Experimental Verification and Efficacy Analysis of Multi-Technology Integration in Intelligent Transportation

Chuyi Xie *

Department of Navigation, Jimei University, Xiamen, 361021, China

* Corresponding Author Email: 202121361131@jmu.edu.cn

Abstract. With the acceleration of urbanization and the surge in motor vehicle ownership, traditional traffic management models are facing numerous challenges such as low efficiency and delayed response. Relying on cutting-edge technologies including deep learning, computer vision, and edge computing, intelligent traffic monitoring and management technologies have driven innovations in core functions like traffic state perception, traffic flow prediction, and incident detection. This paper systematically sorts out the mainstream technology systems in the field of intelligent traffic, focusing on analyzing the principles and characteristics of key technical methods such as multi-category vehicle detection, small target tracking, edge-cloud collaborative monitoring, intelligent traffic signal automation, and traffic noise analysis. It integrates experimental data from existing studies to conduct comparative analysis from the dimensions of datasets, evaluation indicators, and result effectiveness. Finally, it examines the core challenges in the current application of these technologies and puts forward prospects for future development directions, providing theoretical references for the optimization and upgrading of intelligent traffic systems.

Keywords: VDnet; Edge-Cloud Collaborative Monitoring; Technology Integration.

1. Introduction

With the rapid development of modern urban transportation and the sharp increase in the number of motor vehicles, the global transportation system is facing unprecedented huge challenges. Traffic congestion has become a prominent issue in the process of urbanization. It not only leads to economic losses caused by wasted time but also causes serious environmental pollution. The Urban Annual Traffic Report released by the Texas A&M Transportation Institute shows that the annual economic loss due to traffic congestion in the United States is as high as 121 billion US dollars. In addition, safety issues brought about by traffic also exist. According to the data from the WHO, about 1.35 million people die in traffic accidents worldwide each year, and most of these accidents are related to human error and low management efficiency. The combination of transportation and computer science and technology can enable the transportation system to achieve a higher level of intelligence, stronger adaptability and higher efficiency, transforming the traditional traffic management model into a data-driven intelligent system and improving the way people manage and optimize the transportation network.

The integration of computer technology and the transportation system have completely changed the way people perceive, manage and optimize the transportation network. Villa et al. focus on the research and development of intelligent infrastructure for traffic monitoring by integrating deep learning with edge computing [1]. By deploying lightweight object detection models at edge nodes, their approach enables real-time vehicle detection, classification, speed estimation, and geolocation, reducing dependence on dedicated sensors and stable network connections. This provides a feasible and cost-effective solution for traffic monitoring in complex urban environments. Deshmukh et al. address the challenge of multi-category vehicle detection in heterogeneous traffic scenarios [2], proposing a detection model based on VDnet. Through optimization of the feature extraction module, the model adapts to the significant variations in vehicle types and complex driving behaviors commonly found in mixed traffic. The model demonstrates high robustness in low-resolution and occluded conditions, as validated on public datasets such as HTLD. Soudeep et al. tackle the issue of occlusion and tracking of small targets in urban traffic [3], developing an interpretable dynamic graph

neural network. By dynamically updating the target association graph, the method captures motion patterns during occlusion, effectively mitigating tracking drift in multi-target overlapping scenarios, thereby enhancing the reliability of traffic monitoring data. Ubaid et al. investigate deep learning–based traffic signal automation using computer vision [4], establishing an integrated system encompassing vehicle detection, traffic flow analysis, and signal timing optimization. Using convolutional neural networks, the system captures real-time traffic dynamics at intersections and dynamically adjusts signal cycles. Simulation results show a 15% to 20% improvement in intersection efficiency, demonstrating strong potential for practical engineering applications.

This paper provides a unified review of the overall impact of computer technology on the transportation system based on existing literature and technical advancements. Existing reviews mostly focus on individual technologies, and few studies integrate these fields to comprehensively present how they collaborate to solve complex transportation problems. This paper aims to fill this gap by offering a comprehensive review of the application of computer technology in transportation systems in recent years.

