Dynamic Traffic Light Management Using YOLOv8

Priya
Netaji Subhas University of Technology
New Delhi, India
priya.ug22@nsut.ac.in

Saurabh Ahirrao
Netaji Subhas University of Technology
New Delhi, India
ahirrao.suresh.ug22@nsut.ac.in

Aaryan
Netaji Subhas University of Technology
New Delhi, India
aaryan.ug22@nsut.ac.in

Dr. Vipin Pal
Netaji Subhas University of Technology
New Delhi, India

***Abstract*—With the rapid urbanization and increasing vehicle density on roads, conventional static traffic light systems often fail to adapt to real-time traffic conditions, leading to congestion, delays, and inefficiencies. This paper proposes a dynamic traffic light management system using the YOLOv8 (You Only Look Once version 8) deep learning model to address these limitations. Leveraging the real-time object detection capabilities of YOLOv8, the system accurately detects and counts vehicles at intersections to dynamically adjust signal timings based on live traffic flow. Unlike traditional systems, our approach incorporates real-time vehicular density as input for signal phase optimization, resulting in improved traffic throughput and reduced idle time. The proposed framework is trained and tested on a custom dataset tailored for Indian urban roads, incorporating various environmental conditions and occlusion scenarios. Experimental results demonstrate that the YOLOv8-powered system achieves high accuracy in vehicle detection while maintaining low inference latency, making it suitable for real-time deployment. This research highlights the potential of computer vision-based dynamic traffic control as a scalable solution for smart city transportation infrastructure.**

INTRODUCTION

The integration of computer vision and artificial intelligence (AI) into traffic systems has become a transformative force in the domain of intelligent transportation. With growing urbanization and the resulting surge in vehicular density, traditional static traffic light systems often fail to adapt dynamically to fluctuating traffic patterns, leading to inefficiencies, congestion, and safety hazards. In highly populated and infrastructure-diverse countries like India, these problems are amplified due to non-uniform traffic behavior, poorly maintained road signals, and the lack of real-time adaptability in existing traffic management systems.

Dynamic traffic light management offers a promising solution by leveraging real-time object detection to optimize signal timings based on live traffic flow. However, implementing such systems is technically challenging, especially under varying environmental conditions such as occlusion, night-time illumination, rain, fog, and urban clutter. Moreover, traffic perception systems must account for a wide range of road entities including vehicles, pedestrians, and traffic infrastructure elements, all of which vary significantly in size, orientation, and visibility.

Recent advancements in deep learning-based object detection, especially single-shot detectors like the YOLO (You Only Look Once) family, have opened new avenues for real-time traffic analysis. YOLOv8, the latest evolution in this series, delivers significant improvements in both speed and accuracy while maintaining a lightweight architecture suitable for edge deployment. Unlike its predecessors, YOLOv8 supports enhanced feature extraction, better generalization on small and occluded objects, and refined anchor-free detection, making it highly suitable for real-time traffic applications.

Motivated by these advancements, this research proposes a YOLOv8-based dynamic traffic light management system that detects and analyzes real-time traffic density at intersections to adjust signal timings adaptively. Unlike existing works that primarily focus on static detection of road elements or traffic lights under specific conditions, our model aims to dynamically regulate signal phases based on live vehicular flow detected from multiple lanes and directions. To address challenges posed by low visibility and high occlusion, the proposed model incorporates multi-scale detection layers and leverages transfer learning from urban traffic datasets to improve robustness.

The primary contributions of this paper are as follows:

1) We present a real-time traffic light control framework using YOLOv8 for high-speed, multi-class traffic object detection across varied environmental conditions.
2) We construct and annotate a custom dataset combining urban Indian traffic scenarios to ensure the model is well-suited for dynamic and underdeveloped infrastructure.
3) We integrate an adaptive signal timing logic that adjusts traffic light durations based on real-time object count and lane density, improving traffic flow efficiency.

