Advancing Urban Transportation Management: A Comprehensive Review of Computer Vision-Based Vehicle Detection and Counting Systems

Manish Mathur[1], Mrinal Kanti Sarkar[2] and G. Uma Devi[1]
[1]*University of Engineering and Management Jaipur, Rajasthan, India*
[2]*Dept. of Computer Science, Sri Ramkrishna Sarada Vidya Mahapitha, West Bengal, India*

Keywords: Urban Transportation Management, Computer Vision, Vehicle Detection, Vehicle Counting, Traffic Control, Real-Time Monitoring, Deep Learning, Traffic Flow Optimization, Transportation Efficiency, Road Safety.

Abstract: In the landscape of urban transportation management, computer vision-based vehicle detection and counting systems have emerged as transformative solutions. This review delves into the evolution and efficacy of such systems in modern traffic control. Examining a spectrum of methodologies, from traditional to deep learning approaches, the study highlights how computer vision accurately tracks and tallies vehicles on roads and highways. These systems provide real-time insights, aiding authorities in identifying congestion points, optimizing signal timings, and implementing dynamic lane management strategies. Moreover, they facilitate diverse applications like toll collection and parking management, enhancing overall transportation efficiency and safety. With their adaptability across environments and seamless integration into existing infrastructure, these systems are indispensable for modern transportation authorities. This review emphasizes their role in advancing urban transportation management, promising tangible enhancements in traffic flow efficiency, safety, and urban mobility.

1 INTRODUCTION

In the landscape of urban transportation management, the efficient flow of vehicles is critical for ensuring smooth mobility, minimizing congestion, and enhancing road safety. However, the increasing complexity of modern road networks coupled with the rise in vehicular traffic poses significant challenges for conventional traffic control methods. In this context, the integration of advanced technologies such as computer vision has emerged as a promising solution to address these challenges.

Computer vision-based vehicle detection and counting systems leverage sophisticated image processing techniques to analyze video feeds from cameras or sensors, enabling the accurate identification and tracking of vehicles on roads and highways. These systems play a pivotal role in providing real-time insights into traffic dynamics, empowering transportation authorities to make data-informed decisions for optimizing traffic flow and alleviating congestion.

This comprehensive review aims to explore the evolution, methodologies, and real-world applications of computer vision-based vehicle detection and counting systems in urban transportation management. By analyzing a diverse range of studies, methodologies, and applications, this review seeks to provide insights into the significance and effectiveness of these systems in revolutionizing traffic control practices.

Through meticulous examination of the existing literature, this review will elucidate the underlying principles of computer vision-based vehicle detection systems, ranging from traditional feature-based approaches to state-of-the-art deep learning techniques. Additionally, it will highlight the various applications of these systems, including toll collection, parking management, and traffic violation detection, emphasizing their role in enhancing overall transportation efficiency and safety. Furthermore, this review will identify key research challenges and opportunities for innovation in the field, aiming to contribute to the advancement of urban transportation management practices. By synthesizing findings from

Mathur, M., Sarkar, M. K. and Devi, G. U.
Advancing Urban Transportation Management: A Comprehensive Review of Computer Vision-Based Vehicle Detection and Counting Systems.
DOI: 10.5220/0013305600004646

In *Proceedings of the 1st International Conference on Cognitive & Cloud Computing (IC3Com 2024)*, pages 196-204
ISBN: 978-989-758-739-9

a wide range of sources, this review seeks to provide a comprehensive understanding of the current state-of-the-art and future directions of computer vision-based vehicle detection and counting systems in real-world traffic management.

2 LITERATURE REVIEW

The literature review encompasses recent advancements in vehicle detection technologies spanning from 2015 to 2023. It discusses methodologies such as SINet for scale-insensitive detection, Faster R-CNN for improved performance, and various approaches addressing challenges like shadow detection, real-time detection, and object classification. The motive for presenting the literature review in tabular format is to provide a concise summary of each technology's, aiding researchers in comprehensively understanding and comparing different methodologies in the field of vehicle detection.

