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Transformer-Based Object Detection Architectures for Autonomous Driving Perception: A Comprehensive Review

Muhammad Hamza

muhammadhamzakhan59@gmail.com

Qassim University, Saudi Arabia

ABSTRACT

Autonomous vehicle perception is one of the most important components in intelligent transportation systems, and the reliable trade-off between high fidelity of detection precision and computational efficiency in real time remains an open problem. Deep learning has proven to be very accurate in controlled settings, but bringing CNN-based solutions to deployment with high latency and substantial memory overhead is often a challenge to the end-to-end deployed Transformer solution. This thorough review provides a systematic analysis of recent developments in transformer-based detection architectures, consolidating 2024–2026 transformer- and CNN-based architectures for detection. It is a thorough review that systematically analyzes recent transformer-based detection architectures, summarizing the current transformer- and CNN-based detection architectures from 2024 to 2026. From our analysis, we can see that there is a clear lack of theoretical sophistication and the real-life edge-deployability of the hardware. In addition, there is a clear disconnection between the 2D camera-based detection approach and the 3D multimodal fusion approach in the literature. The critical research dimensions that are not well met by the current state-of-the-art are identified in this review, including small object detection in dense urban environments and robust inference under challenging weather conditions. This review provides a structured path forward by mapping these interrelated gaps and paving the way for the creation of lightweight, accurate and robust transformer detectors that can be deployed on their own in the field.

Keywords: Autonomous Driving, Object Detection, Detection Transformers (DETR), Vision Transformers (ViT), Real-Time Perception, Edge AI, Multimodal Fusion.

1. INTRODUCTION

To achieve the level of AAD that is required, the technology has to be highly complex and has to be able to navigate in the complex urban environments of which cities are made. Resolving object detection (identification and localization) of entities like pedestrians, vehicles and traffic signals is the basic input for downstream decision making and motion planning [1]. Convolutional Neural Networks (CNNs) are the current mainstream approach in the field, which is efficient in local feature extraction and has spatial inductive bias [4]. But the global dependency is hard to model with CNNs because of their limited ability to capture long-range dependencies, and many hand-crafted components are involved, e.g., Non-Maximum Suppression (NMS), have resulted in the rise of Transformer-based architectures [5].

With the introduction of the DETection TRansformer (DETR), the paradigm was changed to an end-to-end set prediction approach, which did not require complex spatial anchors [7]. Although first generation transformers were thought to be superior at contextual reasoning, they were limited by their computational latency and training convergence rate, which were not sufficient for the requirement of the millisecond latency time of the autonomous vehicle [9]. To overcome this, there has been a recent innovation of multi-scale feature fusion and efficient hybrid encoders like Real-Time Detection Transformers (RT-DETR) [10]. Moreover, recent studies conducted in 2025 and 2026 have proposed adaptive multi-modal fusion transformers, such as AMF-TR, which fuse RGB, LiDAR, and Radar data to make the system work robustly in adverse weather.

A big challenge remains in "edge-optimization," in which models have to run on constrained devices without sacrificing safety. Recent works focus on efficient backbone architectures like MobileNetV4 and VanillaNet in combination with transformer backbones to achieve state-of-the-art (SOTA) performance on nuScenes, BDD100K and similar datasets [12, 14]. This paper presents an overview of these transitions in a systematic way. We assess the performance of various DETR models, examine the effect of attention mechanisms on detecting small objects and pinpoint the "translational gap" between lab trained models and real-world deployment on road [21]. The rest of this review is structured as follows: Section 2 summarizes the literature, Section 3 describes some of the key architectures, and Section 5 summarizes the challenges and future directions.

2. THEORETICAL FRAMEWORK AND ARCHITECTURAL EVOLUTION

The perception shift in autonomous driving is driven by the transition from local feature engineering to global contextual reasoning in architecture. This section provides the theoretical background of Transformer-based detection and a survey of the existing state of the art on high-performance architectures.

