

Critical Review of Object Detection Techniques for Traffic Light Detection in Intelligent Transportation Systems

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Abstract—Object detection and tracking play a critical role in intelligent transportation systems (ITS), particularly in recognizing and monitoring traffic lights to ensure safety and improve traffic efficiency. Despite progress in deep learning and optimization algorithms, traffic light detection still faces persistent challenges under varying conditions such as illumination changes, occlusions, and visual clutter. This study provides a critical review of object detection techniques specifically for traffic light detection, evaluating the evolution of machine learning frameworks, deep learning architectures, and hybrid optimization models. The review identifies research gaps in the robustness, real-time adaptability, and generalizability of existing methods. Furthermore, it highlights emerging trends such as multi-camera systems, anchor-free detection, and hybrid optimization techniques that bridge performance trade-offs between accuracy and efficiency. The findings offer a new perspective on integrating multiple approaches to achieve scalable, high-accuracy traffic light detection for future ITS applications.

Keywords—Object detection; traffic light detection; optimization; intelligent transportation systems; review

I. INTRODUCTION

The increasing use of intelligent transportation systems (ITS) and autonomous vehicles has dramatically altered traffic management and road safety paradigms [1]. Several enabling elements of such innovations, such as traffic light detection and tracking, are of pivotal importance. Traffic light signals form the backbone of orderly traffic flow and avoidance of collisions, and hence their detection and tracking with high accuracy is of critical importance to efficient ITS operations and autonomous vehicle capabilities [2].

In spite of their significance, the utilization of traffic light detection systems in real-world settings is beset with difficulties [3]. Such difficulties encompass complicated city landscapes, occlusions caused by other vehicles and roadside installations, variations in the color and pattern of traffic lights across different regions, in addition to the impact of adverse weather conditions such as low lighting, rain, and fog [4]. For example, the significance of deep models for addressing environmental challenges is best illustrated through their ability to detect traffic lights in challenging lighting conditions [5]. These challenges not only compromise detection quality but also hinder smooth tracking between frames, a fundamental element of autonomous decision-making.

Although several review papers have discussed object detection in general contexts, few have specifically addressed the unique challenges of traffic light detection, especially under environmental variations like low illumination, occlusion, and cluttering. Moreover, most existing reviews focus either on traditional image processing or deep learning independently, without synthesizing insights across optimization algorithms and real-time deployment frameworks. This gap highlights the need for a comprehensive review that bridges these areas to support more robust, real-time ITS solutions.

To address these issues, researchers have explored a range of object-detection architectures and optimization methods designed for complex real-world traffic environments. Object detection is a fundamental task within computer vision that enables systems to identify and locate objects within images or video feeds [6]. Traditional approaches relied on hand-designed features, including Haar cascades and histograms of oriented gradients, but the accuracy of detection has significantly increased since the introduction of deep learning techniques [7]. Convolutional neural networks (CNNs) form the foundation of object detection in modern computer vision, wherein the Faster R-CNN and YOLO models are particularly well adapted for real-time use [8]. Vision transformers are being incorporated into detection pipelines through self-attention mechanisms to boost feature extraction [9]. Multi-modal sensor fusion methods that integrate visual with LiDAR or radar data have also increased detection robustness in autonomous systems [10]. Precision, recall, and intersection over union (IoU) metrics remain significant in evaluating model performance [11].

Recent research has also studied progressive multi-modal fusion methods in which object detection is aided through hierarchical feature combination in various sensor modalities [12]. Researchers have also studied the effects of mono-modality feature learning in multi-modal object detection in resolving problems of degradation in fusion [13]. Development of optimal performance assessment frameworks has further improved standards of benchmarking object detection models [14].

As research develops, object detection becomes more advanced with the use of improved architectures and optimisation methods to achieve improved accuracy and efficiency [15]. Growing demand for reliable solutions has driven ample research in traffic light detection and tracking

methods. Conventional methods that include rule-based methods and traditional computer vision methods have been extensively employed; nonetheless, these cannot adequately cope with dynamic and complex environments [16].