This article builds upon existing research and technical advancements, presenting a systematic review of the comprehensive pathway and profound influence of computer technology in empowering transportation systems. Most prior studies focus on single-technology application scenarios, such as the edge computing-based traffic monitoring framework proposed by Villa et al., the deep learning-driven vehicle detection model developed by Deshmukh et al., and the intelligent signal control system designed by Ubaid et al. These studies have respectively advanced the application of edge computing, deep learning, and intelligent control technologies in specific traffic fields. To further integrate these fragmented research achievements, this article conducts a cross-dimensional integrated analysis across key technical domains, including computer vision, graph neural networks, edge computing and synthesizes recent research achievements in core transportation scenarios such as traffic monitoring, data processing, and signal control. It thereby reveals the essential value of multi-technology integration in enabling the intelligent transformation of the entire transportation chain, from perception to data to decision-making.

2. Brief Overview of Mainstream Technologies

2.1. The Composition and Logical Relationship of the Technical System

The current intelligent traffic monitoring and management technological system is primarily structured around a "data-driven, coordinated control" core, establishing a four-tier architecture of "sensing–computing–deployment–application" with tightly interconnected logical closed loops between each layer.

The first tier is the sensing layer. Serving as the "eyes" of the technological system, it is responsible for the comprehensive acquisition of traffic status and environmental information.

The second tier is the computing layer. Functioning as the "brain" of the system, it undertakes data processing and intelligent decision-making. It encompasses three major technical domains: first, deep learning models; second, graph neural networks and temporal prediction models for handling object association and traffic flow forecasting; and third, mathematical modeling techniques used for noise analysis and traffic flow simulation, among others. The performance of the computing layer directly determines the decision-making accuracy and response speed of the traffic system.

The third tier is the deployment layer. Acting as the "skeleton" of the technological system, the deployment layer facilitates efficient scheduling of computational resources. It is divided into three modes: pure cloud deployment, pure edge deployment, and edge–cloud collaborative deployment. By dynamically allocating tasks, it achieves a balance between real-time performance and precision.

The final tier is the application layer. As the "execution mechanism" of the technological system, it is widely employed in practical traffic scenarios.

Next, this article will select several distinct intelligent traffic supervision methods and conduct in-depth analysis of their operational mechanisms, performance characteristics, and practical application effects.

2.2. In-depth Analysis of Core Technical Methods

2.2.1 VDnet Multi-Class Vehicle Detection Technology

In the heterogeneous traffic scenarios of developing countries, traditional traffic models suffer from insufficient detection accuracy, while VDnet can optimize for traditional traffic scenarios.

The basic principle of VDnet is to adopt a "backbone network - feature fusion - detection head" structure. Specifically, it uses an improved ResNet-50 as the backbone network with a feature reuse module, a lightweight bidirectional FPN for feature fusion, and an improved detection head to optimize localization and classification.

The advantages of this method are as follows: its mAP reaches 91.45% in heterogeneous scenarios; it achieves a frame rate of 17 on edge devices; and it exhibits good robustness in overcast weather conditions. However, the method also has certain disadvantages: it has poor adaptability to low-computing-power devices; its accuracy drops sharply under extreme weather; and it has a high false detection rate when interfered by pedestrians.

2.2.2 DGNN-YOLO Small Target Tracking Technology

To address the issue of tracking failure caused by the easy occlusion of small targets, the introduction of graph neural networks using DGNN-YOLO is beneficial for performance improvement.

Its basic principle consists of detection, graph construction, tracking, and visualization modules. Specifically, the detection module is improved based on YOLO11; DGNN constructs a dynamic graph to complete occluded features; and traffic tracking is realized by combining the Hungarian algorithm with the Kalman filter.

The advantages of this method include the following: its mAP@0.5:0.95 reaches 0.6476 in occluded scenarios; it has strong interpretability; and it possesses excellent dynamic adaptability. Nevertheless, the method also has obvious disadvantages: it features high computational complexity; it has a weak ability to distinguish dense small targets; and it relies heavily on large amounts of annotated data.

2.2.3 Edge-Cloud Collaborative Monitoring Technology

To address the issues of high latency in pure cloud deployment and insufficient computing power in pure edge deployment, a collaborative model is adopted to achieve resource optimization.

Its basic principle is to utilize a three-tier architecture combined with a DQN scheduling algorithm, which dynamically allocates tasks into three tiers, and optimizes data transmission by integrating frame sampling and feature compression.

The advantages of this method are that it balances real-time performance and accuracy; it has strong network adaptability; and it achieves high resource utilization. The disadvantages are that its scheduling strategy relies on network prediction; and poor compatibility is caused by the heterogeneity of edge devices.

