World Journal of Advanced Engineering Technology and Sciences

eISSN: 2582-8266

Cross Ref DOI: 10.30574/wjaets

Journal homepage: https://wjaets.com/

(Review Article)

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Machine learning solutions for adaptive traffic signal control: A review of image-based approaches

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World Journal of Advanced Engineering Technology and Sciences, 2024, 13(01), 476–481

Publication history: Received on 05 August 2024; revised on 18 September 2024; accepted on 20 September 2024

Article DOI: https://doi.org/10.30574/wjaets.2024.13.1.0437

Abstract

This paper gives an overview and performance evaluation of various machine learning models implemented in management of urban traffic congestions, more specifically, adaptive traffic signal control systems. It considers a review of deep learning algorithms including R- CNN, Fast R-CNN, Faster R-CNN, SSD, YOLO v4, and YOLOv8, with regard to their efficiencies for vehicle detection and traffic prediction under varying scenarios. Certain traffic conditions, camera placements, and environmental factors—related performance for each of the models are discussed. The major performance in most of the scenarios was depicted by the YOLO v4. However, at the same time, YOLOv8 has shown potential to do much better than YOLO v4 on image processing and the resultant accuracy. It also proposes a new algorithm for traffic light timing, whose efficacy is tested using the SUMO simulation platform. While results have shown improvements in urban traffic management, a review underlines that such is in deep need of extensive real-world testing. Future directions should include views from varied angles and weather conditions, and the detection of emergency vehicles, probably with specialized datasets.

Keywords: Urban Traffic Management; Machine Learning Models; Adaptive Traffic Signal Control; Deep Learning Algorithms

1. Introduction

Some of the implications of urban traffic congestion include delays, consumption of colossal amounts of fuel, and the environment. Most of the time, the normally used traffic control systems present inefficiencies for every system built to address dynamic traffic, thus calling for innovative ways of intervention. The study applies machine learning in developing an advanced traffic signal system that allows proper flows of traffic without expanding the infrastructure.

The study included several deep learning models for object detection and classification of vehicles, such as R-CNN, Fast R-CNN, Faster R-CNN, SSD, and YOLO v4. It gave excellent results with YOLO v4. It introduced the new semantics-based traffic light timing, hence minimizing the pause time of vehicles at traffic lights.

Methodologically, the research will deploy simulations to forecast and control the traffic flow, with the integration of several machine learning techniques through regression models, reinforcement learning, and real-time data analysis. Machine learning techniques are used in this work to make use of the Simulation of Urban Mobility (SUMO) environment

Key achievements of the study include high accuracy in vehicle detection and significant reductions in vehicle waiting times.

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However, the research also identifies areas for improvement, such as the need for testing under diverse real-world conditions, different weather, and system adjustment to practical camera angles used for traffic monitoring.

The proposed adaptive traffic signal system offers a robust solution toward the enhancement of urban traffic management and reduces the problems related to congestion by addressing such areas of improvement.

2. Literature Review

[1] In this work, Histogram of Oriented Gradients, Local Binary Patterns, and Support Vector Machine are applied for the purpose of estimating traffic density at intersections. Divide it into small cells of 44 × 44 pixels in the ROI; extract HOG and LBP features, which preserve edge, corner, and texture information. All of these features are concatenated into a vector per cell. Trained on 200 frames of two videos, the SVM could achieve a classification accuracy of 94.88% in discriminating the traffic from the road, with a precision and recall of 94.00% and 94.03%, respectively, and an F1 score of 93.99%.