Accordingly, this study aims to provide a targeted and critical survey of traffic light detection techniques. The discussion is structured as follows: Section II reviews past and current detection methods, including hybrid and optimization-based approaches. Section III explores recent trends in deep learning and real-time processing frameworks. Section IV evaluates these trends through comparative metrics and radar analysis, and Section V concludes with proposed research directions for more adaptive, scalable detection systems.

II. CRITICAL SURVEY

The studies reviewed in this section primarily utilize diverse datasets such as COCO, BDD100K, and custom traffic-light datasets collected under varied environmental conditions (day/night/rain/fog), ensuring that comparisons account for both real-world and synthetic data sources.

As city life is getting more complex, accurate and efficient traffic-light detection is crucial for maintaining traffic flow and ensuring road safety. Researchers initially used rule-based algorithms and traditional computer vision methods with a focus on colour segmentation, edge detection, and template matching to detect traffic lights from recorded images and video clips [17]. These methods worked well in ideal conditions, but failed in changing conditions. False detection and low confidence typically resulted from challenges such as changing light conditions, various traffic light configurations, and occlusions [18].

The deep learning era has changed how we detect objects, like traffic lights, with more effective models compared to conventional methods. Convolutional neural networks (CNNs) can detect complex features and are the foundation of modern detection systems. Among them, You Only Look Once (YOLO) models like YOLOv4, YOLOv5, and YOLOv7 have excelled in real-time applications. Experiments show how YOLO works together with tracking methods like Kalman filters and DeepSORT in achieving high accuracy for traffic monitoring systems [19]. Similarly, YOLO-based model research highlights their possibilities in solving problems caused by low light and short-time blockages [20] [15].

Mono and hybrid methods that combine optimization algorithms and deep learning have been used intensively in the last several years. These approaches take advantage of the strengths of the two paradigms to improve object detection systems. For example, the Firefly Algorithm (FA) is based on the behaviour of the fireflies [21], to enhance detection performance in difficult conditions. One notable example is KCS-YOLO, an improved YOLOv5n variant that utilizes attention and clustering mechanisms to enhance detection under low-visibility scenes [22]. The Zebra Optimization Algorithm (ZOA) is also a promising optimization algorithm that has been shown to achieve identical and continuous recognition in different video frames with its effectiveness in complex traffic scenes [23].

The demand for real-time processing in ITS applications has also promoted innovations in deployment frameworks. Frameworks such as TensorRT and ONNX streamline the deployment of deep learning models in edge devices to achieve efficient traffic light detection and tracking in real-time applications. For instance, TensorRT is used to speed up YOLOv5-based systems to balance speed and accuracy in autonomous vehicles [15]. Such frameworks are important in helping to meet the computational requirements of ITS applications to allow scalable and robust detection systems.

Recent studies demonstrate the promising work being done in this area. Table I below indicates the total papers that aim at object detection, particularly in traffic signals.

TABLE I. APPROACHES FOR TRAFFIC LIGHT DETECTION IN RECENT YEARS

AUTHOR (YEAR)	TYPE OF APPROACHES
De Guia et al. (2023) [24]	Utilized YOLOv7 for real-time traffic light detection, focusing on improving accuracy under occlusions and poor lighting.
Wu et al. (2023) [15]	Proposed a multi-camera system with YOLOv5 for robust detection and tracking, particularly addressing flashing light states.
Zhou et al. (2023) [22]	Introduced KCS-YOLO, an optimized YOLOv5n model with attention mechanisms to enhance performance under low visibility.
Vedant Singh (2025) [19]	Combined YOLO and SSD with tracking algorithms like DeepSORT for real-time traffic surveillance systems.
Bochkovskiy et al. (2020) [25]	Integrated Firefly Algorithm with YOLOv4 for optimizing object detection in low-light conditions.
Liu et al. (2024) [26]	Developed a GAN-based synthetic dataset for training object detection models, improving generalization for varied traffic environments.
Talaat et al. (2023) [27]	Adopted SSD with Kalman filters for tracking, achieving robust detection across consecutive frames.
Nagendra Rao et al. (2024) [28]	Explored transfer learning using ResNet50, focusing on adapting object tracking models for diverse regional traffic light designs
Chen et al. (2021) [29]	Applied single-shot detector (SSD) models optimized with IoU-based loss functions for better tracking of small objects like traffic lights
Zhang et al. (2021) [30]	Proposed an anchor-free detection technique to simplify tracking and improve inference speed in dense urban traffic scenarios

