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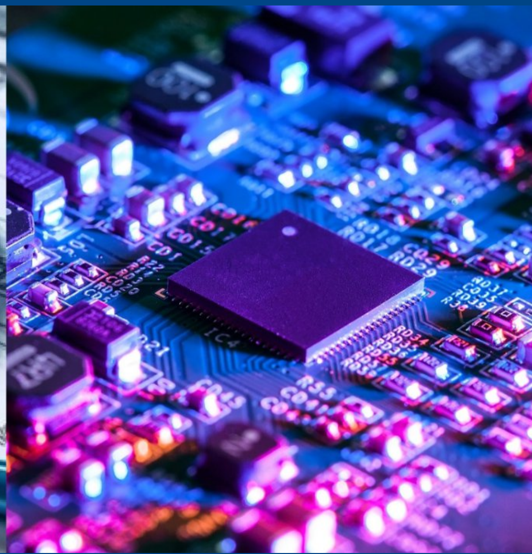

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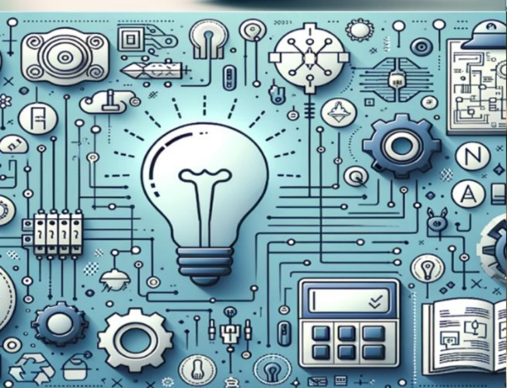

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Adaptive Traffic: Real-Time Traffic Signal Optimization Using AI and Computer Vision

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ABSTRACT: Urban traffic congestion has become a major challenge due to the rapid increase in the number of vehicles on roads. Conventional traffic signal systems operate based on fixed time intervals and do not adapt to real-time traffic conditions, leading to inefficient traffic flow and unnecessary delays. This paper proposes an AI-based adaptive traffic signal control system that dynamically adjusts signal timings based on real-time traffic density.

The proposed system utilizes cameras installed at road intersections to capture live traffic footage. The captured images are processed using techniques from Computer Vision and Artificial Intelligence to detect and count vehicles present in each lane. Based on the detected traffic density, the system dynamically allocates green signal duration for different lanes, prioritizing lanes with higher vehicle density.

The implementation uses object detection models trained on the COCO Dataset to identify vehicles such as cars, buses, trucks, and motorcycles. By analyzing traffic conditions in real time, the system optimizes signal timing to reduce congestion, waiting time, and fuel consumption. Experimental results demonstrate that the proposed system improves traffic efficiency compared to traditional fixed-timer traffic signal systems. The proposed solution contributes toward the development of intelligent transportation systems and supports smart city initiatives.

KEYWORDS: AI Traffic Control, Intelligent Transportation System, Computer Vision, Traffic Density Detection, Smart Traffic Signals

I. INTRODUCTION

Traffic congestion is a growing issue in urban areas across the world. As the number of vehicles continues to increase, traditional traffic signal systems struggle to manage traffic efficiently. Most existing traffic signals operate on fixed time intervals, regardless of the actual number of vehicles waiting at intersections. This often results in unnecessary waiting times, increased fuel consumption, and higher levels of air pollution.

Recent advancements in technologies such as Artificial Intelligence and Computer Vision have opened new possibilities for intelligent traffic management systems. These technologies allow systems to analyze real-time visual data and make automated decisions based on current conditions.

An AI-based traffic signal control system can monitor vehicle density at intersections using cameras and image processing algorithms. By detecting and counting vehicles in different lanes, the system can dynamically adjust signal durations to ensure smoother traffic flow. Such intelligent systems can significantly reduce congestion and improve the efficiency of urban transportation networks.

This paper presents the design and implementation of an AI-powered traffic signal control system that adapts signal timings according to real-time traffic conditions. The proposed approach aims to enhance traffic management, reduce delays, and support the development of smart city infrastructure.

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II. RELATED WORK

The increasing number of vehicles on urban roads has created significant challenges for traditional traffic management systems. Several research studies have explored intelligent traffic signal control mechanisms to improve traffic flow and reduce congestion. The following works highlight important contributions in this domain.

