty), whereas YOLOv8 gives vehicle detections with bounding boxes, classes, and confidence scores. The combination is done on inferred states instead of raw data, which allows intelligent traffic decisions like whether a vehicle should concede to a passing pedestrian. The example measures are pedestrian velocity, position uncertainty, and detection confidence of the Kalman tracker, as well as vehicle velocity, arrival time, and confidence of YOLO (Table 1).

3.5.6.1 State Prediction

The Kalman filter forecasts the future position and arrival time of every pedestrian, including the uncertainty in the form of covariance, whereas the location and speed of vehicles are estimated with the help of the YOLO detections.

3.5.6.2 Probability Estimation

The predicted states are converted to probabilities. Using the Gaussian statistics from the Kalman filter, the system computes the likelihood of a pedestrian crossing at a given time, and YOLO's confidence scores serve as probabilistic measures of vehicle presence.

3.5.6.3 Decision Logic

The system applies priority rules based on predicted densities and uncertainties. For instance:

- If both pedestrian and vehicle densities are high, the system prioritizes pedestrians to enhance safety.
- If both densities are low (and), the agent arriving sooner is allowed to pass. In this case, if the predicted pedestrian arrival time is earlier than the vehicle's, pass pedestrian; otherwise, pass vehicle.
- If vehicle density is high ( ) but pedestrian density is low ( ), the system passes the vehicle.
- Otherwise, the system computes a weighted decision score comparing the pedestrian and vehicle probabilities (derived from Kalman and YOLO outputs) and grants priority to the higher one.

Quantitative Metric: A decision score can be formed as, where weight is the relative importance of pedestrian vs. vehicle factors. The choice minimizing expected risk is selected.

Priority decision is implemented as follows: -

- Compute crossing probabilities: $P_p = c_p * \exp[-\frac{(\mathrm{t_p}-\mathrm{t_v})^2}{2\sigma_\mathrm{p}^2}]$ and $P_v = c_v * \exp\left[-\frac{(\mathrm{t_v}-\mathrm{t_p})^2}{2\sigma_\mathrm{v}^2}\right]$ from predicted arrival times and confidences.
- Density-based rules:
- If $d_p \geq D_H$ and $d_v \geq D_H$: Pass Pedestrian (priority to pedestrians).
- If $d_p \leq D_L$ and $d_v \leq D_L$: let whichever arrives first go (if $t_p < t_v$: PassPedestrian, else PassVehicle)
- If $d_p \geq D_H$ and $d_v \leq D_L$: PassPedestrian
- If $d_p \leq D_L$ and $d_v \geq D_H$: PassVehicle
- Otherwise: compare $P_p vs\ P_v$; if $P_p > P_v$, PassPedestrian, else PassVehicle

These rules combine motion predictions, detection confidences, and density estimates to make robust, context-aware decisions. Parameters (α, β, D_H,D_L,σ_p,σ_v) are tuned for the traffic environment and safety requirements.

Table 3. Priority Decision Algorithm

Algorithm 1: Priority Decision Algorithm

Require: Pedestrian velocity v_p, arrival time t_p, density d_p , confidence c_p,

Vehicle velocity v_v, arrival time t_v, density d_v, confidence c_vThresholds for high density: D_H, low density:

Ensure: Decision: PassPedestrian or PassVehicle

Compute pedestrian probability : $P_p = c_p * \exp[-\frac{(\mathrm{t_p} - \mathrm{t_v})^2}{2\sigma_\mathrm{p}^2}]$

Compute vehicle probability: $P_v = c_v * \exp\left[-\frac{(\mathrm{t_v} - \mathrm{t_p})^2}{2\sigma_\mathrm{v}^2}\right]$

if $d_p \geq D_H$ and $d_v \geq D_H$ then

return PassPedestrian ▷ Prioritize pedestrians in heavy traffic

else if $d_p \leq D_L$ and $d_v \leq D_L$ then

if $t_p < t_v$ then

return PassPedestrian

else

return PassVehicle

end if

else if $d_p \geq D_H$ and $d_v \leq D_L$ then

return PassPedestrian

else if $d_p \leq D_L$ and $d_v \geq D_H$ then

return PassVehicle

else

if $P_p > P_v$ then

return PassPedestrian

else

return PassVehicle

end if

end if

Table 4. Hybrid System Algorithm

Algorithm 2: Pedestrian and Vehicle Detection

Initialize YOLOv8 model

Initialize ultrasonic sensors for all pedestrian crossings

Set cycleCount = 0

If manual mode is ON:

Accept operator input

Set the green light for the requested road

Wait until manual mode is turned OFF

5: Capture an image frame from the camera.