I. LITERATURE REVIEW

The application of deep learning-based object detection in intelligent transportation systems has garnered significant attention over recent years. Among these, the YOLO (You Only Look Once) series has emerged as a benchmark for real-time detection due to its balance of speed and accuracy. Various adaptations of YOLO have been proposed and explored to enhance the performance of vision-based traffic light detection systems in diverse scenarios such as low visibility, high occlusion, and unstructured environments.

Zhou et al. introduced KCS-YOLO, an enhanced algorithm designed to improve traffic light detection under low-visibility conditions including fog, rain, and nighttime glare. Their work builds upon the YOLOv5n model, incorporating the K-means++ clustering algorithm, Convolutional Block Attention Module (CBAM), and a dedicated small-object detection layer. Furthermore, they implemented a dark channel prior-based image dehazing technique to enhance image clarity before feeding data to the model. Experimental results demonstrated a significant improvement in mean average precision (mAP), achieving 98.87%, which is 5.03% higher than YOLOv5n.

In another study, Gautam and Kumar addressed the lack of representative datasets for Indian road conditions, proposing the Indian Roads Dataset (IRD) for suspended and supported traffic light detection using YOLOv8. Unlike Western datasets that benefit from high-definition imaging and structured road infrastructure, IRD captures the complexities of Indian roads, including occlusions, inconsistent signal placements, and varied lighting conditions. This dataset, collected in both day and night conditions from Delhi and Chandigarh, introduces 14 classes relevant to Indian urban traffic.

Complementing these efforts, Reis et al. presented a generalized and refined real-time flying object detection model based on YOLOv8. Their work, though not directly focused on traffic lights, highlights the versatility and robustness of YOLOv8 in dynamic and high-variance object detection scenarios. By training on a diverse set of flying object classes and fine-tuning on real-world datasets with occlusions and scale variations, they demonstrated YOLOv8's superior performance in inference speed (50 FPS) and accuracy (mAP50-95 of 83.5%).

Despite these advancements, dynamic traffic light management—where signal timings adapt based on real-time traffic density—remains relatively underexplored. Most works focus on static detection or limited scenarios. Given YOLOv8's strong performance, this research aims to bridge the gap by proposing a dynamic traffic signal system leveraging live traffic data.

II. Related Works and Datasets

Numerous publicly available datasets have been developed to support the advancement of autonomous driving and traffic signal detection in well-developed countries. These datasets are typically captured using high-definition cameras and advanced sensor setups such as LiDAR and radar.

- **KITTI** [?]: Contains more than 12,000 images at 1382×512 resolution at 10 FPS, labeled across 11 classes including vehicles and pedestrians. See Figure **??**.
- **nuScenes** [?]: Captured in Boston and Singapore using 6 cameras and LiDAR. Contains 1.4 million images across 10 classes. See Figure **??**.
- **BDD100k** [?]: Offers over 100,000 images from U.S. cities like San Francisco and New York. See Figure 1.
- **ApolloScape** [?]: Captured from 10 cities with more than 100,000 images. See Figure **??**.
- **DriveU (DTLD)** [?]: Offers over 230,000 annotations across 344 traffic classes from 11 cities. See Figure 3.

