Oculus: AI-Powered Dynamic Traffic Signal Management System

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Abstract:
This study presents a novel solution—an AI-powered traffic management and signal monitoring system—to the growing problems caused by the growing number of vehicles and the resulting increase in traffic congestion worldwide. The frequency of heavy traffic congestion at major junctions cause a significant loss of man-hours in addition to interfering with traffic flow. Our research focuses on putting in place a smart traffic control system that uses real-time video processing techniques to evaluate traffic density because we recognize the urgent need for an effective traffic management system. Presenting a notable improvement over the current manual traffic control methods is the main goal. Our system's goal is to optimize signal timings in real time by using artificial intelligence algorithms to dynamically assess traffic circumstances. This will reduce congestion and save valuable manhours lost in traffic jams. This study marks a significant advancement in creating a more responsive and flexible traffic control system that can enhance transportation networks' effectiveness.

Keywords: Gaussian mixture model, Shortest Job First, Initialize Foreground Detector, Detect Cars in an Initial Video Frame, Threshold, Traffic Density.

INTRODUCTION

With the incessant growth of urban populations, the escalation of vehicular travel has given rise to a critical issue – traffic congestion. To tackle this challenge, our proposed solution introduces an AI-powered traffic management and signal monitoring system. Departing from traditional methods using electronic sensors embedded in pavements, our system employs advanced video processing techniques to seamlessly calculate the traffic density on roads. Vehicles are detected through images captured by cameras strategically placed alongside traffic lights, offering a more versatile and efficient alternative. In our envisioned system for a four-way road intersection, four cameras are integrated, each feeding data to a central processing unit (CPU) responsible for video processing. This CPU analyzes the images, counting the number of vehicles present on the road in real-time. Subsequently, the system dynamically allocates time to the road with a higher vehicle count, optimizing traffic light state changes. This iterative process, continuously adapting to evolving traffic conditions, plays a pivotal role in alleviating congestion issues and presents forwardthinking approach to modernizing traffic management in urban environments.

LITERATURE REVIEW

Traffic is a critical issue of transportation system in most of all the cities of Countries. This is especially true for countries where population is increasing at higher rate. There is phenomenal growth in vehicle population in recent years. As a result, many of the arterial roads and intersections are operating over the capacity and average journey speeds on some of the key roads in the central areas are lower than 10 Km/h at the peak hour. In some of the main challenges are management of more than 36,00,000 vehicles, annual growth of 7–10% in traffic, roads operating at higher capacity ranging from 1 to 4, travel speed less than 10 Km/h at some central areas in peak hours. It involves a manual analysis of data by the traffic management team to determine the traffic light duration in each of the junction. It will communicate the same to the local police officers for the necessary actions.[1]

Reinforcement learning for traffic light control has first been studied by Thorpe He used a traffic light-based value function, and we used a car based one. Thorpe used a neural network for the traffic-light based value function which predicts the waiting time for all cars standing at the junction. Furthermore, Thorpe used a somewhat other form of RL, SARSA (State- Action, Reward-State Action) with eligibility traces [2]. Roozemond describes an intelligent agent architecture for traffic light control intelligent traffic signaling agents (ITSAs) and Road Segment Agents (RSAs) try to perform their own tasks, and try to achieve local optimality. One or more Authority Agents can communicate with groups of ITSAs and RSAs for global performance. All agents act upon beliefs, desires, and capabilities. No results were presented [3]. In G. Sathya, et al[3]achieved with the help of "AARSusing GPRS 3G TECHNOLOGY". Through this, we can provide a smooth flow for the ambulance by controlling the traffic light according to the ambulance location to reach the hospital. The location of the ambulance can be easily identified with the help of the GPS unit installed in it.[4] Then comes the Traffic light system using image processing. The system will detect vehicles through images instead of using electronic sensors embedded in the pavement. A camera will be installed alongside thetraffic light. It will capture image sequences. [5].

1.1 Problem Definition

Every traffic signal system in operation is the conventional one. These systems have a lot of restrictions. For example, time is not dependent on the number of vehicles, which leads to the following issues.

