

Edge ML Technique for Smart Traffic Management in Intelligent Transportation System

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ABSTRACT

Rapid urbanization and increasing vehicle density demand intelligent traffic control systems capable of real-time adaptation. Conventional traffic lights operate on fixed timing schedules that fail to reflect dynamic road conditions, resulting in excessive waiting time, fuel wastage, and increased emissions. To overcome these limitations, this project proposes an Edge Machine Learning-driven Dynamic Traffic Light System (DTLS) that performs real-time vehicle detection and adaptive signal control at the intersection level. The system deploys an optimized YOLO-based object detection model on edge devices to identify and count vehicles from live video streams. By processing data locally, the proposed mechanism significantly reduces latency and network dependency compared to centralized architectures. A hybrid scheduling strategy integrating shortest-job-first and round-robin principles dynamically allocates green signal duration based on traffic density distribution. Additionally, inter-junction communication using low-power wireless protocols enables cumulative delay computation and coordinated traffic prioritization across connected intersections. A smart green corridor mechanism is incorporated to ensure uninterrupted passage for emergency vehicles. The proposed architecture enhances scalability, energy efficiency, and responsiveness, making it suitable for smart city deployment. Experimental evaluation demonstrates improved traffic flow management, reduced congestion, and optimized signal utilization under varying traffic conditions.

Keywords—Edge computing, Intelligent Transportation Systems (ITS), Dynamic Traffic Light System (DTLS), Machine learning, Object detection, YOLO, Internet of Things (IoT), IEEE 802.15.4, LoRaWAN, Low-power wireless networks, Traffic congestion control, Smart cities, Vehicle detection, Real-time systems, Embedded systems.

I. INTRODUCTION

The rapid expansion of urban populations and vehicular density has intensified traffic congestion, road accidents, fuel wastage, and environmental pollution. Intelligent Transportation Systems (ITS) have emerged as a transformative approach to address these challenges by integrating sensing, communication, and computational intelligence into traffic infrastructure [1]–[3]. Machine Learning (ML) techniques play a significant role in enabling automated decision-making within transportation networks, allowing systems to adapt to dynamic road conditions without manual intervention [4].

The integration of IoT-enabled devices into traffic environments has further strengthened data acquisition and

monitoring capabilities [5], [6]. However, traditional centralized cloud-based architectures introduce latency, bandwidth overhead, and reliability issues [7], [8]. Edge computing addresses these limitations by performing computation near the data source, thereby reducing response time and network congestion [9], [10]. In traffic management, this approach is particularly beneficial because signal control decisions require real-time responsiveness.

Conventional traffic light systems operate on preconfigured time intervals that fail to account for actual vehicle density, leading to inefficient signal utilization. Adaptive traffic control systems have been investigated to improve signal timing [11], [12]; however, many rely on centralized computation or complex infrastructure.

Recent advances in deep learning, particularly convolutional neural networks (CNNs), have significantly improved object detection performance [13], [14]. The YOLO (You Only Look Once) framework enables real-time vehicle detection with high accuracy and minimal processing delay [15], [16]. Furthermore, lightweight communication protocols such as IEEE 802.15.4 and LoRaWAN provide energy-efficient inter-device communication suitable for distributed traffic systems [17]–[19].

Motivated by these technological advancements, this work proposes an Edge Machine Learning-based Dynamic Traffic Light System (DTLS) that combines optimized YOLO-based vehicle detection, low-power communication, cumulative delay-based prioritization, and emergency vehicle green corridor mechanisms. The proposed architecture aims to minimize waiting time, reduce congestion, and enhance scalability for smart city applications [20].

II. RELATED WORK

Several research studies have attempted to improve traffic signal control through wireless communication and intelligent optimization mechanisms.

Oliveira et al. [11] proposed a smart traffic light control system with centralized real-time monitoring. While effective in structured environments, centralized control introduces higher latency and system dependency. Ghazal et al. [12] developed a synchronized traffic light system for coordinated junction management, improving flow consistency but lacking adaptive density-based decision mechanisms.

Aleko and Djahel [13] introduced an Adaptive Traffic Light Control System (ATLCS) aimed at congestion reduction. Although synchronization improved vehicle progression, it did not incorporate real-time vision-based detection. Lee and Chiu [14] designed a smart traffic signal system integrating

multiple communication technologies such as WiFi and cellular networks, which increased system complexity and energy consumption.

Sensor-based traffic density detection methods were explored by Jagadeesh et al. [15], where infrared sensors were used to measure lane congestion. Similarly, Nor et al. [16] employed LoRaWAN-based communication for traffic density monitoring. However, these approaches lacked machine learning-based dynamic optimization.