2.1 From Convolutions to Global Attention

Traditional perception systems have used Convolutional Neural Networks (CNNs) that are based on local receptive fields to extract hierarchical features. Although efficient, CNNs are not suitable for long-range dependencies, which are also crucial for understanding complex traffic scenes [13]. The Self-Attention mechanism lets the model pay attention to all the pixels when deciding whether they are important or not, meaning that it does not matter how far they are away from each other. This over-the-whole approach is essential for identifying occlusion and spatial relationships among vehicles and infrastructure, as demonstrated by recent work on Vision Transformers (ViT) [14, 21].

2.2 DETECTION TRANSFORMER (DETR) FUNDAMENTALS

The DETECTION TRANSFORMER (DETR) paradigm changed the object detection paradigm to a set prediction problem with a bipartite matching loss. A transformer encoder-decoder architecture is used to avoid hand-crafted elements like spatial anchors and Non-Maximum Suppression (NMS) [7]. The original DETR was however, not very efficient in terms of computational costs. Recent approaches such as RT-DETR (Real-Time DETR) [10, 11] have fine-tuned this space by developing hybrid encoders that benefit from the inductive bias of convolutions along with the expressive power and flexibility of transformers to achieve state-of-the-art results on real-time benchmarks.

2.3 Evolution of Feature Extraction Backbones

The world of backbones has changed to "Edge-Optimization". Recent models have introduced light backbones like MobileNetV4 and VanillaNet [3, 11] for real-time performance on automotive hardware. These backbones are mainly used as the primary feature extractors, and then the high-level representations are fed to the transformer decoder for object queries. This hybrid scheme, which incorporates light-weight convolutions for spatial information with transformers for relational information, is currently the theoretical benchmark for autonomous perception [4, 12].

Table 1: Comparison of Core Backbones and Attention Strategies (2024-2026)

Ref	Model Name	Primary Backbone	Attention Type	Detection Focus
[1]	VPF-DETR	VanillaNet	Global Transformer	Traffic Signs
[3]	MobileNet-DETR	MobileNetV4	Hybrid CNN-ViT	General Vehicles
[4]	NV-DETR	Optimized DETR	Hierarchical MS-HAF	Urban Objects
[6]	AMF-TR	Multimodal	Cross-Attention	Adverse Weather
[10]	RT-DETR	ResNet/HGNetv2	Multi-scale	Real-time SOTA

3. METHODOLOGY AND PAPER SELECTION

A systematic approach for literature identification, screening, and selection is used in this review to ensure rigorous and high-quality synthesis of current advancements. The methodology focuses on recent technical contributions over the last three years (2024-2026) that have been published in peer-reviewed journals, books, and conferences, to reflect the cutting-edge in Transformer-based perception.

3.1 Search Strategy and Data Sources

The literature search was carried out in the IEEE Xplore Digital Library using a Boolean search string that aims to target the cross-over between architecture and application. The query used was: ("All Metadata":Transformer OR "All Metadata":Object Detection) AND ("All Metadata":Autonomous Driving).

Table 2: Technical Summary and Performance Comparison of Selected Literature

Authors & Year	Primary Focus	Core Architecture	Dataset Size	Reported Accuracy	Edge Consideration
Madake et al. (2024)	Small object detection in traffic	Custom DETR + Self-Attention	KITTI / BDD	90.0% mAP	High (Optimized FPS)
Zhou et al. (2024)	V2I Cooperative Perception	ViT-FuseNet (Cross-Attn)	DAIR-V2X	8.7% gain	Server-side fusion
An et al. (2024)	Radar-based noise robustness	TransVoxelRadar	Voxel-Radar	High Robustness	Real-time Voxelization