Table 1. Summary of Recent Advancements in Vehicle Detection Technologies (2015-2023).

Ref. (Year)	Technology	Overall Concept
[1] (2024)	The Artificial Hummingbird Optimization Algorithm (AHOA) with Hierarchical Deep Learning for Traffic Management (HDLTM)	Advantages: Improved traffic flow prediction, Enhanced traffic management in smart cities, Real-time traffic flow prediction. Limitations: Complexity in hyperparameter tuning. Datasets: Raw sensor data. Evaluation Criteria: Mean Absolute Percentage Error, Root Mean Square Error, Mean Absolute Error, Equal Coefficient, Runtime.
[2] (2024)	Faster R-CNN with Deformable Convolutional Network	Advantages: Enhanced detection accuracy for vehicles in low-light conditions, Improved precision in bounding box position prediction, Addressing sample imbalance for enhanced learning effectiveness, Reduction in missed detections through Soft-NMS. Limitations: Potential dependency on specific dataset characteristics, Sensitivity to parameter tuning. Datasets: UA-DETRAC, BDD100K. Evaluation Criteria: Nighttime Detection Accuracy, Model Complexity, Learning Effectiveness, Localization Precision.
[3] (2024)	YOLOv8 architecture with FasterNet, Decoupled Head, Deformable Attention Module (DAM), MPDIoU loss function	Advantages: Enhanced feature extraction from satellite images, Improved computational efficiency, Increased sensitivity to small targets, Enhanced feature correlation capture. Limitations: Minor reduction in Frames Per Second (FPS). Datasets: Satellite Remote Sensing Images. Evaluation Criteria: Precision, Recall, Mean Average Precision.
[4] (2024)	MV2_S_YE Object Detection Algorithm	Advantages: MobileNetV2 backbone reduces complexity, improving speed; Integrates channel attention and SENet for accuracy. Limitations: Sacrifices some accuracy, Increased complexity, Requires parameter tuning. Datasets: Pascal VOC, Udacity, KAIST. Evaluation Criteria: mAP at IoU 0.5, FPS detection speed.
[5] (2023)	R-YOLOv5 with Angle Prediction Branch, CSL Angle Classification, Cascaded STrB, FEAM, ASFF	Advantages: Effective detection of rotating vehicles in drone images, Enhanced feature fusion and semantic information, Improved utilization of detailed information through local feature self-supervision, Multi-scale feature fusion for better object detection. Limitations: Potential sensitivity to complex environmental conditions, Performance may vary depending on dataset characteristics. Datasets: Drone-Vehicle Dataset, UCAS-AOD