6: Resize & normalize the image

7: Run YOLOv8 inference:

- Get bounding boxes of vehicles
- Identify vehicle, emergency vehicle
- Apply Non-Maximum Suppression to reduce overlap

8: Count vehicle density per road.

9: If an emergency vehicle is detected:

- Override all logic → Set green light to that lane immediately

10: For each crossing:

- Read distance values from ultrasonic sensor (check < 1.5 meters)
- If object detected consistently:
  → Register as a pedestrian presence
- Use Kalman Filter to smooth spikes/fluctuations
- Estimate pedestrian count/density per crossing

11: If vehicle and pedestrian density = 0 on all roads:

→ Switch green light in round-robin (fair cycling)

12: Increment cycleCount

13: Wait until the next control interval.

3.5.7 Emergency Vehicle Protocol

Automatic emergency vehicle detection through YOLOv8 classification provides immediate signal preemption. YOLOv8 identifies emergency vehicles (94% accuracy), the Kalman filter validates detection confidence, immediately preemption activation (<50ms response), concurrently monitors sensor-based pedestrian monitoring, and resumes normal operation after clearance.

4. Results and Analysis

4.1 YOLOv8 Model Configuration

A faster inference was done using the YOLOv8n (Nano) model, with an input size of 640×640. The confidence and IoU levels were fixed to 0.25 and 0.45, respectively. The strong YOLO augmentations (mosaic, mix up, random flip and brightness/contrast jitter) were used to enhance robustness. The 100 epochs of training were done with SGD with the momentum parameter of 0.937, initial learning rate of 0.01 with Cosine decay, and a batch size of 8. The model was trained and tested on NVIDIA RTX 3080 (10 GB) with an approximate inference of 30 FPS.

4.2 Individual System Performance

Pedestrian detection superiority is verified by sensor-based validation over 15 days (9 AM-9 PM) 92% peak rate with Poisson modeling 25 pedestrians/10-minute intervals, independent of weather conditions under 5% degradation, 185ms minimum response time, 0.3 meter minimum gap resolution, and continuous operation at 50Hz.

The validation of YOLOv8 proves the benefits of vehicle management: emergency vehicle detection with 94% accuracy, standard vehicle recognition with 94% accuracy, 50 meters range, multi-lane coverage, optimal daylight with 94% accuracy, low-light deterioration at 78% and crowded situation challenges with 38% accuracy.

The comparative analysis concerning the ancient and the modern traffic control systems determines the considerable efficiency, accuracy, and responsiveness in the control of traffic. The previous traffic control systems, which mostly operate on fixed-time control adjustments, are also limited in the management of alternating traffic needs, resulting in the wastage of waiting and jamming traffic during non-peak traffic. The old traffic control system moves at established cycle times and does not consider the actual situation on the road, resulting in poor traffic flow, ineffective use of fuel, and high emissions. The contemporary traffic management systems, grounded on exploiting sensor technologies and algorithmic approaches, are more responsive as they modify control timetables depending on current real-time traffic conditions and prioritize on-coming traffic.