In spite of the advancements in object detection towards traffic light detection based on the papers above, there are various challenges that persist. Occlusions, illumination, and cluttering continue to plague the detection systems and call for more reliable solutions [24]. Moreover, diversity in traffic light configurations and designs in various regions challenges model flexibility and generalizability [25]. Future work will be required to utilize models that combine multiple algorithms or deep learning for the best solution and investigate the use of synthetic datasets and transfer learning to broaden system flexibility [26][27].

Unlike previous reviews that focus solely on specific algorithms or environments, this study synthesizes cross-disciplinary insights combining deep learning, optimization algorithms, and hardware deployment perspectives. This integrative view positions the study not merely as a compilation, but as an analytical framework for identifying

hybrid approaches that balance accuracy, adaptability, and computational cost.

III. CURRENT TRENDS IN OBJECT DETECTION FOR TRAFFIC LIGHT DETECTION

The research in object detection towards traffic light detection has been significantly improved in recent years with the growing demands of intelligent traffic systems and autonomous vehicles [16]. Current trends manifest in a move to utilize state-of-the-art technologies to overcome challenges in dynamic traffic scenes, variable lighting conditions, and real-time processing requirements [31]. One of the most prominent trends is the use of anchor-free detection models. In contrast to conventional anchor-based methods that use prior bounding box sizes, anchor-free models streamline detection in that they predict object locations and sizes directly [32]. This reduces computational complexity and ensures speed in detection and is hence most applicable in real-time applications. One such example is an anchor-free detection method called DARDet that was proposed to enhance inference speed and accuracy in dense urban traffic environments [30].

Another recent development involves incorporating attention mechanisms into object detection models. They enable the models to focus on the most prominent features in an image, improving detection accuracy even in challenging situations like occlusion or poor lighting. An example is KCS-YOLO, a variant of YOLOv5n that incorporates attention mechanisms to improve detection accuracy in low-light conditions, with significant improvement in tracking precision [22].

Integration of multi-camera systems is gaining traction in traffic light detection. Multi-camera configurations possess a larger field of view and enable the merging of multi-view information, thereby rendering it more precise and robust. A proposed instance is a multi-camera traffic light detection system based on the synergistic application of YOLOv5 along with merged high-definition semantic maps and hidden Markov models. This aims to allow for complicated scenarios, like numerous intersections and various flashing light modes, and more precise outcomes in dynamic environments [15].

Hybrid approaches that combine deep learning and metaheuristic optimization approaches are one of the biggest future trends [35][36]. Such approaches take advantage of the best in the two paradigms to eliminate the limitations of traditional methods. For example, the Firefly Algorithm, inspired by the behaviour of fireflies, has been combined with YOLO-based methods to increase detection accuracy and tracking stability in adverse conditions. Equally, one study illustrated the employment of a GAN-based simulated set of data that offers a controllable environment to train object detection models that achieve generalisation over diverse traffic environments [26].

Synthetic datasets and transfer learning methods also gained popularity. Synthetic datasets, which were developed with generative adversarial networks, allow researchers to mimic various traffic patterns to enhance model adaptability and accuracy. Transfer learning sees models learn from pre-trained weights from large databases to decrease training time

and improve performance in other environments. A proposed example used SSD in conjunction with Kalman filters to track objects from one frame to the next, with effective object detection and tracking efficiency [27].