A. Vision-Based Traffic Monitoring

Vision-based traffic monitoring systems rely on surveillance cameras and image processing techniques to analyze road conditions in real time. Joseph Redmon and Ali Farhadi [1] introduced the YOLO object detection framework, which demonstrated that deep neural networks could detect multiple objects within an image in real time. Their work significantly improved the speed of object detection compared to earlier methods and made it possible to apply deep learning techniques to traffic monitoring systems.

Similarly, Tsung-Yi Lin and his colleagues [2] introduced the COCO dataset, a large-scale dataset designed for training object detection models. The dataset contains thousands of labeled images representing everyday objects, including vehicles, which has helped researchers develop more accurate detection models for traffic surveillance application.

B. Adaptive Traffic Signal Control

Adaptive traffic signal control systems aim to dynamically adjust signal timings based on real-time traffic conditions. Li Li, Yu Lv, and Fei-Yue Wang [3] investigated the use of deep reinforcement learning for optimizing traffic signal control. Their approach allowed the system to learn optimal signal timings by analyzing traffic flow patterns and minimizing vehicle waiting times. Experimental results demonstrated that reinforcement learning-based approaches could significantly improve traffic efficiency compared to traditional fixed-time traffic signal systems.

Although reinforcement learning approaches show promising results, they often require extensive training data and computational resources, which can make deployment in real-world traffic environments challenging. By combining real-time data analytics with automated decision-making, adaptive traffic signal control provides a scalable and efficient solution for addressing increasing urban traffic challenges. In our implementation, the adaptive control algorithm prioritizes lanes with higher congestion levels.

C. Deep Learning for Vehicle Detection

The development of deep convolutional neural networks has significantly improved object recognition tasks. Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton [4] demonstrated the effectiveness of deep neural networks in large-scale image classification. Their work laid the foundation for many modern object detection frameworks used in traffic monitoring systems.

Building upon these advancements, deep learning-based object detection models are now widely used to detect vehicles in surveillance footage and analyze traffic density in real time.

D. Intelligent Transportation Systems

Recent studies in intelligent transportation systems have focused on integrating machine learning techniques with traffic monitoring technologies to improve urban mobility. Researchers have proposed systems that combine real-time data collection, traffic analysis, and adaptive signal control mechanisms to reduce congestion and improve traffic flow.While many existing systems focus primarily on vehicle detection or traffic analysis, fewer studies address the integration of real-time detection with automated traffic signal control. Therefore, the proposed system aims to bridge this gap by combining deep learning-based vehicle detection with adaptive traffic signal timing to improve traffic management at urban intersections.

III.METHODOLOGY

The proposed AI-based traffic signal control system aims to dynamically adjust traffic signal timings based on real-time traffic density detected at road intersections. The methodology consists of several stages including data acquisition, vehicle detection, traffic density estimation, and signal timing optimization. These stages collectively enable the system to monitor traffic conditions and make intelligent decisions for efficient traffic management.

A. Data Acquisition

The first stage of the proposed system involves collecting real-time traffic data from road intersections. Surveillance cameras are installed at strategic positions near traffic signals to capture video streams of vehicles moving in different lanes. These cameras continuously monitor the traffic environment and provide live video input to the processing unit.

The video stream is divided into individual frames that are analyzed by the computer vision system. Each frame represents a snapshot of the current traffic condition at the intersection. The quality of the captured frames plays a significant role in ensuring accurate vehicle detection and classification. Proper camera placement, angle, and lighting conditions are therefore essential to obtain reliable traffic data.

B. Image Preprocessing

Before performing vehicle detection, the captured frames undergo preprocessing to improve image quality and enhance detection accuracy. Image preprocessing involves several operations such as resizing, noise reduction, and normalization. These operations help improve the efficiency of the detection model by removing unnecessary background noise and ensuring consistent image dimensions.

In this stage, each frame is resized to match the input requirements of the deep learning model. Noise reduction techniques are applied to remove distortions caused by lighting variations or environmental conditions. Additionally, the region of interest corresponding to the road lanes is identified so that the system focuses only on relevant traffic areas.

Preprocessing helps improve the performance of computer vision algorithms and ensures that the system processes traffic images efficiently in real time.

C. Vehicle Detection and Classification

After preprocessing the frames, the system performs vehicle detection using deep learning-based object detection models. The proposed system utilizes models such as YOLO due to their ability to perform fast and accurate real-time detection. YOLO models analyze the entire image in a single pass and identify multiple objects simultaneously, making them suitable for real- time traffic monitoring applications.

