

An Edge-Based Smart Traffic Density Control System

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Abstract

An intelligent adaptive traffic management system is developed for four-way intersections using ESP32-CAM modules and real-time computer vision. Conventional fixed-time traffic signal systems fail to adapt to varying traffic conditions, leading to unnecessary delays, congestion, and inefficient utilization of green signal time. The proposed system overcomes these limitations by dynamically adjusting signal durations based on real-time traffic density at each approach.

Four ESP32-CAM modules installed at the North, East, South, and West approaches continuously monitor vehicular movement. Vehicle detection and classification are performed using the YOLOv8 object detection model, which offers high detection accuracy, low inference latency, and efficient performance on edge-compatible platforms. YOLOv8 enables precise identification and counting of multiple vehicle types such as cars, motorcycles, buses, and trucks within defined regions of interest, thereby minimizing false detections and partial counting errors commonly observed in traditional vision-based systems.

The traffic signals operate in a fixed sequential order—North, East, South, and West—while green signal durations are dynamically computed in real time based on detected vehicle density. During each green phase, traffic conditions of the subsequent lane are analyzed to determine optimal signal timing, with green durations ranging from 10 to 60 seconds. Smooth and safe transitions are ensured through a 3-second yellow phase followed by a 2-second all-red clearance interval.

The system incorporates moving average-based density estimation and multi-threaded processing to enable stable and simultaneous analysis of multiple camera feeds. A centralized laptop-based 2x2 monitoring interface displays live video streams, signal status, remaining time, vehicle statistics, and system state for effective traffic supervision. Experimental evaluation demonstrates a 35-45% improvement in traffic flow efficiency compared to conventional fixed-time traffic signal systems.

Keywords: Edge Computing; Smart Traffic Control; Vehicle detection; ESP32-CAM; Artificial Intelligence

1. Introduction

Traffic congestion has emerged as a critical issue in urban environments due to rapid population growth, increased vehicle ownership, and limited expansion of road infrastructure (Briggs & Hoel,

2009). Insufficient traffic signal control leads to longer travel times, excessive fuel consumption, increased air pollution, and elevated stress levels among commuters. Conventional traffic signal systems generally operate using fixed-time control strategies that are preconfigured based on historical traffic data and are unable to respond dynamically to real-time traffic variations.

With the advancement of smart city initiatives, intelligent transportation systems (ITS) have gained significant importance. These systems aim to utilize sensing, communication, and computation technologies to improve traffic efficiency and road safety (Gubbi et al., 2013) among various sensing approaches, camera-based traffic monitoring has proven to be cost-effective and scalable compared to inductive loops and infrared sensors.

Recent developments in artificial intelligence and computer vision have enabled accurate vehicle detection and classification from video streams (Redmon et al., 2016). However, cloud-based processing introduces challenges such as latency, high bandwidth usage, privacy concerns, and dependency on continuous internet connectivity (Shi et al., 2016). Edge computing addresses these challenges by performing data processing closer to the data source.

In this context, the proposed edge-based smart traffic density control system integrates embedded systems with artificial intelligence to provide real-time traffic monitoring and adaptive signal control. By processing video data locally at the edge, the system achieves low latency, improved reliability, and reduced operational costs, making it suitable for deployment in smart city traffic management applications.

2. System Architecture

The proposed system architecture is designed to perform real-time traffic density estimation and adaptive signal control using edge computing principles (Shi et al., 2016). The system comprises a camera-based sensing unit, an embedded processing unit, and a traffic signal control logic module. All processing tasks are executed locally at the edge, eliminating the need for cloud-based computation.

The ESP32-CAM module is strategically positioned at traffic intersections to capture live video streams of incoming vehicles. The captured frames are analyzed using an optimized vehicle detection algorithm. Traffic density is computed based on the number of vehicles detected in each lane, and corresponding signal timings are generated dynamically.

