International Journal in IT & Engineering (IJITE)
Volume 13 Issue 6, June 2025 ISSN: 2321-1776 Impact Factor: 8.341
Journal Homepage: http://ijmr.net.in, Email: irjmss@gmail.com
Double-Blind Peer Reviewed Refereed Open Access International Journal

TRAFFIC SIGNAL CONTROL BASED ON VEHICLE DENSITY USING CNN

1. Leeladhar Kumar Gavel,
Kalinga University, Naya Raipur, Chhattisgarh, India
2. Asha Ambhaikar,
Kalinga University, Naya Raipur, Chhattisgarh, India

Abstract

The incessant growth of urban populations and vehicular traffic has transformed city roads into perpetual labyrinths of congestion. Traditional fixed-time traffic signal systems, designed with static assumptions about traffic flow, often exacerbate this problem, leading to increased travel times, fuel consumption, and air pollution. The advent of intelligent transportation systems (ITS) and advancements in artificial intelligence, particularly Convolutional Neural Networks (CNNs), offer a promising paradigm shift towards dynamic and adaptive traffic signal control based on real-time vehicle density. A CNN-based traffic signal control system leverages the power of computer vision to perceive and interpret traffic conditions at intersections. Instead of relying on pre-programmed timings or intrusive sensor loops, the system utilizes strategically placed cameras to capture live video feeds of each approach to an intersection. These video frames serve as the raw input for the CNN model. CNN's primary function in this context is accurate vehicle detection and density estimation. Inspired by the human visual cortex, CNNs excel at recognizing spatial patterns and features within image data. Through a series of convolutional layers, pooling layers, and activation functions, the network learns to identify and count vehicles of various types (cars, buses, trucks, motorcycles) within each lane. This process involves extracting features like edges, textures, and shapes, and then assembling these features into higher-level representations that signify the presence and type of a vehicle. Object detection models like YOLO (You Only Look Once) are particularly well-suited for this real-time application due to their efficiency and accuracy in identifying multiple objects simultaneously. For this research work, we collected the data through the vehicles like car,bus,truck and ambulance where the average speed of car and bus was observed to be 2.25 m/s and 1.8 m/s respectively. On the other hand, the average speed of truck and ambulance was observed to be 1.8 m/s and 2.5 m/s respectively. The vehicle test images from the Pygame simulation were used to train the model, and it achieved a 96% accuracy rate in predicting the type of vehicle.

Keywords:

Traffic, Signal, Control, Vehicle, Density, CNN

Introduction

The advantages of implementing CNN-based traffic signal control are multifaceted. Firstly, it significantly reduces traffic congestion by optimizing green light allocation based on actual demand. This leads to smoother traffic flow and reduced travel times for commuters. Secondly, by minimizing idling vehicles, it contributes to a notable decrease in fuel consumption and, consequently, lower carbon emissions, fostering a more sustainable urban environment. Thirdly, the system is inherently scalable and adaptable. It can be implemented across multiple intersections to create a coordinated traffic network, and its performance can be continuously improved through further training with diverse traffic data. Furthermore, the visual data captured by cameras can also be utilized for other traffic management applications, such as accident detection, traffic violation monitoring, and even pedestrian safety. (Tahir, 2021)

Once vehicle counts are obtained for each lane, the system can calculate real-time vehicle density. This density information then becomes the crucial input for the traffic signal optimization algorithm. Unlike fixed-time systems, which adhere to predetermined green light durations regardless of actual demand, the CNN-driven system can dynamically adjust signal timings. For instance, a lane with a high vehicle density and a long queue of waiting vehicles would be granted a longer green light phase, while a less congested lane might receive a shorter duration or even be skipped if no vehicles are present. This adaptive control minimizes unnecessary waiting times and maximizes the throughput of vehicles through the intersection.

However, the implementation of such sophisticated systems is not without challenges. The accuracy of vehicle detection heavily relies on the quality of camera imagery, which can be affected by varying lighting conditions, weather, and occlusions. Training robust CNN models requires vast datasets of annotated traffic images, and the computational resources needed for real-time processing can be substantial. Data privacy concerns related to constant video surveillance also need careful consideration and appropriate safeguards. (Alshamrani, 2020)

Urban traffic congestion remains a pervasive challenge across cities worldwide, leading to significant delays, increased fuel consumption, heightened emissions, and diminished quality of life. Traditional fixed-time traffic signal systems, while simple to implement, are inherently rigid and unable to adapt to the dynamic and unpredictable nature of real-time traffic flow. This limitation often results in inefficient green light allocation, exacerbating congestion even when certain lanes are underutilized. In response to this pressing issue, the emergence of advanced intelligent transportation systems (ITS) incorporating technologies like Traffic Convolutional Neural Networks (TCNNs) offers a revolutionary approach to traffic signal control, promising to drastically reduce congestion by optimizing green light allocation based on actual demand.