		Remote Sensing Dataset. Evaluation Criteria: Detection Accuracy, Parameter Count, Frame Rate.
[6] (2022)	YOLOv4 optimization with attention mechanism and enhanced FPN	Advantages: Suppression of interference features in images, Enhanced feature extraction, Improved object detection and classification performance. Limitations: May require substantial computational resources. Datasets: BIT-Vehicle dataset, UA-DETRAC dataset. Evaluation Criteria: Mean Average Precision (mAP), F1 score.
[7] (2022)	Improved Lightweight RetinaNet for SAR Ship Detection	Advantages: Utilizes ghost modules and reduced deep convolutional layers for efficiency, Embeds spatial and channel attention modules for enhanced detectability, Adjusts aspect ratios using K-means clustering algorithm. Limitations: Potential loss of representation power with shallower convolutional layers, Complexity of architecture may impact interpretability, K-means clustering may require careful parameter tuning. Datasets: SSDD dataset, Gaofen-3 mini dataset, Hisea-1 satellite SAR image. Evaluation Criteria: Detection accuracy, Recall ratio, Reduction in floating-point operations and parameters, Robustness to small datasets.
[8] (2021)	YOLOv4 with Secondary Transfer Learning and Hard Negative Example Mining	Advantages: Enhanced detection of severely occluded vehicles in weak infrared aerial images, Utilization of secondary transfer learning for improved model performance. Limitations: Potential sensitivity to variations and environmental conditions, Computational associated with successive transfer learning. Datasets: UCAS_AOD Visible Dataset, VIVID
		Visible Dataset, VIVID Infrared Dataset. Evaluation Criteria: Average Precision, F1 Score, False Detection Rate Reduction.
[9] (2021)	Computer Vision, Time-Spatial Image (TSI)	Advantages: Fast and accurate vehicle counting, Efficient traffic volume estimation, Utilization of attention mechanism for enhanced feature extraction. Limitations: Reliance on manual annotation for TSI creation, Potential challenges in handling complex traffic scenarios. Datasets: UA-DETRAC Dataset. Evaluation Criteria: Accuracy, Speed, Traffic Volume Estimation.
[10] (2021)	W-Net: Multi-Feature CNN	Advantages: Addresses segmentation challenges, Utilizes contracting/expanding networks, Incorporates inception layers and refinement modules. Limitations: Requires sufficient training data, Increased computational complexity. Datasets: Water body, Crack detection. Evaluation Criteria: Accuracy, IoU, Precision, Recall.
[11] (2020)	Enhanced tiny-YOLOv3 with Contextual Feature Integration, SPP Module, Grid Size Adjustment, K-means Clustering	Advantages: Improved recognition rates in complex road environments, Enhanced real-time performance, Increased feature extraction capability through contextual information and SPP module. Limitations: Sensitivity to variations in road and lighting conditions, Performance degradation in highly cluttered scenes. Datasets: KITTI Datasets. Evaluation Criteria: Average Accuracy, Detection Speed.
[12] (2020)	Multi-Modal Fusion, DNN	Advantages: Blends features from multiple ConvNets, enhancing DR recognition, Utilizes pooling for better representation, Dropout aids convergence.

		Limitations: Increased computational complexity, Dependency on labeled data, Interpretability challenges. Datasets: Kaggle APTOS 2019. Evaluation Criteria: Accuracy, Kappa Statistic for DR identification and severity prediction.
[13] (2020)	MobileNetV2-SVM	Advantages: Uses efficient MobileNetV2 architecture, Combines with SVM for improved performance, Data augmentation enhances model generalization. Limitations: May capture fewer complex features, Dependency on data quality, SVM integration requires tuning. Datasets: APTOS 2019. Evaluation Criteria: Quadratic Weighted Kappa, Accuracy, AUROC for each DR severity class.
[14] (2020)	Aggregation Channel Attention Network (ACAN) - Deep Learning for Glaucoma Diagnosis	Advantages: Utilizes context information effectively for semantic segmentation, Achieves high accuracy in optic disc segmentation tasks for glaucoma diagnosis. Limitations: May require substantial computational resources due to the integration of channel dependencies and multi-scale information. Datasets: Messidor dataset, RIM-ONE dataset. Evaluation Criteria: Overlapping Error, Segmentation accuracy, Computational Efficiency, DiceCoefficient, Cross Entropy Loss, Balanced contribution of loss functions.
[15] (2019)	Deep learning, object detection, object tracking, trajectory processing	Advantages: Accurate vehicle counting, Comprehensive traffic flow information, High overall accuracy (>90%). Limitations: Processing speed may vary depending on hardware and dataset size. Datasets: Dataset (VDD), Vehicle Counting Results Verification Dataset. Evaluation Criteria: Overall accuracy, Processing speed.
[16] (2019)	Convolutional Neural Networks (CNNs)	Advantages: Effective differentiation between interesting and uninteresting regions, High classification efficiency with maintained accuracy. Limitations: Performance may vary depending on environmental conditions and dataset characteristics. Datasets: CDNET 2014 dataset, Custom dataset. Evaluation Criteria: Classification Speed (fps), Detection Accuracy.
[17] (2019)	Computer Vision, UAV Imagery	Advantages: Automation of labor-intensive counting process, Utilization of multispectral UAV imagery for accurate detection, Potential for cost and time savings in forestry operations. Limitations: Dependence on quality and resolution of UAV imagery, Potential challenges in accurately delineating planting microsites. Datasets: Custom Dataset of Aerial Images. Evaluation Criteria: Efficiency, Validity under Challenging Conditions.
[18] (2019)	Feature Pyramid Siamese Network (FPSN)	Advantages: Extends Siamese architecture with FPN, Incorporates spatiotemporal motion feature for improved MOT performance. Limitations: Potential complexity increase, Dependency on data quality for effective learning, Computational overhead. Datasets: Public MOT challenge benchmark. Evaluation Criteria: MOTA, MOTP, IDF1 compared to