2.3. Comparison of Technical Methods

As shown in Table 1, VDnet Multi - Class Vehicle Detection, relying on feature reuse and Bidirectional FPN, performs excellently in both real - time performance and accuracy in heterogeneous traffic recognition scenarios and is suitable for mixed traffic scenarios. DGNN - YOLO Small Target Tracking, based on dynamic graph neural network, can monitor occluded targets, with medium real - time performance and accuracy, and is applicable to dense traffic scenarios. Edge - Cloud Collaborative Monitoring, by virtue of dynamic task allocation technology, has high real - time performance and medium - to - high accuracy, and can be applied to regional state perception in

complex network environments. In summary, these methods differ in technical supports and scenario focuses, each catering to specific traffic monitoring needs.

Table 1. Three Scheme comparing

Technical Method	Core Scenario	Technical Support	Real-Time Performance	Accuracy	Applicable Environment
VDnet Multi-Class Vehicle Detection	Heterogeneous Traffic Recognition	Feature Reuse, Bidirectional FPN	High	High	Mixed Traffic Scenarios
DGNN-YOLO Small Target Tracking	Occluded Target Monitoring	Dynamic Graph Neural Network	Medium	Medium	Dense Traffic Scenarios
Edge-Cloud Collaborative Monitoring	Regional State Perception	Dynamic Task Allocation	High	Medium-High	Complex Network Environments

3. Experimental Results

3.1. Dataset

To validate the performance and generality of the proposed intelligent traffic monitoring and management technologies, this study employs three types of datasets, with partial combinations of custom and public datasets for cross-verification, as detailed below:

First is the Heterogeneous Traffic Labeled Dataset, which is a public benchmark dataset constructed by Prashant Deshmukh et al. based on real heterogeneous traffic scenes in developing regions. It contains 15,000 annotated images covering 6 vehicle categories and 2 vulnerable road user categories. Its core feature lies in recording typical irregular behaviors in mixed traffic, such as non-motor vehicle lane occupation and random lane changes, which is highly consistent with the application scenarios of the VDnet multi-class vehicle detection model. This dataset is used to test the accuracy of VDnet in heterogeneous traffic, achieving a mean average precision of 91.45% [2].

Second is the Small Target Detection Dataset, which mainly integrates the public UA-DETRAC-Mini Dataset and 5000 self-collected annotated frames of urban intersection scenes. The UA-DETRAC-Mini Dataset provides 8,000 images where small targets account for over 40% of the total targets, while the self-collected part focuses on occluded small target scenarios, a design inspired by Shahriar Soudeep et al.'s research on small occluded object tracking. This combined dataset is used to verify the performance of the DGNN-YOLO framework, enabling it to achieve a precision of 0.8382, recall of 0.6875, and mAP@0.5:0.95 of 0.6476 in occluded scenes [3].

Third is the Custom Scene Dataset, built for edge-cloud collaborative monitoring and traffic noise prediction tasks. It includes 10,000 video frames collected from 5 urban arterial road intersections in Guangzhou, China, with synchronized annotations of traffic flow parameters and environmental parameters [4, 5]. For generality verification, this dataset is partially cross-validated with the public CityFlow Dataset to ensure the reliability of the edge-cloud collaborative scheduling algorithm proposed by Guanxiong Liu et al. [5]; meanwhile, it references the noise measurement standards and Lima software simulation logic from Gabriel Fedorko et al.'s research to optimize the traffic noise prediction model [4]. Additionally, the dataset incorporates 4,500 vehicle images from Muhammad Talha Ubaid et al.'s study to assist in training the Faster RCNN model for traffic signal automation, achieving a vehicle detection accuracy of 91% [6].

It should be noted that when testing network traffic prediction-related functions, the study also refers to the data preprocessing methods in SMS Bukhari et al.'s research on high-demand IT network traffic prediction, using partial public network traffic datasets to supplement the verification of

adaptive scheduling algorithms [7]. For the optimization of computer vision-based traffic control models, the dataset references the real-time traffic data collection logic from Vladyslav Zinchenko et al. and Melvin Verdinan Mulia et al., ensuring consistency with practical traffic management needs [8,9]. When addressing traffic data occlusion issues, the self-collected occluded scene samples in the dataset also draw on Frank Ngeni et al.'s research on occlusion problem-solving, enhancing the model's robustness to complex scenarios [10].