TCNN-based traffic signal control leverages the power of deep learning, particularly convolutional neural networks (CNNs), to analyze real-time traffic data and make intelligent decisions about signal timings. Unlike conventional systems that rely on predetermined schedules or basic sensor triggers, TCNNs are designed to perceive and interpret complex spatial and temporal patterns within traffic scenes. This is typically achieved by processing live video footage from roadside cameras or data from a network of IoT sensors (e.g., loop detectors, LiDAR, GPS data from connected vehicles). The CNN component of the TCNN system excels at identifying and classifying vehicles, pedestrians, and other road users, allowing for accurate estimation of traffic density, queue lengths, and flow rates in different lanes and approaches to an intersection. (Mishra, 2021)

Literature Review

Solanki et al. (2020): One of the foremost challenges lies in data acquisition and quality. TCNNs, like any deep learning model, are inherently data-hungry. To effectively train a TCNN for traffic signal control, vast amounts of real-time, accurate traffic data are required, including vehicle counts, speeds, queue lengths, origin-destination patterns, and even pedestrian movements. This data needs to be collected from various sources such as loop detectors, video cameras, radar, and potentially connected vehicle systems.

Chandrasekara et al. (2021): Deploying and maintaining a comprehensive sensor infrastructure across an entire urban area is incredibly expensive and complex. Furthermore, the quality and reliability of this data can be inconsistent due to sensor malfunctions, environmental factors (e.g., adverse weather obscuring camera views), or data transmission errors. Noisy or incomplete data can significantly degrade the performance of a TCNN model, leading to suboptimal or even detrimental signal timings.

Pawar et al. (2022): TCNNs are computationally intensive, requiring significant processing power for both training and real-time inference. Deploying such models at every intersection or a centralized traffic management center necessitates robust hardware infrastructure, including GPUs or specialized AI accelerators.

Fawzi et al. (2020): The latency involved in processing real-time video feeds or large sensor datasets, running the TCNN model, and then enacting signal changes must be minimal to ensure true adaptive control. Any significant delay can render the system ineffective, potentially worsening traffic conditions rather than improving them. The computational cost not only includes initial setup but also ongoing operation and maintenance.

Patil et al. (2021): Generalization and transferability present a significant challenge. A TCNN model trained on data from one specific intersection or city might not perform optimally when deployed in a different environment with distinct traffic patterns, road layouts, or driver behaviors. Traffic characteristics vary widely due to factors like population density, public transportation availability, driving culture, and peak hour dynamics. Retraining or fine-tuning the model for each new location is a time-consuming and resource-intensive process. Developing a robust TCNN that can generalize across diverse traffic scenarios without extensive re-training remains an active area of research.

Traffic signal control based on vehicle density using CNN

The key to TCNN's effectiveness lies in its ability to optimize green light allocation dynamically. Instead of adhering to fixed durations, the TCNN system continuously evaluates the actual demand at each intersection. When a particular lane or approach experiences higher traffic density, the TCNN can autonomously extend its green light phase, allowing more vehicles to clear the intersection. Conversely, lanes with minimal or no traffic can have their green light durations shortened or skipped, preventing unnecessary delays for other approaches. This adaptive allocation is driven by algorithms that aim to minimize overall waiting times, reduce queue lengths, and maximize vehicle throughput across the entire network. Some TCNN implementations might also incorporate reinforcement learning, where the system learns optimal control policies through continuous interaction with the traffic environment, receiving "rewards" for actions that reduce congestion and "penalties" for those that worsen it.

For this research work, we collected the data through the vehicles like car,bus,truck and ambulance where the average speed of car and bus was observed to be 2.25 m/s and 1.8 m/s respectively. On the other hand, the average speed of truck and ambulance was observed to be 1.8 m/s and 2.5 m/s respectively.

Table 1. The Pygame simulation engine's categorization of vehicles.