		state-of-the-art MOT methods.
[19] (2018)	Magnetic Sensor-based Detection	Advantages: Precise vehicle quantity and category data acquisition, Robustness enhanced with parking-sensitive module, 42-D feature extraction for classification. Limitations: Limited validation on specific traffic scenario, Potential dependence on sensor placement and environment. Datasets: Data collected at a Beijing freeway exit. Evaluation Criteria: Accuracy Rate, Effectiveness in Traffic Environment, Algorithm Robustness, Practicality.
[20] (2018)	Convolutional Neural Networks	Advantages: Efficient and effective vehicle detection, Higher precision and recall rates. Limitations: Performance may vary depending on dataset characteristics and environmental conditions. Datasets: Munich dataset, Overhead Imagery Research Dataset. Evaluation Criteria: Precision, Recall Rate.
[21] (2016)	Faster R-CNN	Advantages: State-of-the-art performance on generic object detection, Adaptable for various applications including vehicle detection. Limitations: Performs unimpressively on large vehicle datasets without suitable parameter tuning and algorithmic modification. Datasets: KITTI vehicle dataset. Evaluation Criteria: Detection accuracy, Precision, Recall, Computational efficiency.
[22] (2016)	YOLO	Advantages: Direct regression approach improves speed and efficiency. Limitations: More localization errors compared to some other methods. Datasets: COCO Dataset, PASCAL VOC Dataset. Evaluation Criteria: Speed, mAP, False Positive Rate, Localization Accuracy.
[23] (2015)	Virtual line-based sensors, gradient and range feature analysis	Advantages: Effective vehicle detection, Robust performance under diverse environmental conditions. Limitations: Potential challenges in complex road layouts. Datasets: Experimentally obtained data. Evaluation Criteria: Accuracy rate, Performance under various conditions.
[24] (2015)	Regression Analysis, Computer Vision	Advantages: Effective in scenarios with severe occlusions or low vehicle resolution, Utilization of warping method to detect foreground segments, Adoption of cascaded regression approach. Limitations: Complexity associated with feature extraction and regression modeling, Potential limitations in handling complex traffic scenarios. Datasets: Custom Dataset. Evaluation Criteria: Accuracy, Robustness, Reliability.

To provide an in-depth comparison of various object detection networks with a focus on their applicability to road object detection, we will analyze YOLOv1, YOLOv2, YOLOv3, YOLOv4, YOLOv5, MobileNet, SENet, and RetinaNet. We will assess their architecture, performance, and suitability for road object detection tasks.

YOLOv1: YOLOv1 (You Only Look Once) [22] was groundbreaking for its real-time object detection capabilities. It divides the input image into a grid and predicts bounding boxes and class probabilities directly from the full image.

- Architecture: YOLOv1 consists of a single convolutional neural network (CNN)[14] that simultaneously predicts bounding boxes and class probabilities.
- Performance: While fast, YOLOv1 struggles with small object detection and localization accuracy due to its coarse feature maps.

- Suitability for Road Object Detection: YOLOv1 may not be ideal for road object detection [4] due to its limitations in handling small objects like road signs and pedestrians.

YOLOv2: YOLOv2 addressed the shortcomings of YOLOv1 by introducing architectural improvements such as anchor boxes, batch normalization, and multi-scale feature extraction.

