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Enhancing traffic control systems with live video analytics: Issues, challenges, opportunities, and recent problems

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ABSTRACT: With the rapid urbanization and increasing number of vehicles on the roads, it has become imperative to develop innovative solutions that can monitor and manage traffic congestion automatically. Traffic congestion harms the economy, environment, and overall quality of life. To address these challenges, smart traffic management systems employ cutting-edge technologies such as live video analytics and sensor-based adaptive traffic control systems. These systems can predict traffic patterns, locate congestion hotspots, and uncover abnormalities contributing to road accidents in real time. However, adopting these technologies for traffic control systems raises important concerns such as robustness and sustainability across different traffic junctions, data integration from multiple sources, and computational feasibility for real-time computation. Therefore, this paper aims to present an overview of the potential benefits and challenges in adapting the latest technologies, including the Internet of Things and machine learning, for sustainable traffic management. Additionally, a case study of a smart city is presented to evaluate an adaptive traffic control system based on live camera feed analytics by leveraging computer vision techniques. The adaptive traffic control system is accurate in vehicle detection and counting. This system is very useful for smart cities where traffic signals need to be automated according to the density of vehicles.

KEYWORDS: smart transport management; real time traffic monitoring; intelligent traffic analysis; object detection in live camera feed; adaptive traffic control system

1. Introduction

Although cities were initially favored for having better infrastructural facilities, efficient and sustainable traffic control systems are crucial for smart cities. Traditional traffic management systems with predetermined traffic light timings have proven inefficient in addressing the rising challenges of traffic congestion, which leads to longer travel time, increased fuel consumption, and health hazards for commuters in cities worldwide[1,2]. As per reports and various studies[1,3–5], billions of economic losses happen every day due to congestion. Additionally, traffic congestion contributes to air pollution, with vehicular emissions being one of the primary sources of harmful pollutants such as Nitrogen Oxides (NO_x) and Particulate Matter (PM). These pollutants have detrimental effects on public health, causing respiratory diseases and other health complications[6,7].

Furthermore, the safety of pedestrians[8] is also compromised by the occurrence of frequent accidents on the road. The factors contributing to these issues include poor road infrastructure, weather conditions, and most importantly, ineffective traffic management[9,10]. Thus, there is a clear need for traffic control systems that effectively mitigate congestion and reduce air pollution. Moreover, the development of sustainable transportation networks that can alleviate congestion and encourage more active, shared transport modes is critical.

1.1. Ecosystem of traffic control systems in smart cities

Smart and efficient transport systems play a vital role in the development of smart cities[11]. The exponential growth in urban populations has led to increased vehicular density, resulting in congestion, longer commute times, and adverse environmental effects. Traditional traffic control systems often struggle to adapt to the dynamic nature of modern traffic patterns[12]. Many developed countries, like the USA, UK, and Australia, have implemented smart traffic management systems to improve the efficiency, safety, and sustainability of transportation[13]. In Singapore, a smart traffic management system uses sensors to monitor traffic conditions and adjust traffic signals in real time. This has helped to reduce traffic congestion by up to 30%. Similarly, a few Indian smart cities like Chennai, Pune, and Vadodara have implemented smart traffic management systems using sensors and cameras with data analytics to monitor traffic conditions and adjust traffic signals in real time. **Figure 1** illustrates a commonly used smart traffic management system in smart cities.

Figure 1. Smart traffic management system.

However, the usage of efficient transportation systems in smart cities is still in the early stages of development[14], and there is potential to revolutionize the way citizens travel. The success of a smart city depends on the seamless integration of traffic control system components, effective collaboration among stakeholders, and a commitment to leveraging technology for sustainable urban mobility. As cities continue to evolve, the ecosystem will adapt and expand to meet the growing demands of an increasingly interconnected transportation network. The goal is to create a safer, more sustainable, and seamless transportation experience for residents and visitors.

1.2. Challenges in traditional traffic control system

Traditional traffic control systems have been the foundation of urban transportation management for decades. However, there are several challenges that hinder their application in addressing modern-day traffic complexities.

1) Fixed timing: Traditional traffic light systems operate on fixed timing patterns that are pre-programmed and do not adapt to real-time traffic conditions. This can result in inefficient traffic flow, especially during periods of varying traffic demand.
2) Lack of coordination across multiple intersections: Traditional traffic light systems often work

independently at each intersection, lacking coordination with nearby intersections. This can lead to suboptimal traffic management, as the timing of traffic lights may not be synchronized to facilitate the smooth movement of vehicles across multiple intersections.