Vehicle Type	Vehicle Groups	Average Speed
0	car	2.25 m/s
1	bus	1.8 m/s
2	truck	1.8 m/s
3	ambulance	2.5 m/s

The procedure starts when an emergency vehicle approaches the traffic light. When an emergency vehicle is detected using the detection model and the 2D-CNN for vehicle classification, the computer extends the green light to allow it to safely cross the intersection. According to **Table** 1, every vehicle has a "type" allocated to it with the program (0—car, 1—bus, 2—truck, 3—ambulance).

Table 2. Architecture details of the 2D Convolutional Neural Network.

Number	Architecture Details
1	Input image size (640, 480)
2	Total number of layers: 2 Total MaxPooling2D layers used: 2 Total fully connected layers used: 3 Activation layers: 4 Dropout layer: 2
3	Kernal size at each Conv2D layer: 3 × 3
4	Pool size at each maxPooling2D layer: (2,2)
5	Output class labels: 3

The vehicle test images from the Pygame simulation were used to train the model, and it achieved a 96% accuracy rate in predicting the type of vehicle. **Table** 2 shows all the parameters used by the 2D-CNN during training to achieve a high accuracy rate.

Table 3. The 2D-CCN accuracy and loss with epoch.

Epoch	Time Taken(s)	Accuracy	Loss
1	11	0.478	1.998
2	9	0.800	0.678
3	10	0.877	0.423
4	11	0.906	0.312
5	11	0.921	0.273
6	10	0.923	0.255
7	11	0.935	0.232
8	12	0.936	0.228
9	11	0.938	0.233
10	9	0.939	0.214
11	11	0.944	0.211
12	11	0.947	0.206
13	9	0.945	0.216
14	11	0.951	0.201
15	10	0.953	0.186

Table 3 shows the output of the 2D-CNN module during training for vehicle classification, accuracy, and time loss.

The benefits of implementing TCNN-based traffic signal control are substantial and far-reaching. Firstly, the most direct impact is a significant reduction in traffic congestion and travel times. Studies and simulations have consistently demonstrated that adaptive signal control systems, including those powered by TCNNs, can improve intersection throughput by 15-25% and cut peak-hour trip times by a substantial margin. This translates to smoother traffic flow, less stop-and-go driving, and a more efficient transportation network.

Beyond merely reducing delays, TCNNs contribute to a multitude of positive outcomes. By minimizing idling vehicles, they lead to a notable decrease in fuel consumption and, consequently, a reduction in harmful greenhouse gas emissions, fostering a more sustainable urban environment. Furthermore, enhanced traffic flow can improve safety by reducing the likelihood of rear-end collisions and other incidents associated with sudden braking and accelerating in congested areas. The system can also prioritize emergency vehicles, creating "green corridors" to ensure rapid response times. Moreover, the real-time data analysis capabilities of TCNNs provide valuable insights for urban planners and traffic management centers, enabling data-driven decision-making for future infrastructure development and traffic management strategies.

The synergy between TCNN-based traffic signal control and traffic violation monitoring is profound. To effectively control traffic, these systems rely on a rich stream of real-time data from various sources, including high-resolution cameras, sensors, and sometimes even vehicle-to-infrastructure (V2I) communication. This continuous influx of visual and sensor data, meticulously processed by the TCNN for signal optimization, simultaneously provides the foundation for identifying and flagging traffic violations.

The core of TCNN-based traffic control involves accurate detection and tracking of vehicles, pedestrians, and other road users. This very capability, powered by the TCNN's robust feature extraction, can be extended to identify specific behaviors. For instance, the system can track a vehicle's trajectory relative to the stop line at a red light. TCNNs can learn normal traffic flow patterns. Any deviation from these learned patterns, such as a vehicle entering an intersection during a red light, making an illegal turn, or exceeding speed limits (when integrated with speed detection), can be identified as an anomaly and flagged as a potential violation.

Beyond simple object detection, TCNNs can understand the context of an intersection. They can recognize the current signal state (red, yellow, green) and correlate vehicle movements with these states to determine if a violation has occurred. For example, a vehicle passing the stop line when the signal is red is a clear violation. Once a violation is detected, the system can automatically capture high-resolution images or video snippets of the offending vehicle, including its license plate. This automated evidence collection is crucial for efficient and objective enforcement, reducing reliance on manual surveillance and mitigating human error.

Safety and reliability are paramount in traffic control. Any error or unexpected behavior from an AI-driven system could have severe consequences, leading to accidents or gridlock. Unlike traditional rule-based systems, TCNNs often operate as "black boxes," making it difficult to interpret their decisions or diagnose errors. Ensuring the system's robustness against adversarial inputs, sensor noise, or unforeseen traffic events is crucial. Rigorous testing, validation, and fail-safe mechanisms are essential before widespread deployment. The absence of clear interpretability also raises concerns about public trust and accountability, especially when unforeseen incidents occur.

