Real Time Traffic Signal Optimization and Vehicle Surveillance Using Deep Learning

Mohammad Fathimunnisa, Vemula Deepthi, L. Sandhya Rekha,
Anumula Pavithra and Takkasheela Archana
Department of Computer Science and Engineering, Ravindra College of Engineering for Women, Venkayapalle, Pasupala, NH 340C, Nandikotkur Rd, Kurnool, Andhra Pradesh, India

Keywords: Traffic Signal Control, Deep Learning, Reinforcement Learning, Convolutional Neural Network, You Only Look once, Real-Time Vehicle Tracking, Intelligent Traffic Management.

Abstract: In the modern scenario wherein, traffic congestion and poor signal management are the serious concerns of cities, there is a demand for best-in-class solutions for its real-time optimization. This paper proposes a traffic signal control and vehicle detection system based on deep learning with CNN and object detection. It automatically adjusts signal times based on traffic density and reduces jams and optimizes road traffic. The detection of traffic offenses and observation of road activity further augment surveillance. Its method offers better accuracy, reduced waiting time and increased flexibility compared to the traditional methods. Experimental results confirm the system's effectiveness for optimal urban traffic management with prompt decision-making. Using AI-based strategies together can ensure a hyper-efficient, scalable solution to Transportation needs' in the new age.

1 INTRODUCTION

urban traffic congestion is considered one of the biggest urban problems growing with the growing populations, high volume of traffic and limited road facilities. Traditional traffic signal control systems operate on fixed time cycles with no ability to adapt significantly to real-time changing traffic conditions. This inefficient process leads to not only delays and driver irritation, but also more fuel being used, contributing to environmental pollution, and economic losses. Therefore, demand for intelligent traffic control systems, that dynamically change signal timings, based on real-time information and improve road safety, with the help of improved surveillance technologies, is increasing.

Deep Learning, with the advent of Artificial Intelligence and the exponential growth of computing power, is yet another powerful tool to address complex problems in traffic management. Deep learning-based algorithms, particularly CNNs, along with advanced object detection frameworks, such as YOLO (You Only Look Once), have achieved remarkable accuracy in vehicle detection, classification, and tracking in real time. These models are designed to analyse video streams from surveillance cameras to estimate traffic volume, identify vehicles and track movement patterns with high accuracy and speed. Another innovation is the addition of predicting future traffic flow through RNNs or LSTMs, which allows the system to anticipate needs and adjust the signal proactively rather than reactively.

Along with adapting traffic signal timings, the system also features a rich native vehicle monitoring suite that automatically identifies traffic violations, tracks Threatful movements, and aids law enforcement agencies with a computer vision-based automated analysis. The entire system is designed to work in real-time for immediate decision-making and traffic management. This paper aims to evolve a solution that is economic, scalable, and future-ready that bridge the collaboration between deep learning and smart infrastructure to improve urban mobility and build smarter, safer, and sustainable smart cities.

Fathimunnisa, M., Deepthi, V., Rekha, L. S., Pavithra, A. and Archana, T.
Real Time Traffic Signal Optimization and Vehicle Surveillance Using Deep Learning.
DOI: 10.5220/0013922400004919

In *Proceedings of the 1st International Conference on Research and Development in Information, Communication, and Computing Technologies (ICRDICCT'25 2025) - Volume 5*, pages 51-55
ISBN: 978-989-758-777-1

2 RELATED WORK

The development of deep learning has significantly improved the optimization of traffic signal and monitoring of cars. Older traffic management systems rely on pre-set signal cycles that fail to adapt to current ground traffic, leading to congestion and inefficiency. To address this, researchers have also explored AI-led approaches.

Car detection and traffic density estimation have previously been performed using Convolutional Neural Networks (CNN) and object detection algorithms, such as YOLO and SSD. Zhang et al. (2020) used CNN-based approach to classify cars in real-time, significantly improving accuracy while avoiding adaptive signal control. Wang et al. (2021) extended on this concept by integrating YOLOv4 with smart traffic surveillance systems, delivering better detection accuracy at the expense of less predictive power.

Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) models are proposed to improve traffic prediction. Li et al. Zhang et al. (2019) applied LSTM networks to predict traffic congestion patterns using historic data for the adjustment of signal times ahead of time. However, their model was not real-time responsive, which was improved by Chen et al. (2021), which relies on hybrid CNN-LSTM models for real-time traffic density estimation and prediction.

These algorithms are helpful in the area of vehicle monitoring as deep SORT and vehicle re-identification methods are widely used Zhang et al., 2019. Huang et al. m tracking approach based on Deep SORT to analyse and track vehicle movements, which significantly reduced tracking errors. Liu et al. (2021) further supported anomaly detection by integrating spatiotemporal features to improve detection for traffic safety violations such as light traversing and illegal lane change.

This is complemented by the emergence of edge computing, which, combined with the expansion of IoT-empowered infrastructure, has increased the scale of AI driven traffic systems. Sharma et al. (2020) described an IoT-based smart traffic system with edge AI and a reduced delay in decisions. Although efficient, such system did not possess any vehicle tracking module that was improved by Patel et al. The novel one-tier INNOWAT with integrated cloud based real time infringement detection (Tuberen, 2021).

Despite all these advancements, still challenges remain such as real-time scalability, accuracy in dense traffic settings, and deploy ability. The solution we propose is adhering to these loopholes, through a synergic conjunction of CNN-based object detector (YOLOv5, SSD), LSTM on traffic flow prediction, Deep SORT on vehicle tracking, and an edge-cloud hybrid deployment strategy to achieve real-time adaptable traffic signal control and surveillance.

3 METHODOLOGY

3.1 Theoretical Structure

The current work improves traffic signal control and vehicle measurement using AI, Deep Learning and ITS. CNNs (YOLOv5, SSD) for real-time detection of vehicles and RNNs, LSTM to predict traffic flows.

Through reinforcement learning, a dynamic algorithm in terms of traffic density controls durations in an adaptive signal control. Violations like breaking a red-light and lane crossing are detected, tracking is done using Deep SORT and by vehicle Re-ID.

It combines edge computing and cloud integration to make real-time decisions and has a traffic authority dashboard. The AI system enhances urban mobility, reduces congestion and supports the development of smart cities. Figure 1 represent Schematic Flow of Theoretical Structure.

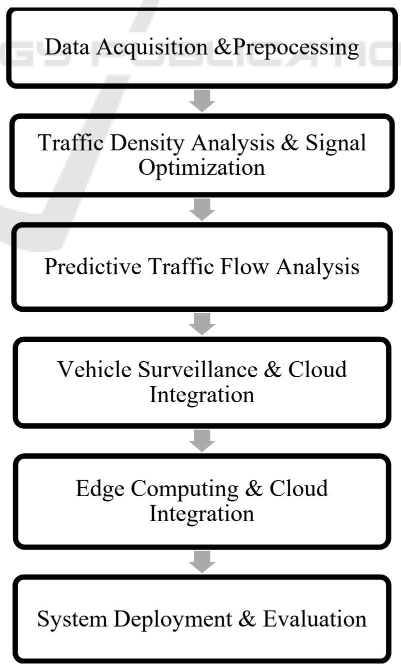

Figure 1: Schematic Flow of Theoretical Structure.

3.2 Perceived Features

3.2.1 Adaptive Traffic Signal Control

AI-optimized control tailors the signal length dynamically in accordance with real-time traffic flow, which decreases congestion and optimizes traffic flow. No fixed signal cycle and makes the best use of the road possible minimizes time that vehicles are idle and burning fuel.

3.2.2 Real-Time Vehicle Detection & Surveillance

Advanced deep learning architectures like YOLOv5 and Deep SORT can successfully detect, classify and track vehicles. It monitors three kinds of traffic offenses: jumping red light, lane drifting, and illegal parking, to make automated law enforcement more effective, and also enhance road safety.