- Architecture: YOLOv2 features a more sophisticated CNN architecture [2] with additional layers for better feature representation.
- Performance: YOLOv2 improved accuracy and expanded its application to smaller objects.
- Suitability for Road Object Detection: YOLOv2 performs better than YOLOv1 for road object detection tasks, but may still struggle with small objects and occlusions.

YOLOv3: YOLOv3 further improved accuracy by introducing a new backbone architecture and incorporating feature pyramid networks (FPN) [21] for better object detection across different scales.

- Architecture: YOLOv3 includes a Darknet-53 backbone and utilizes FPN for multi-scale feature extraction.
- Performance: YOLOv3 achieved notable improvements in accuracy compared to its predecessors.
- Suitability for Road Object Detection: YOLOv3 offers better performance for road object detection, especially for small and occluded objects.

YOLOv4: YOLOv4 pushed the boundaries of object detection with advancements in network architecture [10], data augmentation, and optimization techniques.

- Architecture: YOLOv4 features a more complex backbone network with additional optimization techniques.
- Performance: YOLOv4 achieved state-of-the-art performance in terms of accuracy and speed.
- Suitability for Road Object Detection: YOLOv4 offers excellent performance for road object detection tasks, with improved accuracy and efficiency.

YOLOv5: YOLOv5 introduced a streamlined architecture with a focus on simplicity and efficiency, leveraging advancements in neural architecture search (NAS) [20].

- Architecture: YOLOv5 utilizes a smaller, more efficient CNN architecture compared to previous versions.
- Performance: YOLOv5 achieved competitive performance while being faster and more lightweight.
- Suitability for Road Object Detection: YOLOv5 is well-suited for road object detection, offering a good balance between performance and efficiency [5].

MobileNet: MobileNet is designed for resource-constrained environments such as mobile devices, offering lightweight and efficient CNN architectures.

- Architecture: MobileNet utilizes depthwise separable convolutions to reduce computational complexity.
- Performance: While not as accurate as larger networks, MobileNet offers excellent performance considering its low computational requirements [13].
- Suitability for Road Object Detection: MobileNet is suitable for road object detection applications where computational resources are limited.

SENet: SENet (Squeeze-and-Excitation Network) introduced channel-wise attention mechanisms to enhance feature representation and improve model performance.

- Architecture: SENet integrates attention modules into CNN [21] architectures to adaptively recalibrate feature maps.
- Performance: SENet improves model performance by effectively capturing feature dependencies .
- Suitability for Road Object Detection: SENet can enhance the performance of object detection models for road scenes by improving feature representation and context awareness.

RetinaNet : RetinaNet introduced focal loss to address the class imbalance problem in object detection, focusing training on hard examples [7].

- Architecture: RetinaNet utilizes a feature pyramid network (FPN) [18] backbone and a two-branch detection head.
- Performance: RetinaNet achieved state-of-the-art performance by effectively handling class imbalance and small object detection.
- Suitability for Road Object Detection: RetinaNet excels in road object detection tasks, particularly in scenarios with small objects and class imbalance, making it the best choice among the discussed networks.

RetinaNet stands out as the best choice for road object detection due to its ability to handle small objects, class imbalance, and occlusions effectively. Its performance surpasses other networks like YOLOv3, YOLOv4, and MobileNet, offering state-of-the-art accuracy while maintaining efficiency. By addressing key challenges in road object detection, RetinaNet provides superior performance and reliability, making it the preferred choice for various road safety and autonomous driving applications.

Nasaruddin Nasaruddin et al [16] introduce a novel attention-based detection system designed to handle challenging outdoor scenarios characterized by swaying movement, camera jitter, and adverse weather conditions. they innovative approach employs bilateral texturing to construct a robust model capable of accurately identifying moving vehicle areas.

In their methodology, they generate an attention region that encompasses the entirety of the moving vehicle areas by leveraging bilateral texturing. This attention region is then fed into the classification module as a grid input. Subsequently, the classification module produces a class map of probabilities along with the final detections.