Shang et al. (2025)	Lightweight urban detection	NV-DETR (SPD-Conv)	KITTI	92.4% mAP	17.7% GFLOP reduction
Zhao et al. (2024)	Real-time end-to-end detection	RT-DETR (Hybrid Encoder)	COCO / BDD	54.8% mAP	SOTA Latency-Accuracy
Jain et al. (2026)	Adverse weather robustness	AMF-TR (Redundancy Module)	nuScenes	71.2% mAP	Safety-centric hardware
Wang et al. (2025)	Traffic sign localization	VPF-DETR (VanillaNet)	GTSDB	94.2% mAP	Minimalist Backbone
Babu et al. (2025)	Accessible AI descriptions	ViT + Text-to-Speech	Standard	~93%	Mobile-integrated
Han et al. (2025)	Comprehensive ViT Survey	Various Transformers	Survey	N/A	Extensive Latency review
Kim et al. (2025)	Temporal Camera-only 3D	OnlineBEV	nuScenes	52.1% mDS	On-device inference
Rossi et al. (2024)	Occupancy Grid Mapping	Transformer Grid	Custom	Moderate	Real-time Navigation
Martin et al. (2026)	Multi-modal IoT perception	Custom CNN-Transformer	Thermal/RGB	98.5%	IoT mentioned

3.2 Inclusion and Exclusion Criteria

The inclusion and exclusion of participants were based on the following criteria:

Three main criteria were used to select papers: (i) the paper was published between 2024 and 2026; (ii) the paper included empirical results based on industry standard datasets like KITTI, BDD100K, or nuScenes; and (iii) the paper was novel in terms of the architectural backbone or attention mechanism used for real-time constraints.

3.3 Data Synthesis

A sub-sample of high impact papers was chosen for detailed technical analysis. These papers were classified based on the key technologies they use, such as "Next-Gen DETR Variants" and "Edge-Optimized Architectures. This review enables the identification of the current performance Pareto-front for autonomous systems by plotting the accuracy of each system with a computational cost.

4. PERFORMANCE EVALUATION AND ARCHITECTURAL BENCHMARKS

Assessment of Transformer-based models in autonomous driving is characterized by a strict comparison with CNN-based baselines. The reported performance metrics for this state of the art (SOTA) architectures are covered and analyzed in this section, specifically with respect to mean Average Precision (mAP) and computational throughput.

4.1 Accuracy Benchmarks on Standard Datasets

Recent papers point out that the Transformer-based detectors easily outperform the more cumbersome CNN baselines on big datasets. One example is RT-DETR [10] which sets a new state-of-the-art, with mAP comparable to YOLOv8 and with lower inference time. The same applies to NV-DETR [4] that achieved 92.4% mAP on the KITTI urban dataset, which outperformed the traditional ResNet based detectors greatly in terms of accuracy in detecting small pixel footprints, such as traffic cones and distant pedestrians. These benchmarks show that transformers' global receptive field is better for understanding the spatial context of complex road scenes.

4.2 Latency and Real-Time Viability

One of the most important metrics in the field of Autonomous Perception is "Inference Latency. The criticism was that the early transformers were too expensive to compute, but the state of the art 2024–2026 has changed drastically for that. Real-time performance has been reported by TransVOD [1] on high-end GPUs and also by minimalist frameworks such as VPF-DETR [11] that use VanillaNet backbones to reduce the "memory wall" effect on edge devices. The combination of multi-modal query (LiDAR/Radar) increases computational cost, however, as presented in AMF-TR [6] benchmarking, the time is still within the safety-critical window of 30ms-50ms for autonomous systems in Level 4.

4.3 Comparative Metric Analysis

The "Precision-to-GFLOPs" ratio is the most important metric to consider when comparing SOTA models. Nowadays, the Pareto front is hybrid models based on CNN backbones to extract local features and transformer decoders to query objects. The viability of achieving "Laboratory Accuracy" (mAP > 50 on COCO) while avoiding the large number of parameters in original ViT is shown in these architectures. The new "efficient precision" is the hallmark of the 2025-2026 architecture.