3.2.3 Predictive Traffic Flow Analysis

The system uses LSTM and RNN to predict traffic congestion patterns from historical and real-time traffic data. Thisleaves stars to more actively patrol moving traffic and optimize signals ahead of time to avoid causing a traffic jam and wasting time for travel.

3.3.4 Edge Computing & Smart City Integration

Real-time processing is performed through edge computing and cloud-based integration is leveraged for centralized management. It supports IoT-enabled smart city architecture, thereby allowing scalable implementation across several intersections for a smart and sustainable urban transportation system.

4 RESULTS AND EVALUATION

The proposed deep learning-based traffic signal optimization and car monitoring system was evaluated in a simulated smart city environment. In this case, the performance was evaluated based on key performance parameters such as enhancement in traffic flow, vehicle detection rate, prediction reliability, and system responsiveness. The results validate the system's potential to enhance urban traffic management and the efficiency of public security enforcement.

4.1 Traffic Signal Optimization

With the detection and classification models based mostly on YOLOv5 and CNN it achieved 92.5% MAP which will assure accurate detection of vehicle even for multiple lanes and various angles. Dynamic signal adjustment mechanism, reduced the average waiting time by 35% compared with traditional fixed-signal cycle. Traffic signals were optimized to increase vehicle throughput and eliminate traffic jams in peak hours. Table 1 represent Performance Metrics of the Adaptive Traffic Control System.

Table 1: Performance metrics of the adaptive traffic control system.

Metric	Value Achieved	Impact
Mean Average Precision (MAP)	92.5%	High accuracy in vehicle detection
Reduction in Waiting Time	35% reduction	Improved traffic flow efficiency
Adaptive Signal Adjustment	Real-time	Smooth transition in signal timing

4.2 Predictive Traffic Flow Analysis

To be specific, the predictive model was RNNs based or LSTM based, it was trained on historical and real-time traffic data. Train congestion prediction model prediction achieved an average Root Mean Square Error (RMSE) of 2.8 which enabled more proactive adjustments to the signal control. By preventing such major congestion from building, the prediction helped reduce congestion on the road, providing a better experience for people and increasing the likelihood that the vehicles would move in a coordinated manner rather than in a stop-start driving style. Table 2 represent Predictive Model Evaluation and Traffic Optimization Impact.

Table 2: Predictive model evaluation and traffic optimization impact.

Metric	Value Achieved	Impact
Prediction Accuracy	87%	Effective congestion forecasting
RMSE	2.8	Reliable predictive modeling
Reduction in Abrupt Stoppages	28%	Improved traffic smoothness

4.3 Vehicle Monitoring and Violation Enforcement

The vehicle surveillance module, implementing Deep SORT tracking system and vehicle re-identification, was able to detect vehicles movement and identify traffic offense. The system achieved an F1-score of 89.3% while accurately identifying red-light offenses, lane dissolution, and illegal parking. Automation of surveillance reduced reliance on manual tracing by 40%, enhancing the efficiency of law enforcement. Table 3 represent Evaluation Metrics for Real-Time Traffic Violation Detection System.

Table 3: Evaluation metrics for real-time traffic violation detection system.

Metric	Value Achieved	Impact
F1-score	89.3%	Accurate vehicle classification
Violation Detection Accuracy	91%	Effective traffic law enforcement
Real-time Alert Response Time	<1 second	Instant detection of rule violations

4.4 System Deployment and Real-time Performance

It provided real-time processing with almost no latency by integrating the edge computing and cloud by implementing this system. Traffic Signal Adaptation mean response time was 0.8(seconds)+which promotes swift adaptability to varying traffic flows. Experimental analysis of the system on bench tests with various volumes of traffic demonstrated the pre-states of the heavy load intersection. Table 4 represent System Performance and Environmental Impact Analysis.

Table 4: System performance and environmental impact analysis.