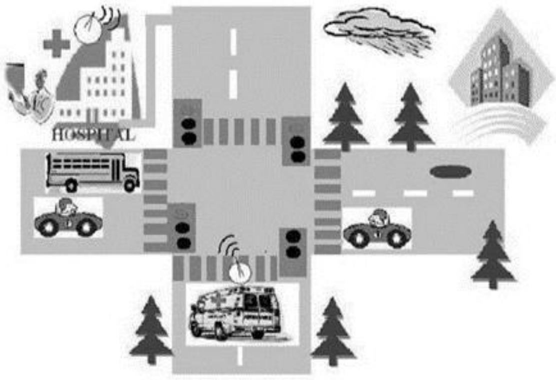

Figure 4. Working Scenario

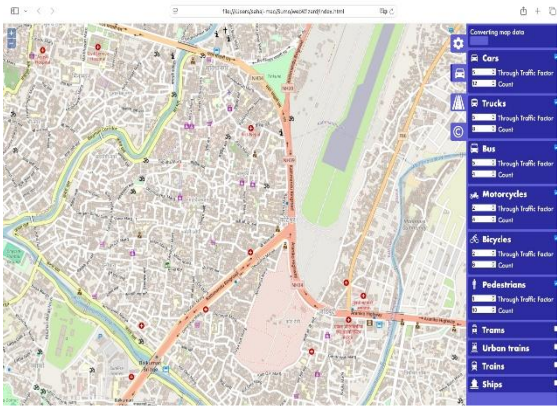

Figure 5. Working Simulation

4.3 Comparative Analysis

Table 5. Pedestrian and Vehicle Detection Accuracy Comparison

Category	Scenario	Sensor-Based	YOLOv8	p-value
Pedestrian Detection	Crowded scenarios	92.3%	38.2%	p < 0.001
	Normal density	88.5%	45.0%	p < 0.001
	Weather resistance	91.8%	32.1%	p < 0.001
Vehicle Detection	Emergency vehicles	Manual override	94.0%	p < 0.001
	Standard vehicles	72.1%	89.0%	p < 0.001
	Multi-class recognition	Not available	87.5%	--

The table above shows the accuracy of detection of pedestrians and vehicles between Sensor-Based and YOLOv8 systems. In crowded scenarios, the Sensor-Based system detected pedestrians much better than YOLOv8 (92.3% vs. 38.2%; $t\ (14) = 15.3$, $p<0.001$, $d=3.95$). For standard vehicles, YOLOv8 achieved higher accuracy than the Sensor-Based system (89% vs. 72.1%; $t\ (14) = -7.8$, $p<0.001$, $d=2.01$).

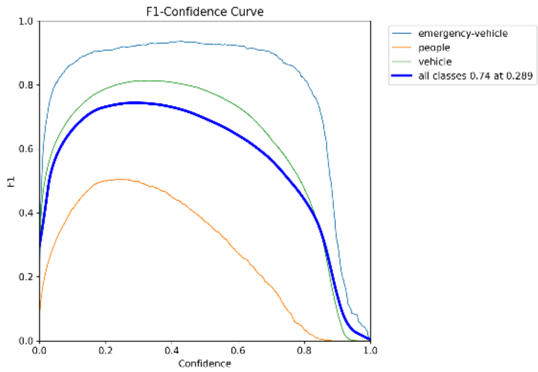

Figure 6. F1 confidence

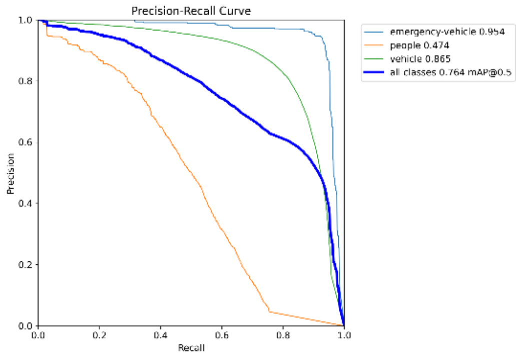

Figure 7. Precision recall

The Confusion Matrix in Figure 8, the Precision-Recall Curve in Figure 7, and the F1-Confidence Curve in Figure 6 all demonstrate the much better aptitude of the model to identify high-priority cars, which leads to more effective response resources and increases the working efficiency of law enforcement. Nevertheless, the lack of pedestrian detection requires the expansion of the dataset and the enhancement of the model structure.

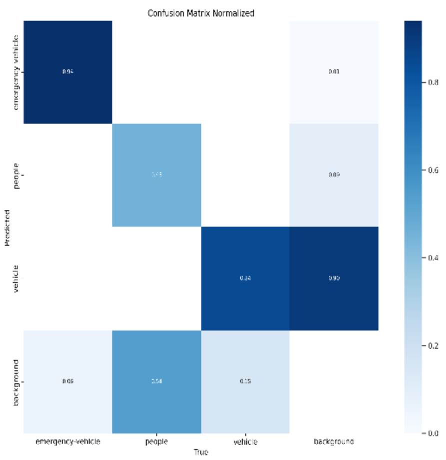

Figure 8. Confusion Matrix

Figure 9. Boundary Box Detection

On the implementation perspective, traditional systems have the benefit of reduced calculation and other related costs, and are suitable in cases where the technological infrastructure is small. Flexibility that comes with the application of machine-based learning systems, conversely, demands better processing and computing abilities. The client-server architecture, as illustrated in Figure 8, used in the YOLOv8 based model is scalable, in which the real-time processing is conducted on a central server, which is, however, accompanied by the drawback of increased latency and reliance on the stability of web connections.