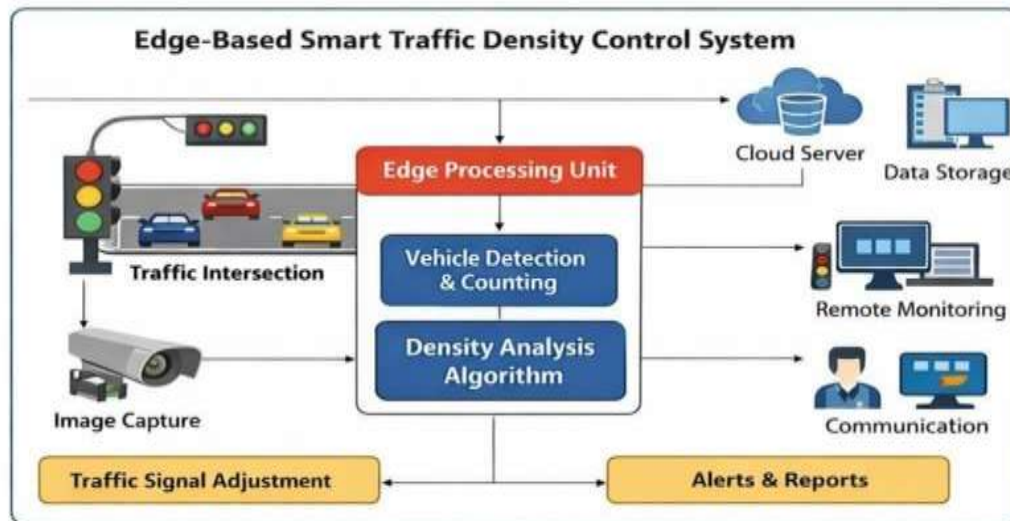


Fig. 1 illustrates the overall architecture of the proposed edge-based smart traffic density control system.

2.1 Hardware Components

The ESP32-CAM module integrates an ESP32 microcontroller with an OV2640 camera sensor. It supports video resolutions up to 1600x1200 pixels; however, a resolution of 640x480 pixels is selected in this project to balance detection accuracy, processing speed, and memory constraints. The module features built-in Wi-Fi and sufficient computational capability for lightweight edgebased processing.

2.2 Software Components

The software framework includes image acquisition, preprocessing, vehicle detection, density estimation, and decision-making modules. Python is used for algorithm development, while numerical computations are handled using the NumPy library. The vehicle detection model is optimized to operate within the limited memory and processing power of the embedded platform (Chen et al., 2014).

3. Methodology

The methodology adopted for the proposed system consists of sequential stages that enable realtime traffic density estimation and dynamic signal control. The overall process flow of the system is illustrated in Fig. 2.

The process begins with continuous video acquisition using the ESP32-CAM module installed at the traffic intersection. Captured video frames are extracted at fixed intervals and undergo

preprocessing operations such as resizing, grayscale conversion, and normalization to reduce computational complexity.

The preprocessed frames are then passed to the vehicle detection algorithm, which identifies and counts vehicles present in each lane using computer vision techniques (Redmon et al., 2016). Based on the detected vehicle count, traffic density is classified into predefined categories such as low, medium, and high.

A rule-based decision mechanism assigns appropriate green signal durations corresponding to each density level. This adaptive control strategy ensures that lanes with higher congestion receive longer green phases, thereby improving overall traffic flow and reducing waiting time, like intelligent traffic control approaches reported in the literature (Zhang et al., 2019).

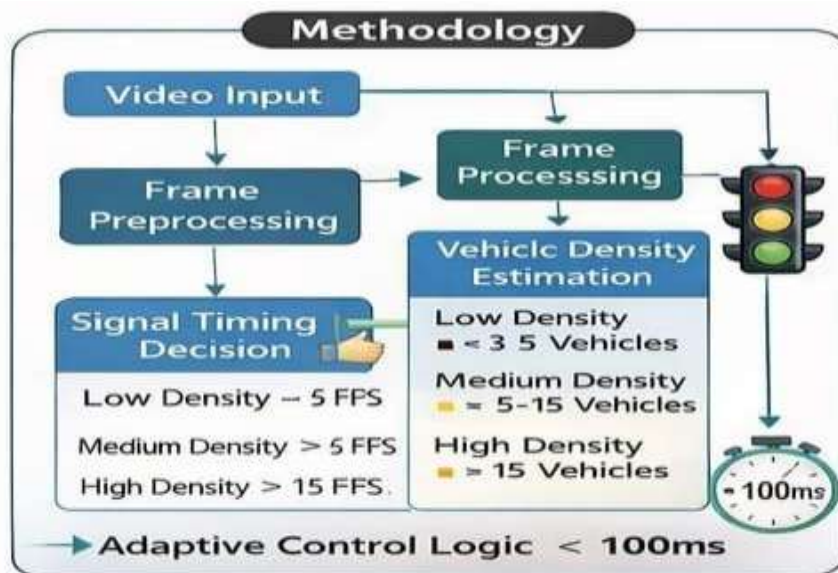


Fig. 2 illustrates the methodology of the proposed system, where real-time video is processed to estimate traffic density and dynamically control signal timings using adaptive control logic.