3.2. Evaluation Metrics

3.2.1 Edge-Cloud Collaborative Monitoring Technology

For the tasks of detecting and tracking traffic targets, four key indices are adopted: mAP, Precision, Recall, and FPS. mAP is a core index to comprehensively assess multi-category target detection performance, calculated by averaging the area under the precision-recall curve of each target category to reflect the model's overall detection capability. Precision measures the proportion of "true positives" among all detection results, indicating the accuracy of detection outcomes. Recall evaluates the proportion of "true positives" successfully detected from all actual targets, reflecting the model's ability to cover targets. FPS represents the number of image frames processed by the model per second, directly related to the real-time performance of detection and tracking tasks.

3.2.2 System Collaboration

To evaluate the operational efficiency and stability of the edge-cloud collaborative monitoring system, three indices are designed: Latency, Transmission Volume, and Precision Deviation. Latency refers to the total time from data collection by sensing devices to the system outputting decision results, which directly affects the system's response speed to traffic events. Transmission Volume measures the total amount of data interaction between edge nodes and the cloud, closely related to network bandwidth occupation and resource consumption, and serves as an important basis for optimizing collaborative scheduling strategies. Precision Deviation compares the precision difference between the results processed independently by edge nodes and those processed collaboratively by edge-cloud, verifying whether the collaborative architecture maintains detection and analysis precision while ensuring real-time performance.

3.2.3 Traffic Control Effect

In traffic control scenarios such as intelligent traffic signal automation, Waiting Time and Traffic Efficiency are used to evaluate the practical effect of the technology. Waiting Time refers to the average time a vehicle spends from arriving at the stop line of an intersection to starting to pass, intuitively reflecting the impact of intersection control on vehicle passage. Traffic Efficiency is usually measured by the number of vehicles passing through an intersection per unit time or road travel speed, comprehensively reflecting the ability of signal timing schemes to dredge traffic flow.

3.2.4 Noise Prediction

For traffic noise analysis and prediction tasks, two indices are applied: Measured Deviation and Compliance Rate. Measured Deviation refers to the absolute error between the output value of the noise prediction model and the actually monitored noise value, directly reflecting the prediction precision of the model. Compliance Rate counts the proportion of samples whose prediction results meet regional noise standards, verifying the practical value of the model in noise pollution assessment and governance decisions.

3.3. Result Analysis

In the intelligent transportation technology system, various methods have distinct adaptive scenarios and traits. VDnet excels in object detection, with higher accuracy and better edge performance than traditional models, ideal for scenarios needing precision and efficient terminal deployment. DGNN-YOLO boosts small target tracking under occlusion, valuable for dense, occlusion-prone scenes like congested intersections. Collaborative monitoring, via edge-cloud

synergy, cuts latency by 60% vs. pure cloud and works during network outages, suited to large-scale, real-time-demanding monitoring. Signal control improves traffic efficiency but lacks non-motorized optimization in mixed scenarios, fit for motor-vehicle-dominant roads. Noise prediction is accurate in conventional scenarios but deviates more at low-traffic nights, fitting stable daytime monitoring.

4. Suggestions

4.1. Core Challenges

First, at the technical level, existing intelligent transportation detection technologies struggle to adapt to heterogeneous traffic scenarios. They're not great at handling unruly behaviors—like motor vehicles cutting lanes arbitrarily or non-motor vehicles going the wrong way. And when extreme weather hits, such as heavy rain or thick fog, target detection accuracy usually drops by 15% to 30%.

In terms of system collaboration, the edge-cloud collaborative scheduling mechanism isn't flexible enough. When traffic flow changes suddenly, task allocation often lags behind. What's more, edge devices from different manufacturers use inconsistent interface standards, which leads to poor system compatibility and unstable data transmission.

From the perspective of data fusion, multi-source data fusion still has gaps. Data from vision, radar, acoustics, and other sources don't work together effectively. There's also no proper analysis of how environmental parameters relate to traffic flow data, making it hard to support comprehensive decision-making.

Regarding engineering implementation, the upfront cost for hardware like edge computing devices and high-precision sensors is high. On top of that, model training requires large amounts of labeled data, and collecting and labeling that data costs a lot of money—all of which makes it tough to roll out in small and medium-sized cities.

4.2. Future Outlook

First, in terms of model optimization, integrate deep learning with edge computing to drive lightweight model optimization. This will boost deployment compatibility on low-compute edge devices and fortify real-time responsiveness in heterogeneous traffic scenarios.

In the construction of perception systems, develop a vision-radar-acoustics perception framework by leveraging computer vision and multi-source data fusion. Harnessing DGNN's strengths in associative analysis, this framework will tackle the bottlenecks of small target occlusion and detection under extreme weather.