5. MODEL OPTIMIZATION AND EDGE DEPLOYMENT CHALLENGES

While Transformer-based architectures are being moved from the laboratory high performance computing (HPC) world to the automotive electronic control unit (ECU) system, several engineering challenges arise. The technical literature that was identified through the 2024-2026 period will be discussed in this section with regards to its deployment challenges and optimization strategies.

5.1 Computational Complexity and Memory Constraints

Self-attention is still the biggest sticking point for edge deployment, with its quadratic complexity. In contrast to CNNs, standard Transformers need to store a number of memory items that grow with the number of input tokens [13]. Recent efforts have focused on mitigating this by introducing a "Token Sparsification" module and a "Linear Attention" module to maintain the need for the global context for road safety while keeping the number of GFLOPs low [38]. The use of these sparse operations on the common automotive hardware, which is normally optimized for dense matrix multiplication, introduces a major "hardware-software misalignment" [4] that is significant.

5.2 Quantization and Pruning for Real-Time Inference

Model compression is necessary in order to reach the sub-50ms latency needed for autonomous braking and steering. The use of Post-Training Quantization (PTQ) to quantize the 32-bit floating point weights to 8-bit integers (INT8) has been emphasized in studies of RT-DETR and MobileNet-based transformers [30]. This is very helpful for chips at the edge, such as NVIDIA Orin or NVIDIA Horizon Robotics series, but may cause a small loss of mAP, especially for low-contrast objects under night driving conditions [31]. For the compression step, researchers are now studying Quantization-Aware Training (QAT), which aims at maintaining accuracy throughout the compression process [34].

5.3 Thermal and power management in automotive units.

Real time object detection is a CPU consuming process. If the high-resolution transformers are constantly used, they can also cause thermal throttling in fanless automotive enclosures, thus limiting the frame rate (FPS) and compromising safety [12]. To overcome this, the trend of "Minimalist Backbone" has been introduced, for example, VPF-DETR [11] uses VanillaNet for its backbone. Still, "Safety-Critical Precision" and "Thermal Sustainability" are still a critical research dimension that needs to be further optimized across the fields of hardware engineers and AI architects [25].

6. RESEARCH GAPS AND FUTURE DIRECTIONS

Transformer-based models have been shown to perform well on benchmark datasets; however, their performance is one of the main challenges for them in the real world, where the data is not controlled. This portion examines the adaptation of architecture to preserve the accuracy of the perception, in the face of adverse conditions.

6.1 Attention Stability in Low-Visibility Scenarios

The learner will understand how to stay alert in the event of low visibility. The learner will know how to be alert in low visibility situations. In the typical self-attention-based Vision Transformers (ViTs), low-level image noise like rain streaks, heavy fog and night time glare can make a difference. Transformers do not have the local pooling mechanism found in CNNs, which suppresses noise in the image, and may assign high attention weights to environmental artifacts. More recent works suggest using uncertainty-aware attention layers that are able to adaptively filter out noisy tokens in order to ensure that the model stays focused on important road entities even in the case of degraded visibility [25].

6.2 Multi-modal Redundancy and Cross-Attention Fusion

The ability to integrate redundant sensor data is an important aspect of robustness. It is evident from the literature in the last three years (2024-2026) that methods based on Transformers are gradually replacing "Early Fusion" of RGB and LiDAR/Radar streams. Such models as AMF-TR [6] can leverage cross attention modules to focus on radar point clouds when camera input is unavailable. A crucial architectural redundancy for the safety critical level 4 systems is that the failure of any sensor should not affect the perception stack as a whole.

6.3 Temporal Consistency and Motion Modeling

Robustness also means temporal stability, which means that if an object is seen in frame N it will be seen in frame N+1. Recent studies are moving from the 2D approach of detection to 3D temporal transformers with 'Memory Queues' containing past features. This means the pedestrian can be maintained in the memory even when he/she is temporarily blocked by other people or objects, which is something between the mere detection and the full awareness of the surrounding environment [16, 17].

7. SYNTHESIS OF IDENTIFIED RESEARCH GAPS

The critical gaps identified in the literature for full scale implementation of the Transformer-based detectors in an autonomous vehicle are summarized below based on the systematic analysis of the literature conducted in 2024–2026.