The classification task in our system involves four classes: car, truck, bus, and motorcycle. To train their model, they utilize a dataset comprising 49,652 annotated training samples.

Figure 1 provides an overview of our system workflow, illustrating the key components and their interactions. The subsequent sections delve into the intricate details of their approach, specifically focusing on attention-based detection and lightweight fine-grained classification techniques. Through this comprehensive exploration, their aim to present a robust and efficient solution for vehicle detection in challenging outdoor environments

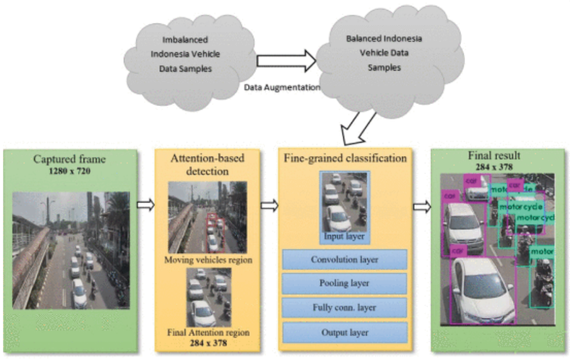

Figure 1: System workflow of our approach [16].

Basis of current exposure, in the future they could focus on advancing neural network architectures for attention-based detection in outdoor scenes, addressing challenges like swaying movement and adverse weather. Optimizing algorithms for real-time performance on edge devices and embedding multimodal sensor data could enhance detection reliability. Additionally, exploring domain adaptation techniques and transfer learning could improve model generalization across diverse conditions and datasets. These advancements aim to bolster the robustness and applicability of attention-based detection systems in practical scenarios.

3 RESEARCH GAP

We focus on the evolution and efficacy of computer vision-based vehicle detection and counting systems in urban transportation management. Through meticulous examination of existing literature and methodologies, we have identified several research gaps that need to be addressed:

- Limited Generalizability: Many existing studies focus on specific scenarios or datasets, which may not accurately represent the diverse range of environmental conditions and road networks encountered in real-world traffic management scenarios. There is a need for research that explores the adaptability of vehicle detection systems across various contexts to ensure their effectiveness in different urban environments.
- Lack of Standardized Evaluation Metrics: The absence of standardized evaluation metrics and benchmarks hinders fair comparisons between different methodologies. This makes it challenging for researchers and practitioners to assess the performance of vehicle detection systems accurately. Addressing this gap requires the development of standardized evaluation protocols that encompass a wide range of scenarios and conditions.
- Practical Deployment Challenges: While the theoretical effectiveness of computer vision-based systems is well-documented, there is limited discussion on the practical challenges and considerations involved in deploying these systems in real-world traffic management scenarios. Our aims to bridge this gap by investigating the practical implications of implementing vehicle detection systems, including cost, scalability, and integration with existing infrastructure.

4 RESEARCH CHALLENGES

- Data Collection and Annotation: Gathering large-scale datasets with diverse environmental conditions and ground truth annotations is a significant challenge. We need to collaborate with transportation authorities and industry partners to collect high-quality data that accurately represents real-world scenarios.

- Algorithm Development and Optimization: Developing and optimizing algorithms for vehicle detection and counting requires expertise in computer vision, machine learning, and optimization techniques. Our collaborate with interdisciplinary teams to develop state-of-the-art algorithms that balance accuracy, efficiency, and scalability.
- Integration with Existing Infrastructure: Integrating computer vision-based systems with existing traffic management infrastructure poses technical and logistical challenges. Our works closely with stakeholders to ensure seamless integration and compatibility with existing systems and protocols.

5 CONCLUSION

In the realm of urban transportation management, the integration of computer vision-based vehicle detection systems marks a significant stride towards enhancing traffic control and optimization. Through a comprehensive review spanning methodologies from traditional to deep learning approaches, this research has elucidated the evolution and efficacy of such systems in modern traffic management.