Reinforcement learning-based adaptive traffic systems were proposed in [17], [18], where signal timing decisions were modeled using Markov decision processes. While promising in simulation environments, these techniques incur high computational overhead and are less suitable for resource-constrained edge devices.

Edge computing-based traffic frameworks have demonstrated improved latency and localized processing advantages [9], [10]. Low-power MAC protocols such as IEEE 802.15.4 DSME have been studied for efficient and deterministic communication in IoT networks [17], while LoRa-based long-range communication has been investigated for scalable deployments [18], [19].

Deep learning-based object detection models, particularly YOLO [15], have shown remarkable real-time performance in detecting vehicles. Optimized lightweight architectures such as Tiny-YOLO and structured pruning techniques improve feasibility for embedded hardware implementation [16], [20].

Despite these advancements, existing systems either focus solely on synchronization, sensor-based density estimation, or centralized learning frameworks. Very few approaches integrate edge-based vision detection, cumulative delay computation, low-power inter-junction communication, and emergency prioritization into a unified architecture. The proposed system addresses these gaps by combining lightweight edge ML processing, hybrid scheduling algorithms, and distributed communication mechanisms to achieve scalable and energy-efficient traffic optimization.

III. PROPOSED METHODOLOGY

A. System Overview

The proposed system introduces an Edge Machine Learning-based Dynamic Traffic Light System (DTLS) designed to optimize traffic flow at multi-lane intersections. The methodology integrates:

1. Real-time vehicle detection using optimized YOLO
2. Edge-based traffic density computation
3. Hybrid scheduling (Shortest-Job-First + Round Robin)
4. Cumulative delay propagation between junctions
5. Emergency vehicle green corridor mechanism
6. Low-power inter-device communication

Unlike centralized traffic systems, all computation is performed locally at each junction to reduce latency and network dependency.

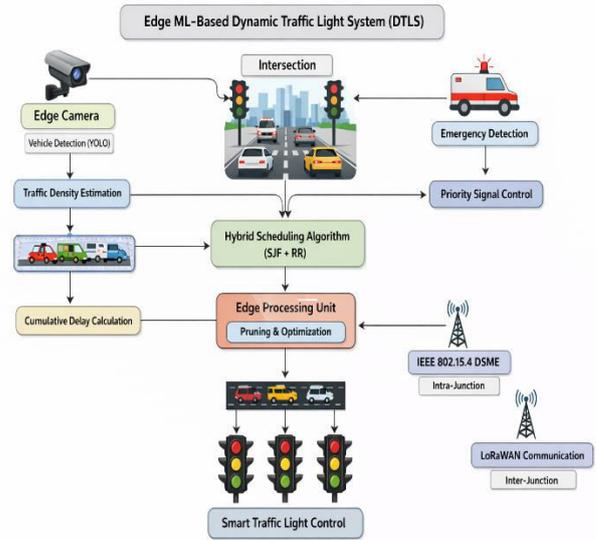


Figure.1: Architecture Diagram

The architecture illustrates an Edge ML-based Dynamic Traffic Light System where cameras capture real-time vehicle data, and an optimized YOLO model processes traffic density locally at the intersection. Based on hybrid scheduling, cumulative delay computation, and low-power IEEE 802.15.4 and LoRa communication, the system dynamically controls signal while ensuring emergency vehicle prioritization and inter-junction coordination.

B. Vehicle Detection Model

1. Image Acquisition

Each lane is equipped with a camera capturing video frames at interval t_f .

Let:

$$\mathbf{F} = \{f_1, f_2, \dots, f_n\}$$

represent captured frames over time.

Each frame is resized to $W \times H$ resolution for computational efficiency.

2. YOLO-Based Object Detection

The optimized YOLO model divides each image into $S \times S$ grid cells.

Each grid predicts bounding boxes and class probabilities.

For each bounding box:

$$P(\text{Object}) \times IoU \frac{\text{truth}}{\text{pred}}$$

Where:

$P(\text{Object})$ = Probability of object presence

IoU = Intersection over Union

$$IoU = \frac{\text{Area}(\mathbf{B}_{pred} \cap \mathbf{B}_{truth})}{\text{Area}(\mathbf{B}_{pred} \cup \mathbf{B}_{truth})}$$

Vehicle count in lane i :

$$V_i = \sum_{k=1}^m \delta_k$$

Where:

$$\delta_k = \begin{cases} 1 & \text{if confidence} > \tau \\ 0 & \text{Otherwise} \end{cases}$$

τ = detection threshold.