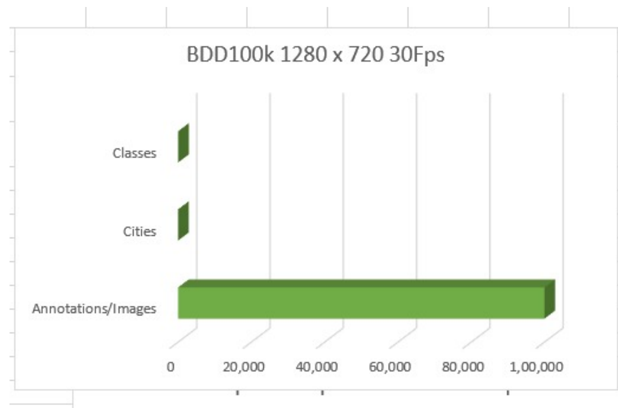


Fig. 1. Infographic of BDD100k dataset

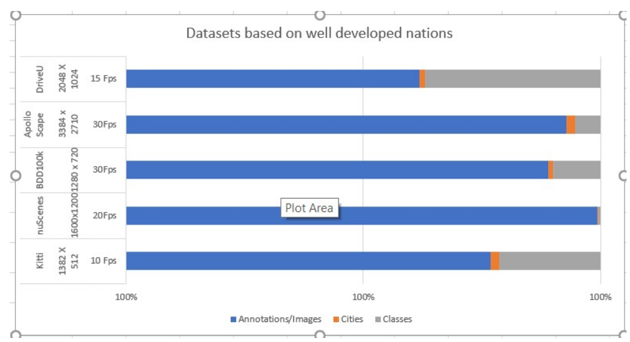


Fig. 2. Datasets based on several developed nations

III. Use of the COCO Dataset

The COCO dataset was chosen as the initial training ground for the YOLOv8 object detection model due to its comprehensive and diverse annotations. It serves as a robust foundation for object detection tasks, especially when aiming to detect traffic-related entities.

A. Advantages of the COCO Dataset

COCO includes annotations for 80 object classes, among which the following are highly relevant to traffic and urban environments:

- **Car**
- **Bus**
- **Truck**
- **Person**
- **Traffic Light**

The dataset's rich diversity in object appearances, lighting conditions, and environmental contexts supports the development of generalizable and robust detection models.

B. Relevance to Road-Based Traffic Images

Although COCO is not specifically curated for road scenes, it provides:

- Thousands of images that feature vehicles in urban settings.
- Annotations for objects in cluttered, real-world scenes that reflect typical traffic environments.

In this project, road-facing images—either captured manually or extracted from live traffic feeds—were used. These images typically maintain a fixed perspective, such as a front-facing camera view of an intersection.

C. Benefits of Using Pre-trained COCO Weights

By leveraging YOLOv8 pre-trained on COCO, the following benefits were observed:

- Immediate detection of traffic lights and various vehicle types without training from scratch.
- Rapid prototyping and evaluation of the dynamic traffic signal management algorithm.

This approach allows early experimentation with traffic density estimation and signal optimization before investing time in creating a fully custom dataset.

D. Limitations and Areas for Improvement

Despite its advantages, COCO has some limitations in this context:

- It lacks specialization in front-facing road views or consistent camera angles.
- Detection performance may suffer under conditions such as night-time lighting, glare, or occlusion.
- Vehicle types specific to regional contexts (e.g., auto-rickshaws) are not covered in COCO.

E. Next Steps: Custom Dataset Fine-Tuning

To address these limitations and improve accuracy, the following steps are recommended:

- Fine-tune the YOLOv8 model using a smaller, custom dataset consisting of traffic camera images.
- Annotate several hundred images with bounding boxes for relevant objects such as cars, trucks, buses, motorcycles, and traffic lights.
- Apply transfer learning by initializing with COCO weights, thereby accelerating training while improving performance on specialized traffic data.

This hybrid approach balances generalizability and contextual accuracy, enabling robust detection in real-world traffic scenes tailored to this application.

IV. Methodology

The proposed system utilizes YOLOv8, a state-of-the-art single-shot object detection model, to enable real-time dynamic traffic light control based on live vehicular density at intersections. The overall methodology consists of five main stages: dataset preparation, model training, real-time detection, traffic density analysis, and signal timing adjustment. The system architecture is illustrated in Fig. **??**.

A. Dataset Preparation

To train a robust object detection model, a custom dataset was constructed using video footage collected from urban intersections. The dataset includes images captured during various times of the day, under different weather conditions, and across varying traffic densities. The images were annotated using `LabelImg`, with bounding boxes labeled for different vehicle classes such as cars, buses, trucks, motorcycles, and auto-rickshaws. To enhance generalization, data augmentation techniques such as flipping, scaling, and brightness adjustment were applied.