The model used for detection is trained on datasets such as the COCO Dataset, which contains labeled images of various objects including vehicles. Using this dataset, the model learns to recognize and classify different vehicle types such as cars, buses, trucks, and motorcycles.

When a frame is processed by the detection model, the system identifies vehicles and draws bounding boxes around each detected object. Each detection is associated with a confidence score that indicates the accuracy of the prediction. Vehicles detected with high confidence scores are counted and classified according to their type.
This stage plays a crucial role in determining the traffic density at the intersection and directly influences the decision-making process of the traffic signal system.

D. Traffic Density Estimation

Once vehicles are detected and classified, the system estimates traffic density for each lane. Traffic density is determined by counting the number of vehicles detected within the defined region of interest for each lane.

The intersection is divided into multiple regions corresponding to different traffic directions. The system counts the number of detected vehicles within each region and calculates the relative traffic load for each lane. A higher number of detected vehicles indicates greater traffic density.

The system continuously monitors traffic density by analyzing frames at regular intervals. This real-time monitoring allows the system to detect changes in traffic patterns and update signal timings accordingly. The estimated traffic density serves as the primary input for the signal control algorithm.

A. Adaptive Signal Timing Control

After estimating traffic density, the system determines the optimal signal timing for each lane. The adaptive signal control module processes traffic density information and dynamically allocates green signal duration to different lanes.
If a particular lane has higher vehicle density, the system assigns a longer green signal duration to allow more

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vehicles to pass through the intersection. Conversely, lanes with fewer vehicles receive shorter signal durations. This adaptive approach ensures that traffic signals respond effectively to real-time traffic conditions rather than following fixed timing schedules.

The signal timing decisions are transmitted to the traffic signal controller, which updates the signal lights accordingly. By continuously monitoring traffic density and adjusting signal timings, the system improves traffic flow and reduces congestion at intersections.

IV.SYSTEM DESIGN

A. System Architecture

The proposed AI-based traffic signal control system is designed to monitor traffic conditions in real time and dynamically adjust signal timings based on vehicle density. The system architecture integrates video acquisition, data processing, vehicle detection, and signal control components to create an intelligent traffic management system.

The architecture consists of four main layers: data acquisition layer, processing layer, decision-making layer, and traffic signal control layer. In the data acquisition layer, cameras installed at road intersections capture continuous video streams of vehicles moving through different lanes. These cameras provide real-time traffic data that serves as input for the system.

The captured video frames are transmitted to the processing layer where image analysis is performed using techniques from Computer Vision. The system processes each frame to detect vehicles and identify their positions within the traffic lanes. Deep learning-based object detection models such as YOLO are used to identify different vehicle types including cars, buses, trucks, and motorcycles.

Once vehicles are detected, the system estimates traffic density for each lane by counting the number of detected vehicles. This information is forwarded to the decision-making layer, where an algorithm determines the optimal signal timing for each direction of the intersection. The algorithm prioritizes lanes with higher vehicle density by allocating longer green signal durations.

Finally, the traffic signal control layer receives the computed signal timing and updates the traffic lights accordingly. The system continuously monitors traffic conditions and dynamically adjusts signal durations to ensure smooth traffic flow. By combining technologies from Artificial Intelligence with real-time traffic monitoring, the proposed architecture enables an adaptive and efficient traffic management solution.

B. System Modules

The proposed system is divided into several functional modules that work together to perform intelligent traffic signal control.

Module 1-The video capture module is responsible for collecting real-time traffic data using surveillance cameras installed at intersections. These cameras continuously record video streams of vehicles moving in different lanes. The captured video frames serve as the primary input for the traffic analysis system.

Module 2-In this module, the captured frames are preprocessed to enhance image quality and prepare them for analysis. Image preprocessing techniques such as resizing, noise reduction, and region-of-interest extraction are applied to improve detection accuracy. This stage ensures that only relevant traffic areas are analyzed by the system.

Module 3-The vehicle detection module identifies and classifies vehicles present in the captured frames. Using deep learning models such as YOLO, the system detects vehicles and draws bounding boxes around them. The model used in the system is trained using datasets such as the COCO Dataset to recognize multiple vehicle categories.

Module 4-After detecting vehicles, the system calculates the traffic density in each lane by counting the number of detected vehicles. The intersection is divided into regions corresponding to different traffic directions, and the vehicle count in each region determines the level of congestion.