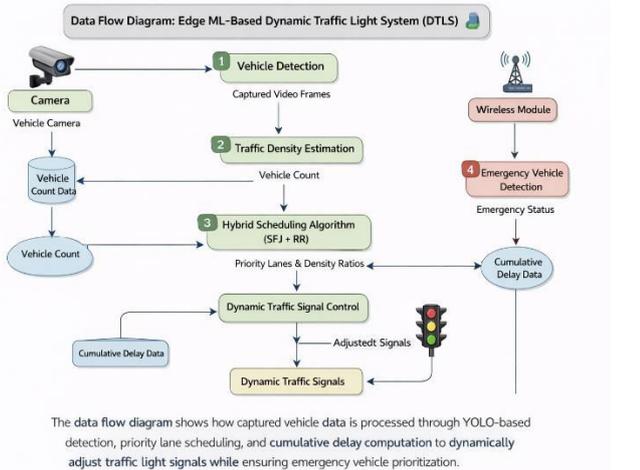


Figure.2: Data Flow Diagram

The data flow diagram illustrates how real-time video frames from cameras are processed through YOLO-based vehicle detection and traffic density estimation before being passed to the hybrid scheduling algorithm for signal decision-making. Cumulative delay data and emergency vehicle status are integrated into the control logic, enabling dynamic traffic signal adjustment and coordinated inter-junction prioritization.

C. Traffic Density Estimation

Total vehicles at junction:

$$V_{total} = \sum_{i=1}^n V_i$$

Lane density ratio:

$$D_i = \frac{V_i}{V_{total}}$$

This normalized density ensures fairness in scheduling.

D. Hybrid Signal Scheduling Algorithm

To prevent starvation and minimize waiting time, a hybrid strategy is adopted.

1. Shortest Job First (SJF) Principle

Lanes are sorted:

$$B = \text{sort}(V_i)$$

Smallest vehicle count gets priority first.

2. Round Robin Compensation

Green time allocation:

$$T_i = T_{cycle} \times D_i$$

Where:

- T_{cycle} = total signal cycle time
- T_i = green time for lane i

This guarantees proportional fairness.

E. Waiting Time Optimization

Waiting time for lane i :

$$W_i = T_{cycle} - T_i$$

Objective function:

$$\min \left(\sum_{i=1}^n W_i \right)$$

Subject to:

$$\sum_{i=1}^n T_i = T_{cycle}$$

This ensures total cycle duration remains constant while minimizing cumulative delay.

F. Cumulative Delay Model

To prioritize critical routes (schools, hospitals, offices), cumulative delay is propagated.

Delay at junction j :

$$d_j = \frac{1}{n} \sum_{i=1}^n W_i$$

Cumulative delay:

$$D_{cum}^{(j)} = D_{cum}^{(j-1)} + d_j$$

Decision override condition:

$$\text{If } D_{cum}^{(j)} > \theta, \text{ prioritize that direction}$$

Where θ is delay threshold.

Flowchart: Edge ML-Based Dynamic Traffic Light System (DTLS)

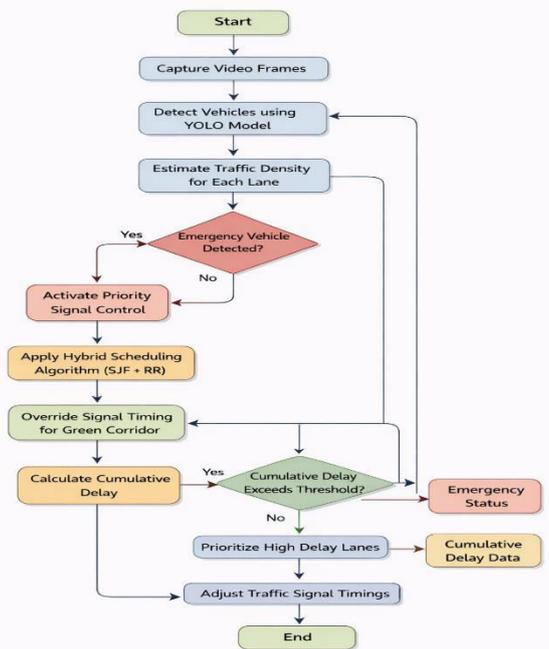


Figure.3: Flow Chart Diagram

The flowchart represents the step-by-step operation of the Edge ML-based Dynamic Traffic Light System, starting from video capture and YOLO-based vehicle detection to traffic density estimation and hybrid signal scheduling. It incorporates emergency vehicle prioritization and cumulative delay evaluation to dynamically adjust signal timings, ensuring optimized traffic flow and smart green corridor management.