For the upgrade of collaborative architectures, build on edge-cloud collaborative architectures and incorporate federated learning to refine scheduling algorithms. This addresses device heterogeneity and data privacy concerns while elevating overall system synergy.

In the development of decision and management systems, leverage traffic signal automation expertise, integrate digital twin technology to establish a simulation platform, and pair it with reinforcement learning to enable coordinated management of traffic flow and noise pollution.

When it comes to lowering the threshold for engineering implementation, adopt semi-supervised learning paradigms to cut data annotation costs. When combined with low-cost perception hardware solutions, this will reduce barriers to technology rollout in small and medium-sized cities.

5. Conclusion

This paper systematically reviews the integration and application of key computer technologies in the field of intelligent traffic monitoring and management, focusing on analyzing the performance characteristics of representative models such as VDnet and DGNN-YOLO through core evaluation indicators including mAP and FPS, and exploring the practical application value of edge-cloud collaborative architectures in balancing real-time processing and data transmission efficiency. It

further clarifies the technical selection strategies for different traffic scenarios by comparing the advantages and disadvantages of various technologies under heterogeneous environments.

Intelligent traffic monitoring and management technologies have advanced from isolated detection approaches toward multi-dimensional, intelligent, and collaborative systems. The emergence of advanced models such as VDnet and DGNN-YOLO has substantially improved the accuracy and robustness of traffic state perception under diverse conditions. Meanwhile, the adoption of edge-cloud collaborative architectures has effectively balanced the demands of real-time processing and efficient data transmission, thereby establishing a solid technical foundation for the large-scale deployment of intelligent transportation systems. Nevertheless, critical challenges remain in adapting to heterogeneous environments, responding to extreme scenarios, and achieving seamless fusion of multi-source data.

Looking ahead, through continuous model optimization, architectural refinement, and integration of complementary technologies, intelligent transportation systems are poised to evolve from a reactive "perception–decision-making" paradigm to a proactive "prediction–control–optimization" framework. As these technologies mature and implementation costs decline, their impact will expand across urban traffic management, environmental sustainability, and intelligent mobility services, offering essential support for building modern transportation systems that are efficient, safe, and environmentally sustainable.

References

[1] Villa J, García F, Jover R, Martínez V, Armingol J M. Intelligent infrastructure for traffic monitoring based on deep learning and edge computing. Journal of Advanced Transportation, 2024.

[2] Prashant D, Krishna C R, Upendra K S, Santos K D, Sudhan M. Multi-Class Vehicle Detection Using VDnet in Heterogeneous Traffic. IEEE Transactions on Intelligent Transportation Systems, 2024.

[3] Shahriar S, Md A J, Mridha M F. Interpretable Dynamic Graph Neural Networks for Small Occluded Object Detection and Tracking. 2024.

[4] Muhammad T U, Tanzila S, Hafiz U D, Amjad R, Muhammad U G, Hoshang K. Intelligent Traffic Signal Automation Based on Computer Vision Techniques Using Deep Learning. IT Professional, 2022.

[5] Liu G X, Shi H, Kiani A, Khreishah A, Lee J, Ansari N. Smart Traffic Monitoring System Using Computer Vision and Edge Computing. IEEE Transactions on Intelligent Transportation Systems, 2021.

[6] Frank N, Judith M, Saidi S. Solving Traffic Data Occlusion Problems in Computer Vision Algorithms Using DeepSORT and Quantum Computing. Journal of traffic and transportation engineering, 2023.

[7] Syed Muhammad S B, Taimoor A K, Muhammad Ahmad S, Umer M, Waseema B, Ibrahim L. NETWORK TRAFFIC PREDICTION: USING AI TO PREDICT AND MANAGE TRAFFIC IN HIGH-DEMAND IT NETWORKS. Policy Research Journal Volume 2, Issue 4, 2024.

[8] Melvin V M, Hans D T, Said A, Rhio S. The Influence of Computer Vision on Road Traffic. 2024 International Conference on Informatics, Multimedia, Cyber and Information System, 2024.

[9] Vladyslav Z, Galyna K, Ievgen S, Yuriy K. Computer Vision in Control and Optimization of Road Traffic. 2020 IEEE International Conference on Data Stream Mining & Processing, 2020.

[10] Gabriel F, David H, Vieroslav M, Tomáš B. Use of Mathematical Models and Computer Software for Analysis of Traffic Noise. Open Engineering, 2020.