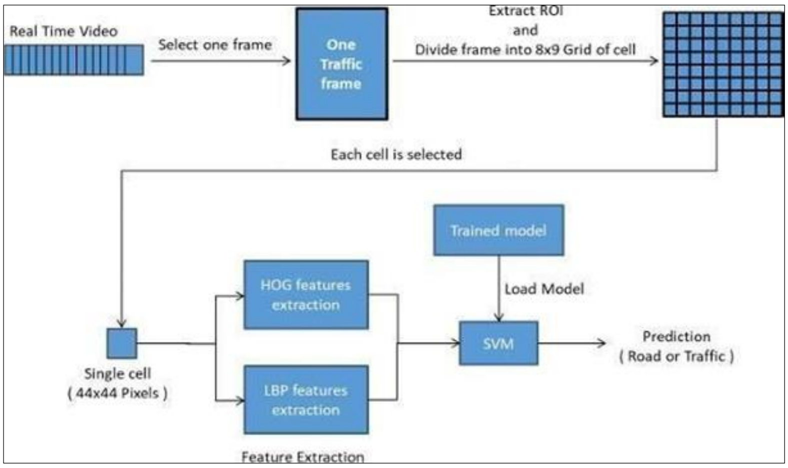

Figure 1 Flow of execution for prediction.

This approach is very computationally efficient and hence suitable for low-power devices like Raspberry Pi. However, to conform with the government regulation regarding CCTV footage, Otherwise, more evolved models such as YOLOv8 could be contemplated.

[2] The research will help solve the problem of severe traffic congestion in Jordan by applying machine learning techniques to the development of an adaptive traffic light system that optimizes the management of traffic without resulting in infrastructure expansion. In the paper, several deep learning algorithms—the R-CNN, Fast R-CNN, Faster R-CNN, SSD, and YOLO v4—were used in training models with respect to vehicle detection. Among them, the YOLO v4 algorithm performed the best with a mean AP of 86.4%. Besides that, a new formula for estimating traffic light timing was proposed, and the result gave an approximate decrease of 10% in waiting time. Although the result of the research is very promising, it also raised future work. Specifically, the system proposed needs testing with more real-world scenarios such as weather conditions robustness.

$ni = 4 \times T + 2 \times B + C + V + M \times T + 0.5 \times M$ (1)

$Avg = n1 + n2 + n3 \ldots + nk / K$ (2)

$ti = ni \times 27 / Avg$ (3)

The dataset utilized in the study was gathered from ground- level angles, whereas practical applications typically involve CCTV cameras positioned to cover broader areas. This discrepancy in camera angles could impact the accuracy and effectiveness of the vehicle detection models when implemented in real-world traffic environments.

[3] The study optimizes the control of traffic lights through the use of a combination of Q-learning and deep neural networks. Q-learning is a model-free type of reinforcement learning; it is used to assign Q-values to actions in light of the prevalent state in the respective traffic scenario. The deep neural network to estimate Q-values realizes the decision

strategy in more complex traffic situations. Simulations that have been realized using the Simulation of Urban Mobility (SUMO) evaluated the performance of the proposed system. In result, average vehicle queue time in an individual intersection went down by 34% in comparison to the fixed-time traffic signal system. In two neighboring intersections that have agents in pairs, while agents can communicate with each other, the overall reduction in average queue lengths of agents got to 24% under the peak condition of traffic. This then allows adaptive traffic lights to work dynamically depending on current conditions using reinforcement learning, while SVM and YOLOv4 focus on the object detection and classification.

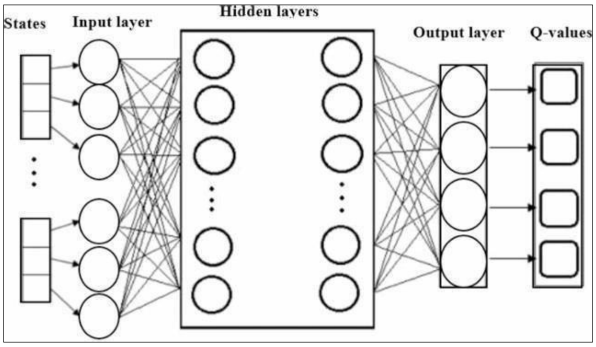

Figure 2 Neural network structure used to determine the Q-values

The Q-learning approach offers flexible, adaptive traffic control in dynamic environments, unlike static models like SVM or object detection frameworks like YOLOv4.