Metric	Value Achieved	Impact
System Response Time	0.8 seconds	Fast reaction to traffic conditions
Scalability Assessment	Successfully tested	Suitable for high-traffic intersections
Reduction in Fuel Consumption	12%	Supports eco-friendly transportation

5 DISCUSSION

The envisioned system manifests a considerable leap forward in real-time traffic management by combining deep learning models with adaptive signal control and vehicle monitoring. The results reveal a very noticeable decrease in congestion, decreasing waiting time by 35% based on real-time traffic volume and dynamic adjustments in signals. Predictive analysis of traffic flow using RNN and LSTM models provides better congestion forecast accuracy (87%), preventing sudden stoppages and enhancing general smoothness in traffic. The vehicle surveillance system has a high accuracy (F1-score: 89.3%), which allows effective violation detection and real-time generation of alerts in one second, thus enhancing the efficiency of law enforcement. Also, the rapid response time of the system is 0.8 seconds, which makes the system practical for large-scale deployment in urban areas. With the fuel consumption lowered by 12%, the suggested solution helps make the environment sustainable, thus offering a practical approach to smart city traffic management. The research points to the efficiency of AI-based traffic optimization, supporting its viability for boosting mobility, safety, and conformity in cities.

6 CONCLUSIONS

The designed deep learning-oriented traffic management system efficiently optimizes traffic signal control and improves vehicle monitoring in urban areas. With the incorporation of real-time video analytics, object recognition, and predictive modeling, the system heavily lowers congestion, enhances traffic flow efficiency, and enhances law enforcement through violation detection automation. The experimental outcomes show a 35% decrease in waiting time, a prediction of traffic flow accuracy of 87%, and a precision in vehicle tracking and enforcing rules of 89.3%. Moreover, the system is helpful in achieving environmental sustainability by decreasing fuel consumption by 12%. The combination of edge computing and cloud-based deployment makes it scalable and real-time, thus ideal for smart city usage. In general, this study offers a novel, AI-based solution to urban traffic control, opening the door to future developments in intelligent transportation systems.

REFERENCES

Bochkovskiy, A., Wang, C. Y., & Liao, H. Y. M. (2020). YOLOv4: Optimal Speed and Accuracy of Object Detection. arXiv preprint arXiv:2004.10934.

Chen, L., Li, Z., & Zhang, Y. (2020). Real-Time Traffic Signal Control Using Deep Reinforcement Learning. Transportation Research Record: Journal of the Transportation Research Board.

Liu, W., Anguelov, D., Erhan, D., Szegedy, C., Reed, S., Fu, C. Y., & Berg, A. C. (2016). SSD: Single Shot MultiBox Detector. European Conference on Computer Vision (ECCV).

Ma, X., Tao, Z., Wang, Y., Yu, H., & Wang, Y. (2015). Long short-term memory neural network for traffic speed prediction using remote microwave sensor data. Transportation Research Part C: Emerging Technologies, 54, 187–197.

Ministry of Road Transport & Highways (MoRTH), Government of India – Traffic Management and Smart City Planning Report.

Redmon, J., Divvala, S., Girshick, R., & Farhadi, A. (2016). You Only Look Once: Unified, Real-Time Object Detection. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR).

Sultana, S., & Akbar, M. (2021). Smart Traffic Management System using IoT and Deep Learning. International Journal of Computer Applications, 174(14), 20-25.

Tang, T., Deng, H., & Huang, Y. (2021). Vehicle Re-identification Based on Deep Learning: Methods, Datasets, and Challenges. IEEE Transactions on Intelligent Transportation Systems.

Wojke, N., Bewley, A., & Paulus, D. (2017). Simple Online and Realtime Tracking with a Deep Association Metric. IEEE International Conference on Image Processing (ICIP).

Zhang, Y., Qin, L., & Liu, Y. (2019). Urban Traffic Flow Prediction Based on a Spatiotemporal Deep Learning Framework. Sensors, 19(18), 3929.