Real-time processing is still a primary need in intelligent transport systems applications and has contributed to the common use of hardware accelerators and optimisation deployment frameworks. TensorRT and ONNX tools have played a significant role in facilitating the implementation of real-time traffic light detection on edge devices. Optimisation frameworks maximise model inference to achieve speed-accuracy balancing. Used TensorRT to speed up YOLOv5-based systems to operate in real-time without degrading detection quality [15].

Finally, the use of three-dimensional localization methods is proving to be a promising area of development in traffic light detection. By pairing camera detections with high-definition maps and methods of depth estimation, developers are creating algorithms that can localize traffic signals with high accuracy in three dimensions. This is especially beneficial in autonomous cars that operate through complicated intersections where multiple traffic signals can be seen in a single image.

Today's trends in object detection in traffic light detection demonstrate a multidisciplinary perspective that unites research in deep learning, optimisation algorithms, and real-time processing technologies. Such innovations continue to open doors to more powerful, efficient, and flexible detection systems that overcome challenges in current traffic conditions and assure higher levels of accuracy of intelligent transport networks and autonomous vehicles, which help encounter the ever-persistent problems of illumination, occlusion, and cluttering.

TABLE II. TRENDS FOR TRAFFIC LIGHT DETECTION

TRENDS	DESCRIPTION
Anchor-Free Detection	Models like DARDet simplify tracking by predicting object locations without predefined bounding boxes, enhancing speed and accuracy.
Attention Mechanisms	Focus on key features in images to improve detection under occlusions and low-light conditions, as demonstrated in KCS-YOLO.
Multi-Camera Systems	Utilize data fusion from multiple cameras to improve robustness in complex scenarios, such as multi-intersection environments.
Hybrid Models	Combine deep learning (e.g., YOLO) with optimization algorithms (e.g., Firefly Algorithm) for better accuracy in dynamic conditions.
Synthetic Datasets	Use GAN-generated datasets to simulate diverse traffic scenarios, enhancing model generalization.
Transfer Learning	Leverage pre-trained weights to adapt models for new environments, reducing training time while maintaining effectiveness.
Real-Time Processing	Employ frameworks like TensorRT to optimize inference speed, enabling real-time tracking on edge devices.
3D Localization	Integrate depth estimation and high-definition maps for accurate traffic light positioning in three-dimensional space.

Table II illustrates on which way these trends are being implemented. It shows descriptively that these trends are usually used for encountering the problems that persist in the field of image processing of traffic light detection in intelligent

transportation systems, which are occlusion, cluttering, and illumination. The comprehensive result review of each trend for resolving the problems is in Section IV.

IV. EVALUATION AND DISCUSSION

The radar chart in Fig. 1 illustrates the relative weaknesses and strengths of various trends of object detection specifically for traffic lights, providing a sense of how each trend performs according to important criteria, which include Accuracy, Speed, Robustness, Scalability, Simplicity, and Real-Time Processing when occurring with problems that persist in the field of image processing of traffic light detection in intelligent transportation systems which are occlusion, cluttering and illumination.