The findings underscore the pivotal role of computer vision technologies in providing real-time insights into traffic dynamics. These systems offer accurate tracking and counting of vehicles, empowering transportation authorities to make data-informed decisions for optimizing traffic flow, identifying congestion points, and implementing dynamic lane management strategies. Moreover, the adaptability of these systems across diverse environments and their seamless integration into existing infrastructure make them indispensable tools for modern transportation authorities.

While the review has highlighted the efficacy of various methodologies, including deep learning techniques like RetinaNet, it also identifies several research challenges and opportunities for innovation. Performance evaluation remains a crucial aspect, necessitating standardized benchmarks and evaluation metrics for fair comparisons. Additionally, there is a need for further research into the adaptability of vehicle detection systems across different environmental conditions and road networks.

In conclusion, computer vision-based vehicle detection systems hold immense promise for revolutionizing urban transportation management practices. By addressing the identified challenges and capitalizing on opportunities for innovation, researchers and practitioners can unlock the full potential of these systems, leading to tangible enhancements in traffic flow efficiency, safety, and urban mobility. Ultimately, the integration of advanced technologies like computer vision lays the foundation for a smarter, more efficient transportation ecosystem, benefiting communities and societies worldwide.

REFERENCES

1. IEEE Journals & Magazine, 2024. "Artificial Hummingbird Optimization Algorithm With Hierarchical Deep Learning for Traffic Management in Intelligent Transportation Systems." Accessed April 05, 2024. https://ieeexplore.ieee.org/document/10379096.
2. Xu, Y., Chu, K., Zhang, J., 2024. Nighttime Vehicle Detection Algorithm Based on Improved Faster-RCNN. IEEE Access, 12, 19299–19306. https://doi.org/ 10.1109/ACCESS.2023.3347791.
3. IEEE Journals & Magazine, 2024. "SatDetX-YOLO: A More Accurate Method for Vehicle Target Detection in Satellite Remote Sensing Imagery." Accessed April 05, 2024. https://ieeexplore.ieee.org/document/10480425.
4. Wang, P., Wang, X., Liu, Y., Song, J., 2024. Research on Road Object Detection Model Based on YOLOv4 of Autonomous Vehicle. IEEE Access, 12, 8198–8206. https://doi.org/10.1109/ACCESS.2024.3351771.
5. Li, Z., Pang, C., Dong, C., Zeng, X., 2023. R-YOLOv5: A Lightweight Rotational Object Detection Algorithm for Real-Time Detection of Vehicles in Dense Scenes. IEEE Access, 11, 61546–61559. https://doi.org/ 10.1109/ACCESS.2023.3262601.
6. IEEE Journals & Magazine, 2024. "Improved Vision-Based Vehicle Detection and Classification by Optimized YOLOv4." Accessed February 22, 2024. https://ieeexplore.ieee.org/document/9681804.
7. Miao, T., et al., 2022. An Improved Lightweight RetinaNet for Ship Detection in SAR Images. IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens., 15, 4667–4679. https://doi.org/10.1109/JSTARS.2022.3180159.
8. Du, S., Zhang, P., Zhang, B., Xu, H., 2021. Weak and Occluded Vehicle Detection in Complex Infrared Environment Based on Improved YOLOv4. IEEE Access, 9, 25671–25680. https://doi.org/10. 1109/ACCESS.2021.3057723.
9. Yang, H., Zhang, Y., Zhang, Y., Meng, H., Li, S., Dai, X., 2021. A Fast Vehicle Counting and Traffic Volume Estimation Method Based on Convolutional Neural