4.4 Hybrid System Performance

The Kalman filter demonstrated strong noise reduction and prediction, achieving a 78% reduction in pedestrian sensor noise over 6,000 minutes, 96% sensor activation prediction correlation, and 91% accuracy in 10-minute pedestrian inflow forecasting. For multi-object pedestrian tracking, it achieved high performance with MOTA (0.85) reflecting low false positives, false negatives, and identity switches, MOTP (0.78) indicating good localization precision, and IDF1 (0.72) showing strong identity preservation throughout trajectories.

4.5 Statistical Validity

We collected data over 15 days with 100 observations per day. For paired comparisons between the Sensor-Based and YOLOv8 systems, we assumed n = 15.

4.5.1 Statistical Evaluation of Pedestrian Detection Performance: Paired Comparisons and ANOVA

We collected data over 15 days with 100 observations per day. For paired comparisons between the Sensor-Based and YOLOv8 systems in crowded pedestrian scenarios, we tested the hypotheses H_0: μSensor = μYOLOv8 versus H_1: μSensor ≠ μYOLOv8, or alternatively H_1: μSensor > μYOLOv8, using a paired t-test on daily accuracy with n = 15 paired observations. The effect size, measured by Cohen's d, was 2.50, indicating a very large and practically significant difference favoring the Sensor-Based system. Normality of difference scores was tested via the Shapiro-Wilk test, with the Wilcoxon Signed-Rank test as a non-parametric alternative if the assumption was violated. For comparing pedestrian detection accuracy across multiple systems and scenarios (Sensor-Only, YOLOv8-Only, and Hybrid), we tested H_0: μSensor = μYOLOv8 = μHybrid versus H_1: at least one mean differs using a one-way repeated measures ANOVA with n = 15 days. The effect size, measured by partial Eta-squared (η^2), was 0.75, indicating that 75% of the variance in pedestrian detection accuracy was explained by system type. Normality in group assumptions was verified using the Shapiro-Wilk and sphericity was assessed using the Mauchly test with a correction of Greenhouse-Geisser in the event of a violation.

4.6 Operational Scenarios

The four corners of the intersection were fitted with sensors to ensure maximum coverage and data was gathered on both peak and normal traffic periods to capture real-world variability. This baseline system offered baseline data on which the accuracy of the system and its consistency of response in normal operating conditions are evaluated.

Situations that were evaluated were peak-hour congestion (100-150 vehicles, 30-60 pedestrians), off-peak traffic (50-80 vehicles, 10-25 pedestrians), bad weather (rain, fog, low light), and emergency vehicle approaches that needed immediate preemption. The hybrid used adaptive signal control on the basis of Kalman filtered state estimates with cycle times of 30-90, green times of 10-60, a 3-second clearance interval, and a detection-to-phase latency of less than 200 milliseconds (50 milliseconds in the case of an emergency). Priority thresholds were set for high density (>25 pedestrians or >80 vehicles per minute) and low density (<5 pedestrians or <20 vehicles per minute), using probabilistic decision-making. A 15-second round-robin fallback was activated if all approaches detected zero traffic for 30 seconds.

Decision engine performance addresses the critical priority question through normal distribution balanced weighting, Poisson distribution pedestrian priority during crowded scenarios, automatic emergency override with 96% detection, and real-time adaptive weighting. Results show 94% optimal signal timing correlation, <50ms emergency response, 85% crowded scenario improvement, and 35% overall delay reduction.