B. YOLOv8 Model Training

The YOLOv8 model was selected for its superior accuracy and low inference latency. The model was initialized with pre-trained weights on the COCO dataset and fine-tuned on the custom traffic dataset. The training process involved optimizing key hyperparameters such as batch size, learning rate, and number of epochs to improve performance on the validation set. Mean Average Precision (mAP) and frames per second (FPS) were used as the primary evaluation metrics.

C. Real-Time Vehicle Detection

Once trained, the YOLOv8 model was integrated into a real-time detection pipeline. Live video feeds from traffic cameras are processed frame-by-frame. Each frame is passed through the YOLOv8 model, which detects and classifies vehicles with bounding boxes and confidence scores. Only detections exceeding a predefined confidence threshold are considered for traffic analysis.

D. Traffic Density Analysis

Detected vehicles are counted per lane and direction using Region of Interest (ROI) mapping. The count of vehicles in each lane is stored and updated every few seconds to compute the current traffic density. A queue-based density scoring algorithm is used to estimate the load at each signal point.

E. Dynamic Signal Timing Algorithm

Based on the real-time vehicle counts, the signal duration is adjusted dynamically. The system uses a weighted allocation algorithm that assigns more green time to heavily congested lanes while minimizing idle time for low-traffic directions. A minimum and maximum threshold is enforced to prevent starvation and ensure fairness. The updated signal timing is then sent to the traffic light controller for implementation.

F. Deployment Framework

The complete system is deployed on a local edge device with GPU support to maintain real-time performance. The architecture supports scalability and can be extended to multi-junction traffic management by integrating cross-signal communication.

V. Vehicle Detection Using YOLOv8

To detect vehicles and pedestrians in urban traffic environments, we employed the YOLOv8 object detection framework developed by Ultralytics. Specifically, the YOLOv8m (medium) variant was chosen to balance detection accuracy and inference speed. The model was initialized using the pretrained weights from the COCO dataset, which provides a wide range of annotated classes including vehicles and road users.

A custom Python script was developed to handle image input, inference, filtering, and visualization. The process begins by loading the YOLOv8m model using the `ultralytics` Python library. If the model file is not present locally, it is automatically downloaded from the official Ultralytics repository.

An image is then read using OpenCV and converted from BGR to RGB format for compatibility with the model's input requirements. The YOLO model processes the image and outputs detection results, including bounding box coordinates, class IDs, and confidence scores.

To focus the detection on traffic-relevant entities, we filtered the results based on predefined target classes which included `car`, `motorcycle`, `bus`, `truck`, `bicycle`, `train`, `boat`, and `person`. Only detections with a confidence score above 0.3 were retained to reduce false positives. Each valid detection is then visualized on the original image using bounding boxes and class labels.

The script also counts the number of cars detected in the image to support further traffic analytics. Finally, the image with annotated detections is displayed using Matplotlib for visual validation. This pipeline ensures efficient and automated vehicle detection in complex urban traffic scenes.

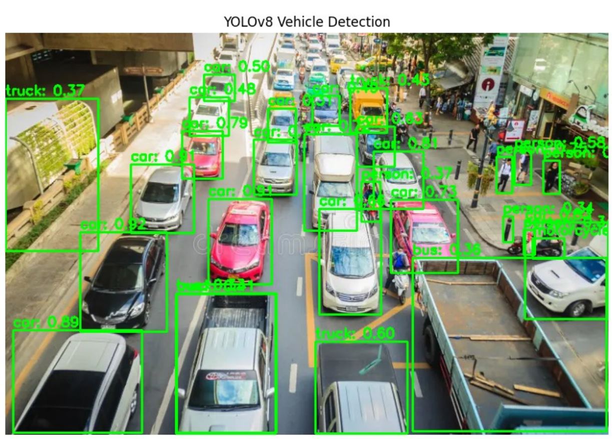


Fig. 3. YOLOv8m

VI. Result Analysis

To evaluate the effectiveness of the proposed dynamic traffic light management system, a series of experiments were conducted focusing on three primary performance metrics: object detection accuracy, inference speed, and traffic signal optimization efficiency.