Network. IEEE Access, 9, 150522–150531. https://doi.org/10.1109/ACCESS.2021.3124675.
10. Tambe, R.G., Talbar, S.N., Chavan, S.S., 2021. Deep Multi-Feature Learning Architecture for Water Body Segmentation from Satellite Images. J. Vis. Commun. Image Represent., 77, 103141. https://doi.org/10.1016/j.jvcir.2021.103141.
11. Wang, X., Wang, S., Cao, J., Wang, Y., 2020. Data-Driven Based Tiny-YOLOv3 Method for Front Vehicle Detection Inducing SPP-Net. IEEE Access, 8, 110227–110236.https://doi.org/10.1109/ACCESS.2020.3001279
12. Bodapati, J.D., et al., 2020. Blended Multi-Modal Deep ConvNet Features for Diabetic Retinopathy Severity Prediction. Electronics, 9(6), 6. https://doi.org/10.3390/electronics9060914.
13. Taufiqurrahman, S., Handayani, A., Hermanto, B.R., Mengko, T.L.E.R., 2020. Diabetic Retinopathy Classification Using A Hybrid and Efficient MobileNetV2-SVM Model. In: 2020 IEEE Region 10 Conference (TENCON). pp. 235–240. https://doi.org/10.1109/TENCON50793.2020.9293739.
14. Jin, B., Liu, P., Wang, P., Shi, L., Zhao, J., 2020. Optic Disc Segmentation Using Attention-Based U-Net and the Improved Cross-Entropy Convolutional Neural Network. Entropy, 22(8), 8. https://doi.org/10.3390/e22080844.
15. Dai, Z., et al., 2019. Video-Based Vehicle Counting Framework. IEEE Access, 7, 64460–64470. https://doi.org/10.1109/ACCESS.2019.2914254.
16. Nasaruddin, N., Muchtar, K., Afdhal, A., 2019. A Lightweight Moving Vehicle Classification System Through Attention-Based Method and Deep Learning. IEEE Access, 7, 157564–157573. https://doi.org/10.1109/ACCESS.2019.2950162.
17. Bouachir, W., Ihou, K.E., Gueziri, H.-E., Bouguila, N., Bélanger, N., 2019. Computer Vision System for Automatic Counting of Planting Microsites Using UAV Imagery. IEEE Access, 7, 82491–82500. https://doi.org/10.1109/ACCESS.2019.2923765.
18. IEEE Journals & Magazine, 2024. "Multiple Object Tracking via Feature Pyramid Siamese Networks." Accessed April 06, 2024. https://ieeexplore.ieee.org/document/8587153.
19. Dong, H., Wang, X., Zhang, C., He, R., Jia, L., Qin, Y., 2018. Improved Robust Vehicle Detection and Identification Based on Single Magnetic Sensor. IEEE Access, 6, 5247–5255. https://doi.org/10.1109/ACCESS.2018.2791446.
20. Tayara, H., Gil Soo, K., Chong, K.T., 2018. Vehicle Detection and Counting in High-Resolution Aerial Images Using Convolutional Regression Neural Network. IEEE Access, 6, 2220–2230. https://doi.org/10.1109/ACCESS.2017.2782260.
21. Fan, Q., Brown, L., Smith, J., 2016. A Closer Look at Faster R-CNN for Vehicle Detection. In: 2016 IEEE Intelligent Vehicles Symposium (IV). pp. 124–129. https://doi.org/10.1109/IVS.2016.7535375.
22. Redmon, J., Divvala, S., Girshick, R., Farhadi, A., 2016. You Only Look Once: Unified, Real-Time Object Detection. In: 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR). pp. 779–788. https://doi.org/10.1109/CVPR.2016.91.
23. Tian, Y., Wang, Y., Song, R., Song, H., 2015. Accurate Vehicle Detection and Counting Algorithm for Traffic Data Collection. In: 2015 International Conference on Connected Vehicles and Expo (ICCVE). pp. 285–290. https://doi.org/10.1109/ICCVE.2015.60.
24. Liang, M., Huang, X., Chen, C.-H., Chen, X., Tokuta, A., 2015. Counting and Classification of Highway Vehicles by Regression Analysis. IEEE Trans. Intell. Transp. Syst., 16(5), 2878–2888. https://doi.org/10.1109/TITS.2015.2424917.