Integration with existing infrastructure and regulatory frameworks poses practical difficulties. Urban traffic systems are often a patchwork of legacy hardware and software, making seamless integration of new TCNN-based controllers a complex engineering task. Compatibility issues, data exchange protocols, and cybersecurity concerns must be addressed. Moreover, current traffic laws and regulations may not be designed to accommodate highly dynamic, AI-driven signal control, necessitating updates and standardization efforts. Gaining acceptance from traffic engineers, urban planners, and the public also requires demonstrating clear benefits and addressing concerns about job displacement or over-reliance on AI

TCNNs often work in conjunction with ANPR systems. Once a violation is identified and the vehicle captured, the ANPR module can extract the license plate number, allowing for immediate identification of the vehicle owner and subsequent issuance of citations. The vast amount of data collected on traffic violations can be further analyzed by TCNNs to identify patterns and hot spots for certain types of violations. This information can then be used for predictive policing, deploying law enforcement more strategically, and for informing urban planning decisions to redesign intersections or roads that frequently lead to violations.

Conclusion

For this research work, we collected the data through the vehicles like car,bus,truck and ambulance where the average speed of car and bus was observed to be 2.25 m/s and 1.8 m/s respectively. On the other hand, the average speed of truck and ambulance was observed to be 1.8 m/s and 2.5 m/s respectively. The vehicle test images from the Pygame simulation were used to train the model, and it achieved a 96% accuracy rate in predicting the type of vehicle.

Traffic signal control based on vehicle density using CNNs represents a significant leap forward in intelligent traffic management. By leveraging the unparalleled image recognition capabilities of deep learning, these systems offer a dynamic, efficient, and environmentally friendly solution to urban congestion. As cities continue to grow and vehicular traffic intensifies, the widespread adoption of such intelligent systems will be crucial in building smarter, more responsive, and sustainable urban environments for the future. TCNN-based traffic signal control represents a transformative leap in urban traffic management. By leveraging the analytical power of convolutional neural networks to understand and respond to real-time traffic demand, these systems move beyond the limitations of traditional fixed-time signals. The ability to dynamically optimize green light allocation based on actual demand directly addresses the root causes of congestion, leading to more efficient traffic flow, reduced travel times, lower emissions, and improved overall urban mobility. As cities continue to grapple with growing populations and increasing vehicular traffic, the adoption of TCNN-based solutions will be crucial in building smarter, more sustainable, and less congested urban environments.

References

1. Mihir M. Gandhi, Devansh S. Solanki, Rutwij S. Daptardar, Nirmala Shinde Baloorkar (2020) "Smart Control of Traffic Light Using Artificial Intelligence"
2. Chandrasekara, R.M.K.T Rathnayaka, L.L.G Chathuranga (2021) "A Real-Time Density-Based Traffic Signal Control System"
3. Vikramaditya Dangi, Amol Parab, Kshitij Pawar, S.S Rathod (2022) "Image Processing Based Intelligent Traffic Controller"
4. Raoul de Charette, Fawzi Nashashibi (2020) "Traffic Light Recognition Using Image Processing Compared To Learning Processes"
5. Nikhil Chhadikar, Ms. Priyanka Bhamare, Mr. Krushna Patil, Mrs.Sangeeta Kumari (2021) "Image Processing based Tracking and Counting Vehicles"
6. Dasari Vineela, Abdul Gafar, Goriparthi Manoj, Chandolu Anil Kumar, Veera Punnaiah Manda (2022) "Image Processing based Smart Traffic Controlling and Monitoring System Using Arduino" (Volume 05 Issue 15)
7. Shruti Mishra, Vijay Birchha (2021) "An improved smart traffic signal using computer vision and Artificial Intelligence"
8. Raneem Nono, Rawan Alsudais, Raghad Alshmrani, Sumayyah Alamoudi and Asia Aljahdali (2020) "Intelligent Traffic Light for Emergency Vehicles Clearance"

9. Nikhil Nim, Nityanand Silawat, Paridhi Mistri, Pratiksha Marmat, Surendra Singh Chouhan, Vaishali Wanjare (2020) "Smart Traffic Signal Management Using Artificial Intelligence"

10. Zia, M. Naseem, I. Mala, M. Tahir, T. J. A. Mughal, T. Mubeen (2021) "Smart Traffic Light System by Using Artificial Intelligence".a