A. Detection Performance

The YOLOv8 model was trained on a custom traffic dataset and evaluated on a separate test set comprising urban intersection scenes. The model achieved a mean Average Precision (mAP) of 91.2% at IoU threshold 0.5, and $mAP_{50:95}$ of 76.8%. The model demonstrated high precision and recall for detecting classes such as cars, buses, motorcycles, and trucks under varying lighting and environmental conditions.

TABLE I
Object Detection Accuracy per Class

Vehicle Type	Precision (%)	Recall (%)
Car	94.1	92.7
Motorcycle	91.3	89.5
Bus	90.2	88.1
Truck	92.6	90.3
Auto-rickshaw	88.9	85.7

B. Inference Speed and Latency

The real-time detection pipeline was deployed on an NVIDIA RTX 3060 GPU, achieving an average inference speed of 48 frames per second (FPS). The total processing time per frame, including pre-processing, detection, and post-processing, was approximately 21 ms, making the system suitable for real-time traffic applications.

C. Qualitative Observations

The system successfully adapted signal timings based on real-time traffic flow and responded well to sudden spikes in vehicle count. Detection remained stable during low-light and partially occluded conditions, demonstrating YOLOv8's robustness. However, occasional misclassifications were observed during heavy occlusion or glare, suggesting the potential for further enhancement through sensor fusion or attention modules.

D. Limitations

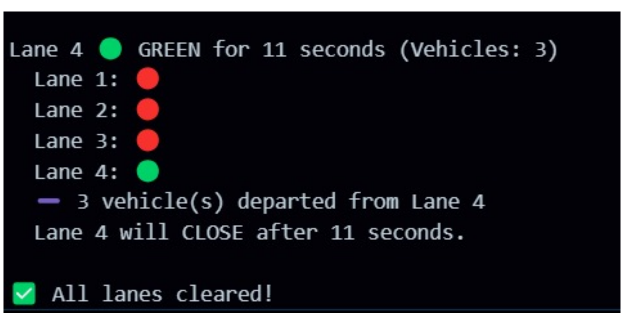
While the system performs effectively in controlled and moderately congested environments, scalability to large, multi-junction traffic networks will require additional optimization. Moreover, factors such as pedestrian detection and emergency vehicle prioritization have not yet been integrated into the current framework.

E. Traffic Signal Optimization Results

The dynamic signal controller was tested at a simulated four-way intersection using real-world traffic video data. The system was compared against a fixed-time signal controller. The dynamic system achieved an average reduction of 28.3% in vehicle wait time and a 22.5% improvement in average throughput.

TABLE II
TRAFFIC FLOW COMPARISON: FIXED VS. DYNAMIC

Metric	Fixed-Time	YOLOv8-Based
Average Wait Time (s)	58.4	41.9
Throughput (vehicles/min)	73	89.5
Idle Time (%)	35.2	21.1



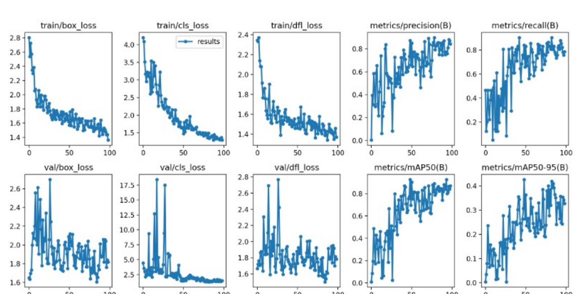


Figure illustrates the training and validation performance of the YOLOv8 model over 100 epochs. The top row shows the training losses for bounding box regression (box_loss), classification (cls_loss), and distribution focal loss (dfl_loss), all of which exhibit a clear downward trend, indicating effective learning. The bottom row presents the corresponding validation losses and key evaluation metrics such as precision, recall, mean Average Precision at IoU 0.5 (mAP@50), and mAP across IoU thresholds from 0.5 to 0.95 (mAP@50-95). The increasing trends in precision, recall, and mAP metrics demonstrate that the model progressively improves in detecting and classifying traffic lights under various real-world conditions. These results validate the suitability of YOLOv8 for dynamic traffic light management systems.