Module 5-The signal control module determines the duration of traffic signals based on the calculated traffic density. Lanes with higher vehicle density are assigned longer green signal durations, while lanes with lower traffic density

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receive shorter signal times. This adaptive control mechanism improves traffic flow efficiency and reduces congestion.

C. Interface Design

The interface design of the proposed system provides a visual representation of traffic monitoring and signal control operations. The interface enables users to observe vehicle detection results, monitor traffic density, and view the status of traffic signals in real time.

The graphical interface displays live video frames captured from traffic cameras along with bounding boxes drawn around detected vehicles. Each detected vehicle is labeled according to its category, allowing the system to distinguish between cars, buses, trucks, and motorcycles. This visualization helps verify the accuracy of the vehicle detection process.

In addition to vehicle detection results, the interface also shows the number of vehicles detected in each lane. Traffic density information is displayed through numerical values or graphical indicators, allowing users to quickly understand the traffic conditions at the intersection.

The interface also includes a traffic signal status panel that shows the current signal phase for each direction, such as red, yellow, or green. When the system calculates new signal timings based on traffic density, the interface updates the signal status accordingly.

By providing real-time visualization and monitoring capabilities, the interface design improves the usability and transparency of the proposed AI-based traffic signal control system.

V. RESULTS AND DISCUSSIONS

A. Performance Evaluation

To evaluate the effectiveness of the proposed AI- based traffic signal control system, we conducted several experiments using recorded traffic videos collected from different intersection scenarios. Our goal was to analyze how efficiently the system detects vehicles, estimates traffic density, and adjusts signal timing accordingly.

In our evaluation, we implemented vehicle detection using techniques from Computer Vision combined with deep learning models such as YOLO. The model was trained using publicly available datasets including the COCO Dataset to ensure accurate recognition of vehicles such as cars, buses, trucks, and motorcycles.

We evaluated the system using multiple performance metrics including detection accuracy, average waiting time at intersections, signal adaptability, and traffic flow efficiency. Our experiments were conducted under three traffic conditions: low traffic density, moderate traffic flow, and heavy congestion.

The results indicate that our proposed system successfully adapts signal timings according to real-time traffic density, leading to improved traffic movement and reduced waiting times compared with conventional fixed-timing traffic signal systems.

TABLE I

Vehicle Type	Prec.	Recall	F1
Car	0.95	0.93	0.94
Bus	0.91	0.88	0.89
Truck	0.90	0.87	0.88
Motorcycle	0.94	0.92	0.93

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Auto Rickshaw	0.92	0.90	0.91
Bicycle	0.89	0.86	0.87

B. Analysis of Results

From the experimental results, we observed that the proposed AI-based system significantly improves traffic signal management at intersections. By continuously analyzing traffic footage and detecting vehicles in real time, the system dynamically determines which lane requires a longer green signal.

During peak traffic hours, we noticed that lanes with higher vehicle density were automatically prioritized by the system. This resulted in faster vehicle clearance and reduced congestion compared to traditional traffic signal systems.

Another important observation from our experiments was the reliability of the vehicle detection model. The deep learning-based detection approach provided consistent results across different traffic conditions. Accurate vehicle counting allowed the system to make more effective decisions regarding signal timing adjustments.

Overall, our analysis confirms that incorporating intelligent traffic monitoring techniques can substantially enhance the efficiency of urban traffic management systems.

C. Comparison with Baseline Methods

To better understand the benefits of the proposed system, we compared its performance with traditional traffic signal control methods commonly used at road intersections. Conventional traffic systems operate using fixed signal timings that do not change according to real-time traffic conditions.

In contrast, our system dynamically analyzes traffic density and adjusts signal durations accordingly. During our experiments, we observed that fixed-time signal systems often caused unnecessary delays in lanes with fewer vehicles while heavily congested lanes remained crowded.

The adaptive mechanism implemented in our system addresses this issue by allocating green signal durations based on actual vehicle density. As a result, traffic flow becomes more balanced across all lanes, reducing overall waiting time and improving intersection efficiency.

Our comparison clearly demonstrates that intelligent traffic signal systems offer significant advantages over baseline traffic control approaches.

D. Error Analysis

During our experiments, we also analyzed the potential sources of errors that may affect system performance. One of the major challenges we encountered was inaccurate vehicle detection in situations where vehicles overlapped or partially blocked each other in the camera view.