[4] In the paper, machine vision is presented for tracking and analysis of traffic flow parameters with the YOLOv4 neural network and the SORT tracker applied for vehicle classification and detection. Real-time CCTV footage and perspective transformation methods convert the image coordinates into geographic coordinates, which are necessary for the precise measurement of vehicles.

It provides dimensions and speed up to 500 meters. Data augmentation techniques provide stable accuracy in bad weather conditions or at night. The system achieves very high accuracy for vehicle detection and classification—minimum accuracy of 92%—and the vehicle speed estimation error is very small, not more than 1.5 km/h.

The paper proposes integration with other sources, such as GLONASS/GPS, to realize incremental improvements in the future, although this is currently limited.

[5] With the SUMO simulation environment, taking the intersection of Hongyan East Road and Xinwang South Road in Beijing as the simulation case, results showed a remarkable reduction in total vehicle waiting time by 76.3% to 80.4% under various traffic modes, with an average queue length reduced by 33.4% to 50%. The approach dynamically adjusts the phases of the traffic lights according to real-time traffic conditions at the intersection to improve its throughput. This would end up improving the overall efficiency of the traffic.

This work applied methods similar to those used by Mortazavi Azad, S. M., & Ramazani, A. (2023), but it improved results in waiting time reduction and average queue length, which shows that an improved dataset is crucial.

[5,6] It adopts Proximal Policy Optimization to improve the model convergence speed in traffic light control. The discrete traffic state encoding method is used to define vehicle state.

The current reward equation includes green time and traffic flow but could also include emissions, fuel consumption, and overall traffic network performance to make the reward more comprehensive in terms of traffic management strategies.

[7] The paper has proposed regression models and machine learning libraries such as Sklearn, Keras, and TensorFlow for the prediction of traffic patterns. In this study, two datasets, 2015 and 2017, were used, comparing and predicting the traffic for four different road junctions against the historical data. The authors have used several techniques like data preprocessing, feature engineering, and data scaling, model performance. It can successfully predict current and near-future traffic situations up to an hour ahead, it identifies the most congested roads and junctions, and also provides an estimation of the average count of vehicles at junctions.

In a nutshell, these researchers constructed a very robust method to predict short-term traffic patterns based on generally available data and machine learning techniques, thus proving its usefulness in traffic management and routing.

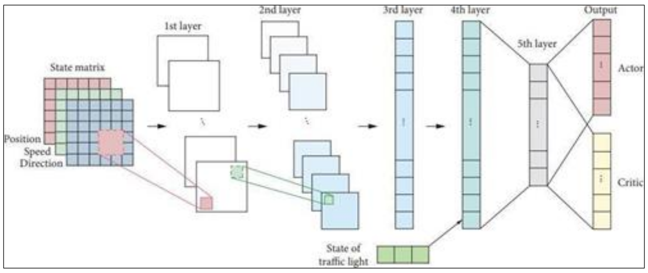

Figure 3 PPO decision network model**.**

[8] The intersection state is defined by vehicle presence, traffic light phases, and vehicle velocities, with rewards based on vehicle delays and queue lengths. The agent was trained over 300 episodes of 1.5 hours each, simulating diverse traffic scenarios to ensure robust performance.

[9] Data was collected using traffic density information is extracted using the HERE maps API, which gives real-time data such as average speed, length of the road, maximum speed, and jam factor. The necessary attributes are then stored as well as cleaned to have all inconsistencies removed.

Naive Bayes was used for dynamically distributing the traffic with the jam factor and the average speed. The machine learning algorithm was developed using Q-values for providing an adaptation for the timings of the traffic signal to the present condition, which shows a reduction in congestion and minimum waiting time.