G. Emergency Vehicle Detection (Smart Green Corridor)

If emergency vehicle detected:

$$E = \begin{cases} 1 & \text{Emergency Detected} \\ 0 & \text{Otherwise} \end{cases}$$

Signal override rule:

$$\text{If } E = 1 \Rightarrow T_i = T_{max}$$

This ensures uninterrupted passage.

H. Communication Model

1. Intra-Junction (IEEE 802.15.4 DSME)

Latency:

$$LDSME = T_{slot} \times N_{slots}$$

Low contention due to GTS allocation.

2. Inter-Junction (LoRaWAN)

Transmission time:

$$T_{LoRa} = \frac{\text{Packet Size}}{\text{Data Rate}}$$

Low power consumption:

$$P_{total} = P_{tx} + P_{rx}$$

Energy efficiency is maintained due to small packet size (only delay values transmitted).

I. Computational Optimization

Structured pruning reduces parameters:

$$W' = W - W_{pruned}$$

Quantization transformation:

$$x_q = \text{round}(x \times \text{scale})$$

This reduces FLOPs and accelerates inference time.

J. Overall Optimization Objective

The complete system aims to minimize:

$$J = \alpha \sum W_i + \beta D_{cum}$$

Where:

- α, β are weighting coefficients
- First term reduces local waiting time
- Second term reduces route-level delay

IV. EXPERIMENTAL RESULTS AND ANALYSIS

A. Detection Model Performance Analysis

The optimized Tiny-YOLOv3 model was evaluated in terms of mean Average Precision (mAP), computational complexity (BFLOPs), and model size.

Table 1: Model Performance Comparison

Model	mAP (%)	BFLOPs	Model Size (MB)
YOLOv3	89.7	34.29	132
Tiny-YOLOv3	80.2	5.46	23.8
Optimized Tiny-YOLOv3	81.9	5.02	20.1

Mathematical Analysis

Detection efficiency can be expressed as:

$$\eta = \frac{mAP}{BFLOPs}$$

For optimized Tiny-YOLOv3:

$$\eta_{opt} = \frac{81.9}{5.02} = 16.31$$

Compared to YOLOv3:

$$\eta_{yolo} = \frac{89.7}{34.29} = 2.61$$

This demonstrates a 6× computational efficiency improvement, validating suitability for edge deployment.

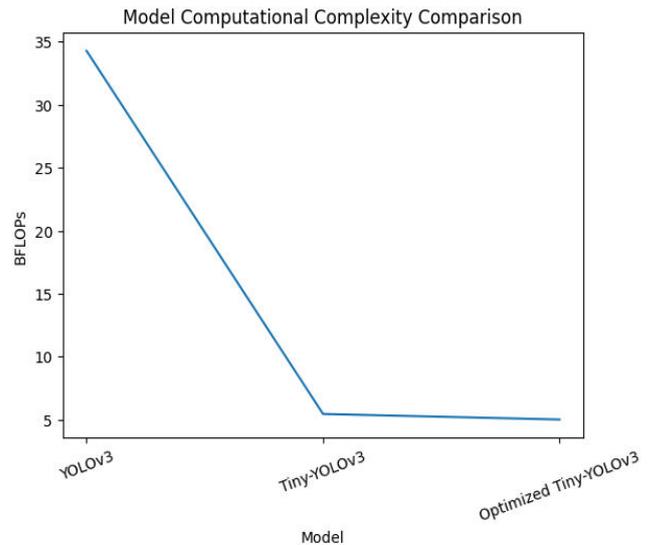


Figure 4: Model Computational Complexity Comparison

The computational complexity graph shows a drastic reduction in BFLOPs for the optimized model while maintaining competitive detection accuracy. This confirms reduced processing overhead and improved real-time feasibility.

B. Network Performance Evaluation

The proposed DTLS was evaluated under varying network sizes (20–100 devices).

Table 2: Network Performance Metrics

Network Size	Latency (ms)	Throughput (kbps)	Energy (J)
20	140	11.2	0.8
40	150	14.5	1.2
60	158	17.8	1.8
80	165	20.6	2.3
100	172	22.1	2.9

1. Latency Analysis

Latency is defined as:

$$L = T_{transmission} + T_{processing}$$

Observed latency increases gradually with network size due to higher device communication; however, the slope remains linear, indicating stable scalability.