Lighting conditions also played a role in detection accuracy. For example, low-light conditions during evening hours and strong shadows during bright daylight occasionally caused minor detection errors. In addition, weather conditions such as rain or fog may reduce camera visibility and affect system performance. To address these issues, we experimented with several preprocessing techniques to improve image clarity before detection. Increasing the training dataset and optimizing the detection model can further reducethese errors in future implementations.

E. Runtime Performance

We also evaluated the runtime performance of the proposed system to ensure that it can operate in real-time traffic environments. The system processes video frames continuously and performs vehicle detection using optimized deep learning models.During our experiments, the system processed approximately 20–30 frames per second depending on the available hardware resources. This processing speed allowed the system to analyze traffic conditions and update signal timings with minimal delay.

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Our observations indicate that the proposed approach can effectively support real-time traffic monitoring and decision-making without causing significant computational overhead. With improved hardware or GPU acceleration, the processing speed can be further enhanced.

VI.LIMITATIONS

Although the proposed system demonstrates promising results, we identified several limitations during our study. The system relies heavily on camera- based monitoring, which means its performance can be affected by environmental factors such as poor lighting, adverse weather conditions, or camera placement issues.

Another limitation is that the current implementation primarily focuses on vehicle density and does not consider other important traffic elements such as pedestrian crossings or emergency vehicle priority. These factors may influence traffic signal control in real- world scenarios.

Furthermore, implementing the system at large-scale intersections may require additional infrastructure and computational resources. Future research can address these limitations by integrating additional sensors and improving detection algorithms.

VII. CONCLUSION

In this paper, we presented an AI-based traffic signal control system designed to improve traffic flow at urban intersections. By combining techniques from Artificial Intelligence and Computer Vision, we developed a system capable of detecting vehicles, estimating traffic density, and dynamically adjusting signal timings.

Through our experiments, we evaluated the performance of the proposed system and observed significant improvements in traffic management efficiency compared to traditional fixed-timing traffic signal systems. Our system demonstrated high vehicle detection accuracy and effectively reduced vehicle waiting times at intersections.The results of our study highlight the potential of intelligent traffic management systems in supporting modern smart city infrastructure. In future work, we plan to extend the system by incorporating pedestrian detection, emergency vehicle prioritization, and large- scale deployment across multiple intersections.

REFERENCES

[1] Joseph Redmon and Ali Farhadi, “YOLO9000: Better, Faster, Stronger,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2017, pp. 6517–6525.
[2] Tsung-Yi Lin, Michael Maire, Serge Belongie, James Hays, Pietro Perona, Deva Ramanan, Piotr Dollár, and C. Lawrence Zitnick, “Microsoft COCO: Common Objects in Context,” in Proceedings of the European Conference on Computer Vision, 2014, pp. 740–755.
[3] Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton, “ImageNet Classification with Deep Convolutional Neural Networks,” in Advances in Neural Information Processing Systems, 2012, pp. 1097–1105.
[4] Li Li, Yu Lv, and Fei-Yue Wang, “Traffic Signal Timing via Deep Reinforcement Learning,” in IEEE Transactions on Intelligent Transportation Systems, vol. 18, no. 8, pp. 2125–2135, 2017.
[5] Shaoqing Ren, Kaiming He, Ross Girshick, and Jian Sun, “Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks,” in IEEE Transactions on Pattern Analysis and Machine Intelligence, 2017.
[6] Wei Liu, Dragomir Anguelov, Dumitru Erhan, et al., “SSD: Single Shot MultiBox Detector,” in Proceedings of the European Conference on Computer Vision, 2016.
[7] Sergey Ioffe and Christian Szegedy, “Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift,” in Proceedings of the International Conference on Machine Learning, 2015.
[8] Marco Wiering, Jelle van Veenen, Jurriaan Vreeken, and Arne Koopman, “Intelligent Traffic Light Control,” in Proceedings of the IEEE Intelligent Vehicles Symposium, 2004.
[9] Yann LeCun, Yoshua Bengio, and Geoffrey Hinton, “Deep Learning,” in Nature, vol. 521, pp. 436–444, 2015.
Sebastian Thrun, Michael Montemerlo, et al., “Stanley: The Robot that Won the DARPA Grand Challenge,” in Journal of Field Robotics, vol. 23, no. 9, pp. 661–692, 2006.
[10] J. K. Kelleher and B. Tierney, Data Science, MIT Press, 2018.
[11] World Health Organization, “Global Status Report on Road Safety,” 2023

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