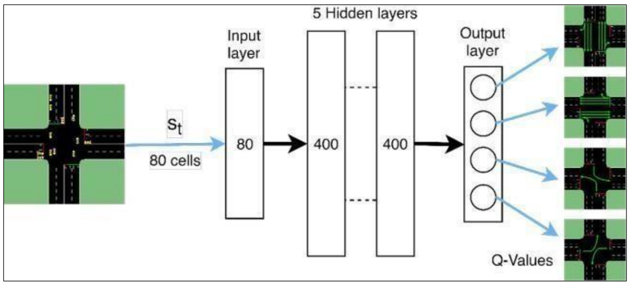

Figure 4 Scheme of the deep neural network

Several techniques are projected for traffic density estimation, including sensors and other hardware-based solutions. Image processing is most preferred due to its cost- effectiveness. compared to hardware-based solutions. These techniques only require cameras, which are already installed at most junctions, eliminating the need for additional sensors.

[10,11] This work integrates some modules for an advanced urban traffic management system. ANETs rely on VANETs for V2V and V2I communications that supply real-time traffic information. The TLC has agents to deal with the management of traffic parameters such as vehicle count, speed, and vehicle type. TLD controls this by diverting the vehicle before entering the congestion zone with the help of the sensors.

It makes use of wireless magnetic sensors for the purpose of vehicle detection, which turn out to be cost-effective against the conventional loop detectors. VANETs ensure real-time data collection and processing to improve responsiveness of the system.

More research is needed on the integration of this system into existing traffic management infrastructure and its applicability to different urban environments and traffic-related circumstances.

3. Research Gap

We better the current adaptive traffic signal system by the application of new technologies and methodologies. Advanced image processing techniques such as YOLOv8 will allow for vehicle detection and classification to be performed more accurately. Additionally, cameras at different angles will add variety to the dataset, making it possible to train comprehensively enough to do much better in real-world scenarios.

An inclusion of the weather equation would make it possible for the system to change the traffic signals according to the weather, making it quite effective in every environmental condition. We will also further take into consideration various types of vehicles and view priorities according to vehicle type; for example, emergency vehicles such as ambulances should get the highest priority in order to make way for them through the traffic.

Ambulances always get stuck in jams because their presence is not identified and acted upon by any conventional traffic signal system. The lane must be cleared for the ambulances to save lives by ensuring timely medical assistance. We can train our model to be able to recognize ambulances using images of them in the dataset by size, and of course, the lights at the top. Recognizing ambulances and treating them as the most important vehicles, with most priority, this system would be able to dynamically change traffic lights and help them go through much faster, which leads to much fewer delays and hence a better response to emergencies.

4. Conclusion

After experimental validation for different scenarios, YOLO v4 performed well and showed high accuracy in vehicle recognition which made it accurate for virtual waiting times of vehicles at intersections. The tool is known for its strong detection rate even in the most complex environments. Although recently created, the YOLOv8 stands to outperform its predecessors when it comes to image processing tasks (as seen in the figures), and thus could be used as the primary model for future implementations once ripe. Although the R-CNN family (R-CNN, Fast R-CNN, and Faster R-CNN) as well as SSDs are high-performance object detection models for various applications but they could not outperform YOLO variants in real-time due to a high computational requirement/long processing time.

While the models were tested on a variety of datasets, they stress that these need to be expanded out into real-world conditions covering diverse weather and varying camera angles. This is important as with current datasets coming from ground-level angles, there may be a skewed representation of CCTV placements in urban settings. For example, applying reinforcement learning in the context of traffic signals using Q-learning has proven to be successful for real-time optimization and lead to much smaller vehicle queue lengths and waiting times.

Beyond this, more specialized datasets and concrete validation in real-world situations is absolutely necessary for models to improve their robustness. Rather than using a pre-trained model, which may not perfectly characterize the complexity of real-world traffic scenarios, it should be possible to build a custom model that fits this specific use case in urban traffic management. This model would be tailored to deal with the complexity of traffic, incorporating several elements like rush hour patterns, types and amounts of vehicles on road at that time, weather conditions prevailing during computation period as well detecting priority vehicles such ambulances or police cars.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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