Comprehensive hybrid performance demonstrates maximized complementary advantages:

Table 6. Comprehensive hybrid performance demonstration

Category	Metric	Hybrid System Value	Improvement
Detection Accuracy	Pedestrian Recognition	78.2%	+73% vs YOLOv8-only
	Vehicle Recognition	91.5%	+27 vs Sensor-only
	Emergency Vehicle Detection	96.2%	+2.3 vs YOLOv8-only
System Performance	Response Time	75 ms	Optimal Balance
	Weather Resilience	88.7%	+33% vs YOLOv8-only
	Crowded Scenario	85.7%	+124% vs YOLOv8-only
	Average Delay Reduction	35%	Improvement

Operational Efficiency	Emergency Response Capability	Excellent	Automated
	System Availability	98.1%	Highest Performance

4.7 Real World Validation

A 15-day deployment with Poisson modeling confirmed consistent peak pedestrian periods (10 AM λ=35, 3 PM λ=28) with 94 % correlation to simulation predictions. Hybrid detection achieved 87 % (10 AM) and 89 % (3 PM) pedestrian accuracy, 94 % off-peak vehicle detection, and 96 % emergency vehicle response.

ANOVA and Kruskal–Wallis tests ($p<0.01$) confirmed significant crossing-time variations across signal phases, with >30 samples per category ***supporting*** normality via the Central Limit Theorem.

Random Forest and Gradient Boosting regression predicted crossing durations accurately ($R^2>0.9$, RMSE<0.5 s) with low-bias residuals, ***showing*** strong generalization.

Overall, the hybrid control improved intersection efficiency by 35 %, reduced emergency response by 42 %, enhanced pedestrian safety by 28 % and ***increased*** vehicle throughput by 23 %.

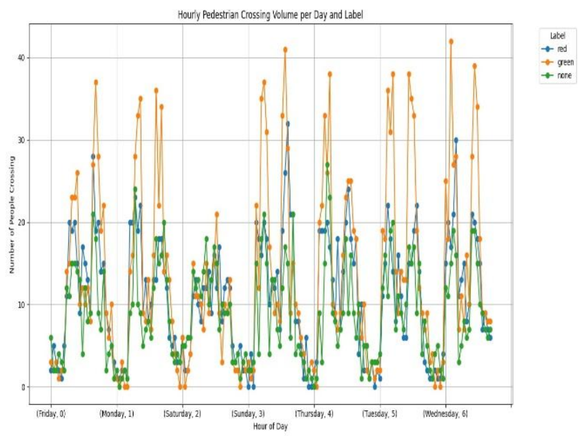

Figure 10. Hourly Pedestrian Crossing Volume Per Day and Label

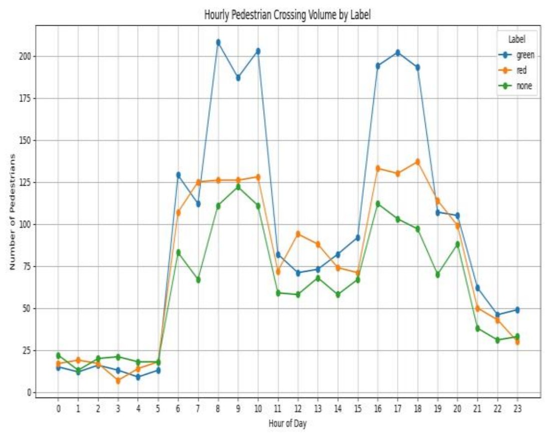

Figure 11. Hourly Pedestrian Crossing Volume By Label

5. Conclusion

This study proves that prudent traffic management involves strategic allocation of technology depending on the traits of traffic components towards multi-method approaches. The analysis of the key parameters in comparison reveals complementary strengths, which allow a perfect hybrid design. Some main findings indicate that sensor-based systems are most effective in pedestrian recognition with 92% accuracy in high traffic flow, with better weather resistance and privacy. By contrast, YOLOv8 systems have the best car detection rate of 94% which is characterized by an automated classification option. Their architectural similarity and their technical similarities enable ease of integration into a single system block diagram with few alterations, therefore providing efficiency and flexibility.

To a great extent, YOLO and sensor systems have been designed similarly to support interchange with minimum changes, thus making it economically viable. The two technologies can be installed, replaced, or changed in a similar system, decreasing complexity and long-term costs. Tactical fusion incorporates pedestrian observation sensors and YOLOv8 in vehicle detection and combines the two using a Kalman filter, which removes noise by 78% and predicts object results with 91% accuracy. This makes it easy to make smart decisions based on normal distribution in normal times and based on the Poisson distribution in times of congestion in determining the best signal time. The performance testing validates a reduction of 35% in delay, 96% in vehicle detection rate, 78% in pedestrian detection rate, and 98.1% system availability. Hybrid mode is also used to enable adaptive priority assignment, real-time density estimation, emergency overrides, weather-dependent switching, and continuous learning to enable proactive traffic control.