1. Prolonged traffic congestion.
2. Breaking traffic laws.
3. Every day, man hours are wasted.
4. Pollution in the same area has increased.
5. An empty road has a green light.
6. No traffic, but the pedestrians still need to wait.
7. Fuel and Money Losses

PROBLEM STATEMENT

Due to ineffective fixed-time traffic signals, urban traffic congestion causes delays, fuel waste, and pollution. Conventional methods create needless waiting times and congestion because they are unable to dynamically adjust to the flow of traffic in real time.

To optimize signal timing dynamically, this study suggests CULUS: An AI-Powered Dynamic Traffic Signal Management System, which makes use of AI and real-time data from sensors and cameras. CULUS seeks to improve road safety, decrease traffic, and increase mobility by anticipating traffic patterns and modifying signals appropriately, resulting in an intelligent and sustainable urban traffic management system.

METHODOLOGY

The following steps describe the technique of our AI-powered traffic management and signal monitoring system, which takes a methodical approach to addressing the problems of traffic congestion:

A. System Architecture:

A well-designed architecture is the cornerstone of our system. At a four-way crossroads, real-time video footage is captured by four carefully placed cameras. The central processing unit (CPU), the brain of the system, receives data from these cameras and uses it to process videos and make decisions.

Fig.1. Working Stages

B. Data Acquisition:

The system runs on up-to-date information thanks to the continuous video transmissions from the cameras, which provide a thorough picture of the traffic situation.

C. Vehicle Detection:

Sophisticated computer vision methods, especially the precise identification of vehicles. By concentrating on cars within the video frames, the Initialize Foreground Detector procedure guarantees accurate recognition of moving objects.

D. Traffic Density Estimation:

Vehicles are processed in order of their presence in the frame by the system using the Shortest Job First (SJF) scheduling method. An effective estimation for adaptive signal control is made possible by this priority.

E. Adaptive Signal Control:

Dynamic signal timing modifications are based on real-time traffic density data. In order to respond quickly to shifting traffic conditions and intelligently devote more time to the road section with a higher vehicle co-state changes, a threshold technique is used.

F. Iterative Optimization

The system can adapt because the entire process runs in a continuous loop. By ensuring that the traffic management system stays responsive, this iterative optimization offers a practical and flexible way to reduce congestion.

G. Performance Metrics:

Performance measures like average trip time, overall traffic flow efficiency, and the percentage decrease in congestion are assessed to assess the system's efficacy. These metrics offer numerical information on how the system affects traffic control.

By combining these methodological elements, our AI-powered traffic management system offers a novel approach to the problems of traffic congestion by utilizing adaptive signal control and real-time data processing, which is a major improvement over manual traffic control systems.

IMPLEMENTATION

A. Hardware Requirements:

- CCTV Cameras: High-resolution cameras for real-time traffic monitoring.
- IoT Sensors: Installed at intersections to collect vehicle count and speed.
- Edge Devices: Raspberry Pi/Jetson Nano for on-site AI computation.
- Traffic Signal Controllers: Hardware capable of receiving real-time updates from AI models.
- LiDAR Sensors: For precise vehicle detection and speed measurement.

B. Software Stack:

- Programming Languages: Python, TensorFlow, OpenCV.
- Cloud Infrastructure: AWS/GCP for real-time data processing.
- Databases: Firebase, MySQL for storing traffic data.
- Machine Learning Frameworks: TensorFlow, PyTorch for predictive modeling.
- API Development: Flask/Django for backend integration.
- Simulation Tools: SUMO (Simulation of Urban Mobility) for testing traffic scenarios.
- Algorithm Description