3) Lack of adaptability and inflexibility: Traditional traffic light systems cannot learn and adapt to changing traffic conditions over time. They cannot take advantage of historical data or predictive analytics to optimize traffic signal timings based on traffic patterns and trends. Furthermore, a traditional traffic system cannot dynamically adjust its settings based on changing traffic patterns or events. It cannot respond to unexpected incidents, road conditions, or special events that may require immediate traffic control adjustments.
4) Limited data utilization: Traditional traffic light systems rely on limited data inputs, typically using fixed sensors or timers to detect vehicles and determine signal timings. They cannot collect and analyze real-time data from various sources, such as traffic cameras, vehicle detectors, or weather conditions, which can provide valuable insights for optimizing traffic flow.
5) Inefficient traffic flow: Due to the static nature of traditional traffic light systems, they may prioritize certain directions or roads without considering the actual demand. This can lead to congestion on some routes while leaving others underutilized, resulting in overall inefficient traffic flow.
6) Limited communication: Traditional traffic light systems typically operate in isolation and lack communication capabilities with other traffic management systems, such as intelligent transportation systems or connected vehicles. This limits their ability to exchange real-time information and collaborate with other entities to improve traffic efficiency.
7) Heavy traffic jams: Under ordinary conditions, when the traffic lane waits for the green light, the time setting is the same and fixed. An increasing number of vehicles on the roads has substantially increased congestion. This is observed usually at main junctions in the morning, during office hours, and after office hours.
8) No traffic, but need to wait: At certain junctions, even if there is no traffic, when the traffic light remains red, the road users have to wait until the light turns green. And if the rule is broken, a fine has to be paid. The solution to this problem is to develop a system that detects traffic density on each road and then sets signal timing accordingly, along with synchronization of the adjacent junction's traffic signal.
9) Inadequate traffic information to users: The conventional traffic system fails to provide traffic status about congested roads, alternate routes, etc. to the road user in advance.

2. Related work

This section presents recent advances in traffic control systems for real-time traffic analysis and traffic congestion management. As smart cities continue to evolve, understanding the implications and effectiveness of the Internet of Things (IoT) and live video analytics in traffic control systems becomes imperative for urban planners, policymakers, and technologists alike[15–18]. By employing advanced computer vision algorithms, machine learning techniques, and data analytics, these approaches promise to revolutionize how cities manage and respond to traffic challenges.

2.1. IoT-based traffic control system

An IoT-based solution for traffic control systems uses sensors and actuators placed at key points in the traffic network to capture traffic flow, pedestrian traffic, and other variables that affect traffic flow[15,17,19]. Traditional adaptive traffic control systems mainly rely on sensors, which can be costly and time-consuming to install[20]. The commonly used key components of an IoT-based traffic control system are as follows:

1) Sensors: IoT sensors are installed at strategic locations, such as traffic lights, intersections, and highways, to collect real-time data on traffic volume, speed, and congestion. This data can be used to create a dynamic traffic model that updates in real time, enabling traffic managers to make more informed decisions.
2) Actuators: Actuators will be used to control traffic lights, lane control devices, and other equipment to optimize traffic flow.
3) Communication infrastructure: An IoT-based traffic control system requires a robust communication infrastructure to transmit data between the sensors, the control center, and the vehicles on the road. This infrastructure can be based on cellular networks, Wi-Fi, or dedicated communication protocols.
4) Cloud-based platform: The data collected by the sensors can be uploaded to a cloud-based platform, where it can be analyzed and processed using machine learning algorithms. The platform can also provide real-time insights and alerts to traffic managers and drivers.
5) Adaptive traffic control algorithms: Machine learning algorithms will analyze the data and develop predictive models that can improve decision-making. These algorithms can adjust traffic light timings, reroute traffic, and provide priority to emergency vehicles.
6) Connected vehicles: Connected vehicles can play a key role in an IoT-based traffic control system. By communicating with the traffic control center, vehicles can receive real-time information on traffic conditions, road hazards, and optimal routes. This information can be displayed on the vehicle's dashboard or integrated into the vehicle's navigation system.
    - Vehicle-to-Infrastructure (V2I) communication: Cars equipped with communication technology can exchange data with traffic infrastructure, receiving information about optimal routes and traffic conditions.
    - Vehicle-to-vehicle (V2V) communication: Cars communicate with each other to improve safety and optimize traffic flow, reducing the risk of accidents and improving overall efficiency.
7) Microcontroller: The sensors are generally interfaced with the Node MCU, Arduino, Peripheral Interface Controller (PIC), Raspberry Pi, or any microcontroller to send the data wirelessly.