Table 3: Matrix of Identified Research Gaps and Strategic Directions

Identified Gap	Current Limitation in Literature	Proposed Research Direction
Small Object Sensitivity	High mAP drop for distant/small entities in dense urban scenes.	Implementation of Zero-Latency Multi-Resolution attention layers.
Environmental Robustness	Models "distracted" by noise in heavy rain, fog, or nighttime glare.	Development of Robustness-Aware Transformers with noise-filtering.

Hardware-NPU Alignment	Mathematical efficiency does not translate to automotive silicon speed.	Hardware-Aware Neural Architecture Search (NAS) for NPUs.
Semantic-Spatial Synergy	Bounding box detection lacks intent and behavioral context.	Integration of Scene Parsing for predictive behavioral analysis.

7.1 The Small Object Detection Sensitivity Gap

Although the SOTA models such as RT-DETR [10] achieved high mean Average Precision (mAP) score, it is noticed that they fail to perform well for small scale objects (e.g., distant traffic signs) in dense urban settings. Multi-scale feature fusion is a remedy for this, but the high-resolution attention layers are too costly for real-time edge hardware.

7.2 Cross-Domain Environmental Robustness Gap

Most of the research that has been identified works with data sets that have high visibility. The technical literature describing the performance of Transformer encoders in the following environmental "Long-Tail" is virtually nonexistent: Heavy sand storms, heavy snowfall. The current attention mechanisms are very susceptible to environmental noise, indicating the necessity of stronger and attentional mechanisms [25, 26].

7.3 Hardware-Software Co-Design Disconnect

One recurring missing component is "Hardware-Awareness". In fact, many innovative transformer variants employ mathematically efficient operations, but are prohibitively expensive in terms of computation on a specific architecture of NPUs (Neural Processing Units) common in modern vehicles. Research is needed on "Hardware-Specific Transformers" which are inherently designed to utilise automotive silicon [4, 30].

7.4 Real-Time Semantic-Spatial Synergy

The progress of object detection is made, but the missing point is the simultaneous integration of "Semantic Understanding" and "Spatial Localization". The next steps involve closing the gap between the simple detection and the more complex task of "Scene Parsing", enabling an autonomous system to anticipate the intent of the object(s) it detects.

8. FUTURE DIRECTIONS AND CONCLUSION

The shift from classic convolutional perception systems to Transformer-based ones marks a pivotal change in the autonomous driving sector. In this review, the authors have painstakingly charted the course of these developments and have focused on the important transition from local reasoning to global reasoning.

8.1 Future Research Pathways

This will not be sufficient to reach the level of autonomy in the future: Research should extend beyond the optimization for the Mean Average Precision (mAP) on static datasets. Key directions include:

Edge-Native Transformers: co-designed architectures optimized for automotive NPU (Neural Processing Unit) constraints, without sacrificing latency-accuracy trade-off.

Proactive multimodal fusion: The shift from "Late Fusion" to "Cross-Attention Early Fusion" to achieve better redundancy in multimodal data fusion such as LiDAR, Radar, and Camera.

Explainable and Trusted Perception: Embedding modules which give real-time explanations of vehicle actions, to ensure regulatory compliance and public trust.

8.2 Concluding Remarks

To conclude, the DEtection TRansformer (DETR) and Vision Transformer (ViT) paradigms have overcome the long-range dependency constraints of CNNs, but they have not yet been widely adopted due to their high computational and environmental demands. Based on our review of the literature for 2024–2026, we believe the future of autonomous perception is 'Efficient-Hybrid' models. These models leverage the fast speeds of light-weight convolutional backbones (such as VanillaNet and MobileNetV4) and the relational intelligence of transformer decoders. Transformer-based perception will fill the gaps in hardware-software alignment and in sensitivity to small objects, and provide the secure and dependable basis for the next generation of intelligent transportation systems.

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