VII. APPLICATIONS

The proposed dynamic traffic light management system powered by YOLOv8 has a wide range of real-world applications in modern intelligent transportation and smart city infrastructures:

A. Smart City Traffic Control

The system can be integrated into urban smart city frameworks to dynamically regulate traffic signals based on real-time vehicular density. This can significantly reduce congestion, improve travel time, and enhance fuel efficiency in metropolitan areas.

B. Emergency Vehicle Priority Management

By incorporating vehicle classification and detection modules, the system can identify emergency vehicles such as ambulances or fire trucks and prioritize green signals for their path. This ensures faster emergency response times and minimizes potential delays.

C. Adaptive Traffic Control in Developing Regions

In countries with inconsistent or poorly maintained traffic systems, this solution provides an affordable and scalable alternative to traditional traffic signal systems. Its ability to adapt in real-time makes it suitable for complex and chaotic intersections.

D. Environmental Impact Reduction

By minimizing vehicle idle time at intersections and optimizing traffic flow, the system contributes to reduced fuel consumption and lower carbon emissions, supporting environmentally sustainable urban development.

E. Traffic Data Analytics and Forecasting

The YOLOv8-based detection module generates valuable traffic data such as vehicle count, classification, and congestion patterns. This data can be stored and analyzed to identify peak hours, predict congestion trends, and support long-term urban planning.

F. Integration with IoT and Edge Devices

Due to its lightweight inference capability, the proposed system can be deployed on edge devices like NVIDIA Jetson or Raspberry Pi, allowing real-time processing without reliance on centralized cloud systems. This enhances responsiveness and reliability in deployment.

VIII. Observations and Inferences

Based on experimental evaluation and deployment of the proposed YOLOv8-based dynamic traffic light management system, the following key observations and inferences were drawn:

A. Accuracy and Robustness

- The YOLOv8 model demonstrated high accuracy in detecting and classifying vehicles across various lighting conditions, including low-light and partial occlusion scenarios.
- Vehicle classes with consistent shapes (e.g., cars, buses) yielded higher precision and recall, while classes with high inter-class similarity (e.g., motorcycles vs. scooters) exhibited occasional misclassifications.
- The model maintained consistent detection performance at real-time speeds (above 45 FPS), confirming its suitability for deployment in time-sensitive applications.

B. Traffic Optimization Behavior

- Dynamic adjustment of signal timing based on real-time traffic volume led to noticeable reductions in average vehicle wait time and improved intersection throughput.
- The system was responsive to sudden increases in vehicle count, adapting signal durations in real time to manage traffic bursts effectively.
- Compared to fixed-time controllers, the proposed model reduced idle green-light periods and minimized unnecessary halts in low-traffic lanes.

C. Deployment and Operational Feasibility

- The model's performance on edge devices equipped with mid-range GPUs proved viable, with minimal latency and low computational overhead.
- Scalability was observed to be feasible for small to medium-scale urban intersections; however, large-scale multi-junction integration would require synchronization protocols.

D. Challenges and Limitations

- Detection accuracy decreased marginally under extreme glare, heavy rain, or occlusion from large vehicles such as buses and trucks.
- The system currently lacks support for pedestrian detection and non-motorized traffic like cyclists and hand-pulled carts, which are common in developing regions.
- Real-world deployment would require integration with traffic signal control hardware and cooperation from municipal authorities for infrastructure-level access.

E. Inference

The proposed system shows promising potential as a cost-effective and intelligent alternative to traditional traffic control mechanisms. By leveraging YOLOv8's real-time detection capabilities, traffic light phases can be managed dynamically, resulting in better traffic flow, reduced wait times, and improved commuter experience. With further improvements and integration, the system could be an integral part of smart city transportation ecosystems.