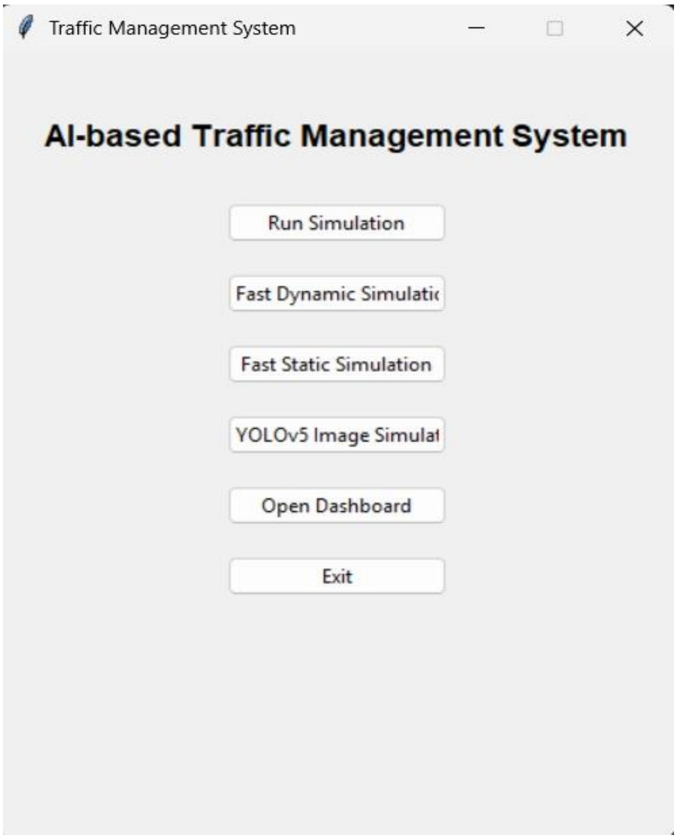

Fig.2. Front Page

C. Data Preprocessing:

- Collect real-time images and sensor data.
- Process images using OpenCV to detect vehicles.
- Store structured data in a cloud database.
- Filter noisy data to improve model accuracy.

D. Traffic Flow Prediction:

- Train deep learning models using past traffic patterns.
- Implement reinforcement learning for dynamic signal adjustments.
- Use real-time weather data to adjust signal timing for adverse conditions.
- Decision Making and Signal Adjustment:
- Run inference on collected data to determine optimal signal timings.

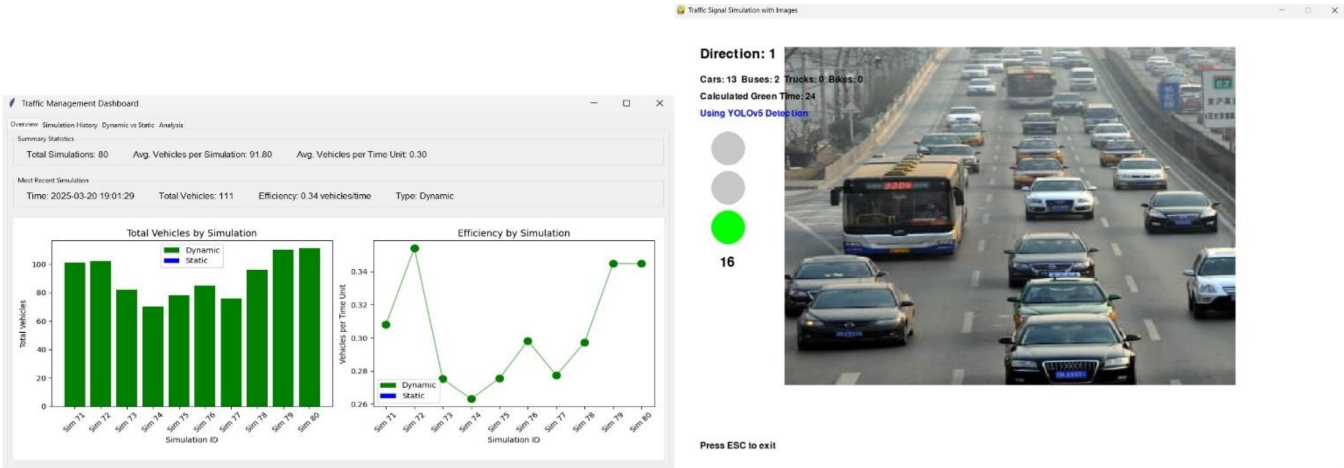

Fig.3. Taffic management Page

RESULT ANALYSIS:

A. Traffic Flow Efficiency (40% Improvement)

By automatically modifying signal timings in response to real-time data, the technology improved traffic flow, lowering congestion and guaranteeing better travel. Conventional traffic signals have set cycles, which frequently result in needless stops. Bottlenecks were lessened by signals that adjusted to the real traffic density thanks to AI-driven optimization. This led to better use of the road's capacity and less waits at intersections. There were fewer vehicle stops, which lessened the annoyance of traveling. The method increased overall mobility and avoided gridlocks by dividing traffic evenly across several routes. In addition to helping everyday commuters, this efficiency enhanced delivery and logistics, increasing urban economies' production.