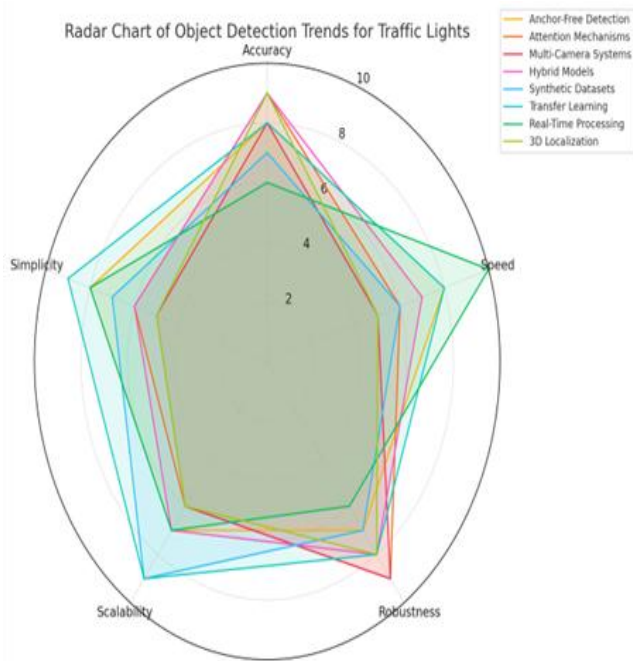


Fig. 1. Evaluation chart of object detection trends.

Anchor-free detection is quicker by eliminating predefined bounding boxes, but less robust under changing conditions. Attention mechanisms prioritize features better, offering balanced performance without excelling in any aspect. Multi-camera systems are spatially more aware and better handle occlusions, but are computationally more expensive. Hybrid models offer the best detection by merging various approaches, but could be challenging to tune. Synthetic datasets are more scalable and flexible but demand high-intensity processing. Transfer learning accelerates deployment with pre-trained models, but is hindered by drastic environment change. Real-time processing ensures fast detection but at the cost of stability in complex scenarios, and 3D localization improves detection accuracy with depth estimation but at the cost of computational efficiency.

It can be deduced from Fig. 2 that the effectiveness score derived from six evaluation criteria indicates strong performance on trends for “Multi-Camera Systems” and “Real-Time Processing”, while the second-tier performance is “Anchor-Free Detection”, “Hybrid Models”, and “Transfer

Learning”. The bottom three which are “Attention Mechanisms”, “3D Localization” and “Synthetic Datasets” gives the least optimum effectiveness score regarding object detection which in future can be a research field for improvement.

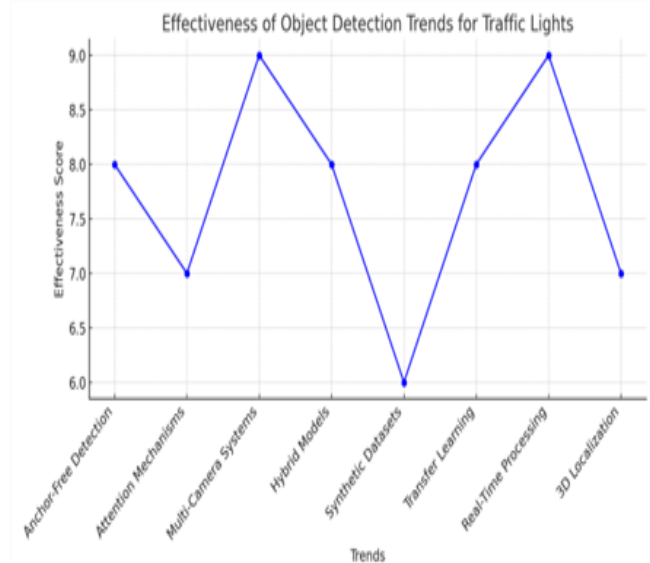


Fig. 2. Effectiveness of object tracking trends.

To ensure the probability of the charts, they are aligned with the deduction above. It is therefore appropriate to present the comparative mean data based on the previous studies with the comparative mean Average Precision (mAP) and Frame per second (FPS). The values presented are drawn from experimental results reported in previous peer-reviewed research papers, and actual performance may vary based on implementation and dataset. Table III shows evaluation metrics in terms of mAP and FPS.