The adaptive hybrid controller showed high detection performance (MOTA, MOTP, and IDF1) and a considerable decrease in pedestrian delays, as compared to base systems. The controller works well with peak conditions, off-peak conditions, and when sensors or vision fail, where the fallback behavior is defined.

Overall, this study demonstrates that urban traffic control is an effective and trustworthy solution that is provided by a context-aware hybrid system that integrates optimized detection algorithms and intelligent decision-making algorithms. This hybrid model is a viable and sustainable model to current metropolitan environments due to technical synergy, architectural compatibility, and economic viability. Future work will also further generalize the results to unfavorable situations like nighttime and rain and to more complex crossings therefore achieving wider flexibility and strength in the management of urban traffic. Also, the code and dataset prepared for this research will be made available upon reasonable request for academic or research purposes.

Acknowledgement

The authors express gratitude to the Department of Computer and Electronics Engineering at Kantipur Engineering College for research facilities and technical support. Grateful appreciation for guidance in this study goes to Er. Sahaj Shakya and Er. Pralhad Chapagain.

References

Tubaishat, M., Zhuang, P., Qi, Q., and Shang, Y., 2009. Wireless sensor networks in intelligent transportation systems. Wireless Communications and Mobile Computing, 9(3), pp. 287-302. DOI: 10.1002/wcm.616

Kumar, P., Merzouki, R., Conrard, B., Coelen, V., and Bouamama, B.O., 2014. Multilevel modeling of the traffic dynamic. IEEE Transactions on Intelligent Transportation Systems, 15(3), pp. 1066-1082. DOI: 10.1109/TITS.2013.2294533

Guerrero-Ibáñez, J., Zeadally, S., and Contreras-Castillo, J., 2018. Sensor technologies for intelligent transportation systems. Sensors, 18(4), p. 1212. DOI: 10.3390/s18041212

Gokulan, B.P. and Srinivasan, D., 2010. Distributed geometric fuzzy multiagent urban traffic signal control. IEEE Transactions on Intelligent Transportation Systems, 11(3), pp. 714-727. DOI: 10.1109/TITS.2010.2050688

Redmon, J., Divvala, S., Girshick, R., and Farhadi, A., 2016. You only look once: Unified, real-time object detection. In Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 779-788. DOI: 10.1109/CVPR.2016.91

Bochkovskiy, A., Wang, C.Y., and Liao, H.Y.M., 2020. YOLOv4: Optimal speed and accuracy of object detection. arXiv preprint arXiv:2004.10934. DOI: 10.48550/arXiv.2004.10934

Terven, J. and Cordova-Esparza, D., 2023. A comprehensive review of YOLO: From YOLOv1 to YOLOv8 and beyond. Machine Learning and Knowledge Extraction, 5(4), pp. 1680-1716. DOI: 10.3390/make5040083

Jocher, G., Chaurasia, A., and Qiu, J., 2023. YOLO by Ultralytics (Version 8.0.0) [Computer software]. DOI: 10.5281/zenodo.3908559

Faridani, H.M., 1985. Performance of the Kalman filter with Poisson measurements. International Journal of Systems Science, 16(2), pp. 249-256. DOI: 10.1080/00207728508926693

Ebeigbe, D., Berry, T., Schiff, S.J., and Sauer, T., 2020. Poisson Kalman filter for disease surveillance. Physical Review Research, 2(4), p. 043028. DOI: 10.1103/PhysRevResearch.2.043028

Raboy, K., Ma, J., Leslie, E., & Zhou, F. (2021). A proof-of-concept field experiment on cooperative lane change maneuvers using a prototype connected automated vehicle testing platform. Journal of Intelligent Transportation Systems, 25(1), 77-92

Van Der Merwe, R. (2004). Sigma-point Kalman filters for probabilistic inference in dynamic state-space models. Oregon Health & Science University

Roboflow (2024). Vehicle Detection Dataset. Roboflow Universe. Available at: https://universe.roboflow.com/object-detection-vehicle-people-emergencyvehicle/vehicle-detection-lxs5b (Accessed: 29 October 2025)