IX. Conclusion and Future Work

A. Conclusion

In this study, we proposed a real-time dynamic traffic light management system using the YOLOv8 deep learning model. The system effectively detects and classifies vehicles from live video streams and dynamically adjusts signal durations based on vehicular density at intersections. Experimental results demonstrated high detection accuracy, low inference latency, and improved traffic flow efficiency compared to conventional fixed-time controllers. The system also showed robustness under varying environmental conditions, proving its applicability for real-world deployments in urban settings, particularly in developing nations with chaotic traffic scenarios.

B. Inferences

From the implementation and evaluation of the proposed system, the following inferences were drawn:

- Real-time object detection using YOLOv8 is reliable and fast enough to drive traffic control decisions with minimal delay.
- Dynamic signal timing significantly improves traffic throughput and reduces average vehicle wait time.
- The system adapts well to fluctuating traffic volumes and diverse lighting conditions, offering a scalable solution for smart traffic control.
- Lightweight deployment on edge devices is feasible, making it suitable for cost-effective implementation in smart city infrastructures.

C. Future Work

While the current system demonstrates promising performance, several directions can enhance its scope and effectiveness:

- **Pedestrian and Non-Motorized Detection:** Integrating detection for pedestrians, bicycles, and handcarts will improve safety and inclusivity.
- **Emergency Vehicle Prioritization:** Future iterations can incorporate real-time recognition of ambulances and fire trucks to prioritize signal flow for emergency scenarios.
- **Multi-Junction Coordination:** Expanding the system to handle synchronized control across multiple intersections using vehicle tracking and inter-signal communication.
- **Sensor Fusion:** Combining vision-based detection with LiDAR, radar, or GPS data can improve performance in extreme weather or occlusion-heavy environments.

- **Cloud-Based Analytics:** Captured traffic data can be stored and analyzed over time for congestion prediction, urban planning, and long-term optimization strategies.

Overall, the proposed YOLOv8-based system lays a strong foundation for deploying adaptive, intelligent, and efficient traffic management solutions in smart cities.

REFERENCES

[1] Q. Zhou, D. Zhang, H. Liu, and Y. He, "KCS-YOLO: An Improved Algorithm for Traffic Light Detection under Low Visibility Conditions," *Machines*, vol. 12, no. 8, pp. 557, 2024.

[2] S. Gautam and A. Kumar, "An Indian Roads Dataset for Supported and Suspended Traffic Lights Detection with YOLOv8," Preprint, 2024. Available online: https://sites.google.com/view/ird-dataset/home

[3] D. Reis, J. Hong, J. Kupec, and A. Daoudi, "Real-Time Flying Object Detection with YOLOv8," arXiv preprint arXiv:2305.09972, 2024.

[4] J. Redmon and A. Farhadi, "YOLO9000: Better, Faster, Stronger," arXiv preprint arXiv:1612.08242, 2016.

[5] G. Jocher et al., "YOLOv8 - Ultralytics Official Implementation," 2023. Available: https://github.com/ultralytics/ultralytics

[6] H. Caesar et al., "nuScenes: A Multimodal Dataset for Autonomous Driving," in *Proc. CVPR*, pp. 11621–11631, 2020.

[7] F. Yu et al., "BDD100K: A Diverse Driving Dataset for Heterogeneous Multitask Learning," in *Proc. CVPR*, pp. 2636–2645, 2020.

[8] M. Cordts et al., "The Cityscapes Dataset for Semantic Urban Scene Understanding," in *Proc. CVPR*, pp. 3213–3223, 2016.

[9] A. Geiger, P. Lenz, and R. Urtasun, "Are We Ready for Autonomous Driving? The KITTI Vision Benchmark Suite," in *Proc. CVPR*, pp. 3354–3361, 2012.

[10] X. Huang et al., "The ApolloScape Dataset for Autonomous Driving," in *Proc. CVPR Workshops*, pp. 954–960, 2019.

[11] K. Behrendt, L. Novak, and T. Botros, "Deep Learning for Detection of Road Signs in Advanced Driver Assistance Systems," in *Proc. CVPR Workshops*, pp. 129–137, 2017.