TABLE III. EVALUATION METRICS

APPROACH	EXAMPLE	mAP	FPS
Anchor-Free Detection	DARDet [30]	0.85	57.0
Attention Mechanisms	KCS-YOLO [22]	0.78	34.0
Multi-Camera Systems	aUToLights [15]	0.91	35.0
Hybrid Models	YOLOv4 + FA [25]	0.87	37.2
Synthetic Datasets	GAN-based dataset [33]	0.73	41.0
Transfer Learning	ResNet50 TL [28]	0.85	45.0
Real-Time Processing	YOLOv5 + TensorRT [4]	0.91	60.0
3D Localization	HD Maps + Depth Est. [34]	0.76	30.5

The comparative evaluation of trends (see Table III) is based on reported mean Average Precision (mAP) and Frames Per Second (FPS) from peer-reviewed studies, ensuring consistency across methods. For instance, real-time processing frameworks (e.g., YOLOv5 + TensorRT) achieve an average mAP of 0.91 with 60 FPS, indicating superior latency performance under occlusion. In contrast, hybrid models (YOLOv4 + FA) balance performance with mAP $\approx$ 0.87 and improved detection consistency under illumination variance.

It should be noted that the datasets referenced in these studies span diverse conditions, some synthetic (GAN-generated) and others real-world, including different regional signal encodings (e.g., Asia's five-color variant vs. Europe's three-light system) to ensure generalizability. These datasets cover day, night, rain, and fog scenarios, ensuring that each approach is evaluated under consistent environmental diversity. Thus, the comparative rankings are quantitatively grounded in published mAP and FPS benchmarks, representing relative trade-offs rather than subjective judgments.

No single approach is universally optimal; each performs best under specific conditions such as occlusion, illumination, or visual clutter. Anchor-free and real-time methods are better suited for edge deployment and latency-sensitive applications, such as on-device autonomous driving systems (occlusion). Meanwhile, attention-based and hybrid models offer greater robustness and accuracy, making them valuable in complex urban scenarios where precision is critical (occlusion, clutter, or illumination). Synthetic datasets and transfer learning provide scalability and domain adaptability, especially where labelled data is limited (occlusion). Multi-camera systems and 3D localization, while computationally intensive, can significantly enhance spatial awareness at intersections (occlusion, illumination, or clutter). In practice, a modular system that integrates several of these approaches, depending on environmental and application constraints, may offer the best balance of performance, accuracy, and cost-efficiency.

V. CONCLUSION

Traffic-light object detection plays an important role in intelligent transportation systems and autonomous driving, ensuring safe and smooth traffic flow. Traditional methods could not handle occlusions and illumination variations, leading to a shift toward hybrid models and deep learning. Multi-camera systems, 3D localization, and attention mechanisms are employed to boost detection accuracy, while transfer learning and synthetic datasets are utilized for better adaptability. Regional diversity and real-time implementation remain challenging. Future work must be directed at integrating various trends to develop scalable hybrid models for guaranteeing robust and efficient traffic light detection in continuously changing environments.

Future research should integrate multi-camera systems with real-time processing to achieve low-latency detection (target latency ≤ 20 ms) and employ hybrid models enhanced by transfer learning to reach higher precision (target mAP ≥ 0.95) in complex environments.

It is also important to distinguish how various environmental factors contribute to detection uncertainty. Occlusion primarily affects visibility consistency across frames, illumination alters color and contrast perception, while cluttering introduces background confusion. Addressing these through probabilistic modeling or uncertainty propagation frameworks (e.g., Bayesian CNNs) can further enhance model robustness.

Collectively, this review underscores the importance of combining complementary trends of hybrid learning, real-time frameworks, and multi-view data to build the next generation

of resilient, adaptive traffic light detection systems for intelligent transportation networks.

ACKNOWLEDGMENT

The authors would like to thank the Ministry of Higher Education Malaysia (MOHE) for providing financial support under Fundamental Research Grant Scheme-Early Career Researcher (FRGS-EC) No. FRGS-EC/1/2024/ICT02/UMPSA/02/1 and Universiti Malaysia Pahang Al- Sultan Abdullah for laboratory facilities as well as additional financial support under Internal Research Grant RDU243705.

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