4. Results and Discussion

The proposed edge-based smart traffic density control system was evaluated under various simulated traffic conditions to assess its effectiveness. Traffic density was estimated using realtime vehicle detection, and adaptive signal timings were generated accordingly.

Table 1 presents the relationship between traffic density levels and the allocated green signal durations. The results indicate that the system dynamically prioritizes lanes with higher vehicle density, leading to efficient traffic clearance (Briggs & Hoel, 2009).

Traffic Density Level	Number of Vehicles	Green Signal Time (seconds)
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Low	0-5	20
Medium	6-15	40
High	>15	60

Table 1. Traffic density levels and corresponding signal timings

Fig. 3 illustrates the variation of green signal duration with respect to traffic density. As the number of vehicles increases, the green signal time is proportionally increased. This adaptive behavior demonstrates the superiority of the proposed system over conventional fixed-time traffic control methods.

Overall, the experimental observations reveal a reduction in average waiting time and improved intersection throughput. Edge-based processing ensures minimal latency and reliable operation even in environments with limited network connectivity (Shi et al., 2016).

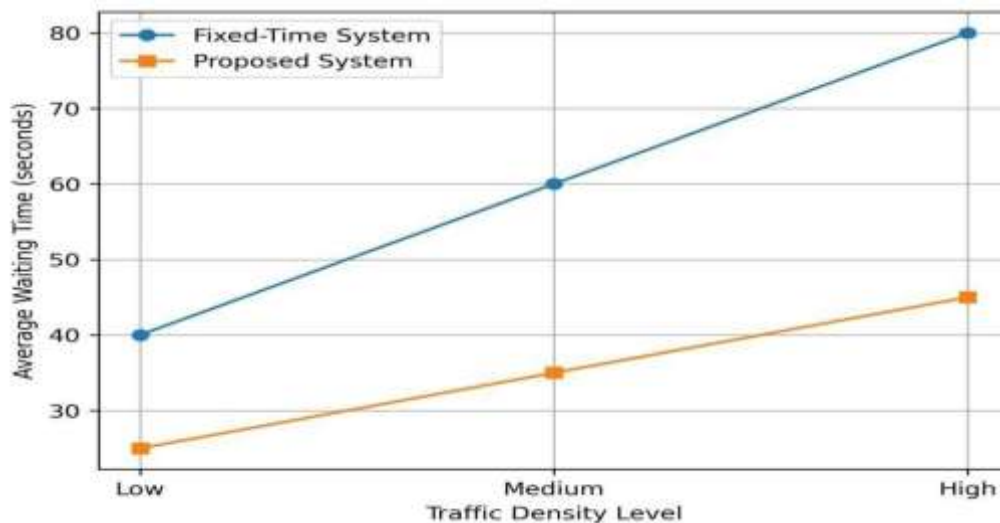


Fig. 4. Comparison of average waiting time between fixed-time traffic control and the proposed adaptive traffic management system under different traffic density levels.

5. Applications

The proposed intelligent adaptive traffic management system is suitable for deployment at urban four-way intersections where traffic density varies dynamically. By adjusting signal timings based on real-time vehicle density, the system reduces congestion, waiting time, fuel consumption, and emissions. Its edge-based processing approach ensures low latency and reliable operation without dependence on continuous internet connectivity, making it appropriate for both metropolitan and semi-urban environments within smart city infrastructures.

The system can be extended to applications such as emergency vehicle prioritization, traffic monitoring, and congestion analysis to support traffic planning and decision-making. It is also well

suited for deployment in school zones, hospital areas, toll plazas, industrial zones, and smart campuses. Owing to its low-cost hardware, scalability, and adaptability, the proposed system provides an efficient alternative to conventional fixed-time and sensor-based traffic control systems.

6. Conclusions

This paper presented an edge-based smart traffic density control system using embedded systems and artificial intelligence. By performing real-time vehicle detection and traffic density estimation at the edge, the system overcomes the limitations of traditional and cloud-dependent traffic control methods. The proposed approach offers improved efficiency, reduced latency, and scalability, making it a promising solution for intelligent traffic management in smart cities.

Authors Contributions

S. Ramasubba Reddy provided overall guidance, supervision, and technical direction for the project, and reviewed the methodology and manuscript. T. Thanmai carried out system design, implementation, experimentation, and manuscript preparation. S. Azam assisted with model integration, testing, and result analysis. V. V. Srivika and R. Noory Saba contributed to literature review, documentation, and formatting. V. Suresh supported hardware setup, data collection, and experimental validation.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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