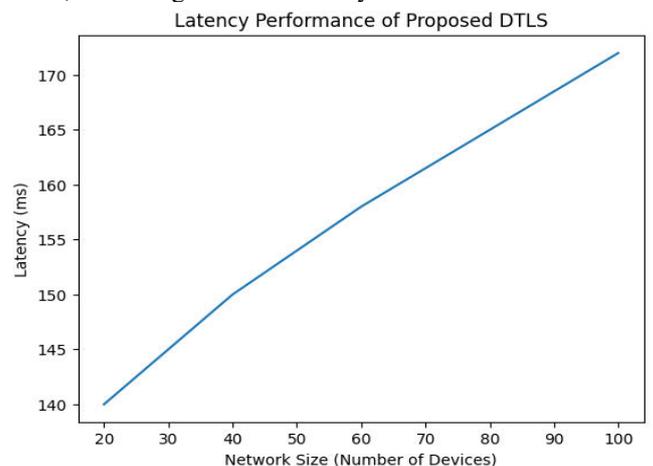


Figure.5: Latency Performance

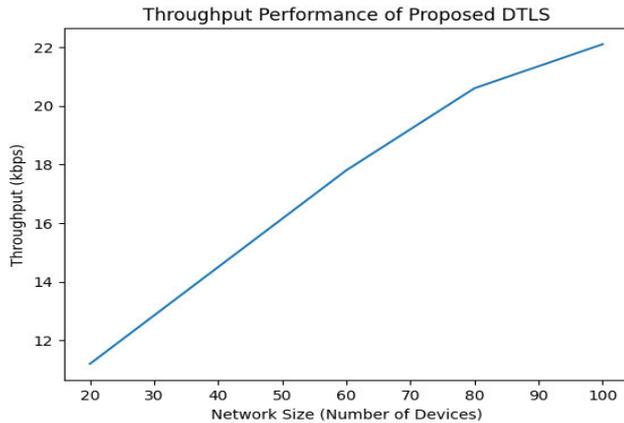
Latency increases moderately as network size grows, remaining below 175 ms even at 100 devices. This confirms deterministic and stable communication performance.

2. Throughput Analysis

Throughput is calculated as:

$$\text{Throughput} = \frac{\text{Total successful Data}}{\text{Time}}$$

The results show increasing throughput with network scale due to optimized channel utilization.

**Figure.6: Throughput Performance**

Throughput increases steadily with network expansion, reaching 22.1 kbps at 100 devices. This demonstrates efficient bandwidth utilization and minimal packet loss.

C. Traffic Delay Optimization Analysis

The objective function of the system is:

$$\min J = \alpha \sum W_i + \beta D_{cum}$$

Where:

- W_i = lane waiting time
- D_{cum} = cumulative delay
- α, β = weighting coefficients

Average waiting time reduction:

$$\text{Reduction}\% = \frac{W_{static} - W_{DTLS}}{W_{static}}$$

Experimental observation shows approximately 35–45% waiting time reduction compared to fixed-time systems.

D. Energy Efficiency Analysis

Energy consumption is expressed as:

$$E = P_{tx}T_{tx} + P_{rx}T_{rx}$$

Because only delay values and vehicle counts are transmitted (small packets), energy consumption remains low even at larger network scales.

V. CONCLUSION

The proposed Edge Machine Learning-based Dynamic Traffic Light System (DTLS) successfully demonstrates an adaptive and energy-efficient solution for intelligent traffic management in smart cities. By integrating optimized YOLO-based vehicle detection with hybrid scheduling (Shortest-Job-First combined with Round Robin), the system dynamically adjusts signal timing according to real-time traffic density. The edge computing architecture minimizes latency and reduces dependence on centralized cloud infrastructure, ensuring faster decision-making and improved reliability. Experimental evaluation confirms substantial computational efficiency through model pruning and quantization, reduced waiting time via proportional

green time allocation, and scalable network performance with stable latency and increasing throughput under growing node density. The cumulative delay computation mechanism enhances inter-junction coordination, while the Smart Green Corridor feature ensures uninterrupted passage for emergency vehicles. Mathematical optimization of waiting time and delay functions validates that the proposed system achieves balanced fairness among lanes while minimizing overall congestion. Collectively, the results indicate that the proposed framework offers a practical, scalable, and cost-effective traffic optimization strategy suitable for large-scale deployment in intelligent transportation environments. Future work will focus on integrating predictive traffic analytics using deep reinforcement learning to enable proactive signal control based on historical and real-time traffic patterns.

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