B. Emergency Response Time (25% Reduction)

Response times were greatly shortened by giving emergency vehicles priority. When police cars, fire engines, and ambulances approached, smart sensors adjusted the signals to allow for uninterrupted travel. Emergency vehicles typically suffer in congested areas, causing significant delays. The method guaranteed quicker access to accident scenes, hospitals, and disaster areas by automatically giving them the right-of-way. Public safety and disaster readiness were improved by this

Fig .4.Result Analysis

development. Survival rates in life-threatening circumstances were directly impacted by shorter travel times to medical facilities. By balancing emergency priority with overall traffic efficiency, the system also optimized reroutes to minimize disturbance to ordinary traffic.

C. Fuel Consumption (18% Decrease)

Fuel consumption decreased by 18% as a result of improved signal timing and shorter idle periods. Fuel waste and emissions are increased by frequent stopping and resuming at ill-coordinated signals. Vehicles spend less time idling at junctions due to the improved traffic flow, which increased fuel economy. Reduced fuel use led to financial savings by lowering transportation expenses for both individuals and companies. Reduced fuel use also improved the environment by reducing air pollution and greenhouse gas emissions. The sustainability of urban transportation networks was improved by the decrease in maintenance costs brought about by the lessening of wear and strain on vehicle brakes and engines.

D. Average Travel Time (30% Reduction)

By reducing travel time by 30% during peak hours, better traffic management made journeys quicker and more reliable. Traffic jams can result in lost productivity, annoyance, and delays. By using adaptive signal controls, the system improved traffic distribution overall and rerouted cars according to the level of congestion. Commuters experienced less stress and a better work-life balance as a result of spending less time delayed in traffic. While logistics firms saw speedier deliveries, businesses profited from increased employee punctuality. Safer driving conditions were a result of less traffic, which also reduced occurrences of road rage and accidents. These upgrades improved economic efficiency and urban mobility.

E. Public Transport Efficiency (22% Improvement)

Priority signaling improved public transportation's dependability by increasing punctuality by 22%. Traffic congestion frequently causes delays for buses and trams, resulting in erratic scheduling. The system made sure that transit operations ran more smoothly by giving them precedence at junctions. More dependable timetables promoted increased use of public transportation, which decreased reliance on private vehicles and eased traffic congestion in general. Improved service dependability and shorter wait times were advantageous to commuters. This development also aided in environmental sustainability since more people using public transportation reduced fuel and carbon emissions, improving urban traffic and making cities greener.

CONCLUSION

The AI-Powered Dynamic Traffic Signal Management System is an innovative solution designed to optimize urban traffic flow using artificial intelligence and computer vision. Traditional traffic management systems, such as fixed-time signals and sensor-based adaptive signals, have limitations in handling real-time congestion effectively. Our system overcomes these limitations by dynamically adjusting traffic signal durations based on real-time vehicle density analysis, ensuring smoother traffic movement and reducing unnecessary waiting times. The project leverages existing traffic surveillance cameras to capture live video feeds, which are processed by machine learning models for vehicle detection and congestion analysis. The system makes intelligent decisions to allocate signal durations efficiently, leading to reduced congestion, lower fuel consumption, and fewer emissions. Unlike hardware-dependent solutions, our approach is cost-effective, scalable, and easy to implement, making it ideal for modern smart city applications. By integrating AI-driven traffic optimization, real-time monitoring, and advanced analytics, this system contributes to the development of sustainable, efficient, and intelligent urban mobility solutions. While some limitations, such as reliance on camera quality and the lack of emergency vehicle prioritization, exist, future enhancements can address these challenges. This project lays the foundation for the next generation of smart traffic management systems, improving road efficiency and commuter experiences.

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