2.2. Live video analytics-based traffic control system

Computer vision and deep learning techniques have demonstrated remarkable performances in both research and industrial applications. Computer vision algorithms are used to analyze the video feed and make adjustments to traffic control devices in real time. The video analytics-based traffic control system uses live camera feeds from cameras installed at key points in the traffic network to monitor traffic flow and make adjustments to traffic control devices in real time[2,21,22]. These systems are helpful in providing real-time updates to drivers and pedestrians about traffic conditions, helping to reduce congestion and improve safety on the roads[4].

Convolutional Neural Network (CNN) is one of the most commonly used object detection techniques in computer vision that can be used for traffic monitoring and analysis in real time[8,23]. By assessing live video from multiple cameras, CNN can detect the traffic flow to find locations of significant congestion and identify traffic anomalies that may contribute to accidents[4,10,24]. CNNs are also used to improve the efficiency of transport systems in smart cities in several ways, such as identification of traffic signs, vehicle detection and counting, traffic flow prediction, and identification of vehicles violating rules.

The commonly used key components of a traffic control system using live camera feed are as follows:.

1) Cameras: Cameras will be installed at key points in the traffic network to capture live video feeds of traffic flow.
2) Computer vision algorithms: Computer vision algorithms will be used to analyze the video feed and identify vehicles, pedestrians, and other objects in the scene[25]. The algorithms will also detect patterns in traffic flow and make adjustments to traffic control devices accordingly.
3) Traffic control devices: Traffic control devices such as traffic lights, variable message signs, and lane control devices will be used to regulate traffic flow. These devices will be adjusted in real time based on the analysis of the video feed.
4) Communication network: A communication network will be used to connect the cameras, computer vision algorithms, and traffic control devices.
5) Central control center: A central control center will be responsible for receiving and analyzing the video feed and making adjustments to traffic control devices. The control center will also provide real-time updates to drivers and pedestrians about traffic conditions.

3. Case study: Adaptive traffic control system through live video feed analytics

Through a comprehensive examination of existing methodologies, this section presents a case study for a sustainable and adaptive traffic control system. This case study represents a traffic management solution proposed for an Indian smart city, Vadodara, Gujarat. We have given two options for traffic control, namely regular traffic flow signal and adaptive traffic flow signal. Regular traffic flow works in the clockwise direction and gives the green signal at lane no. 1; after that, the signal turns red, and the next lane no. 2 has been given the green signal, and similarly for the other two lanes. When the loop of lane number value reaches a threshold, the signal switches to adaptive mode. The proposed adaptive traffic control system consists of three main components: (1) a live camera feed, (2) a pre-trained CNN, and (3) a real-time traffic control algorithm. This system works in three phases, as shown in **Figure 2**. The first phase is CNN model training using You Look Only Once (YOLO); the second phase detects vehicles and counts them; and the third phase generates a timer for signal generation.

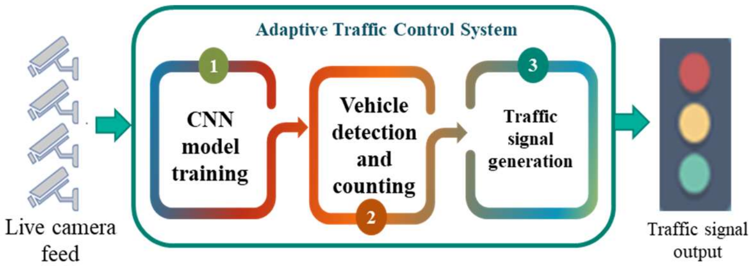


Figure 2. Blocks diagram of proposed traffic control system.

3.1. Methodology

A set of four cameras is used to acquire real-time video frames of the traffic flow through the road, considering four lanes of a traffic junction, namely lane 1, lane 2, lane 3, and lane 4. **Figure 3** shows a flow diagram of an adaptive traffic control system. Initially, the video from the camera installed at a lane where there is a red signal will be sent for processing. Then the YOLO model with the background detector performs object detection, calculates the vehicle count, and sets the lane priorities accordingly.

Each lane will have the same maximum time, indicating how long the green signal will be there. The signals will turn green lane by lane so that there won't be a long waiting time for any lane with a smaller number of vehicles. If the lane is empty, then no green signal will be turned on for that lane till its vehicle count reaches the threshold. The vehicle count for each lane is calculated based on the vehicle category. For example, heavy transport vehicles such as trucks and containers will have more density as compared to vehicles like cars and bikes. Based on vehicle count and given threshold value as two criteria, the timer value is calculated. Finally, the signals are adjusted as per the timer value adaptively.

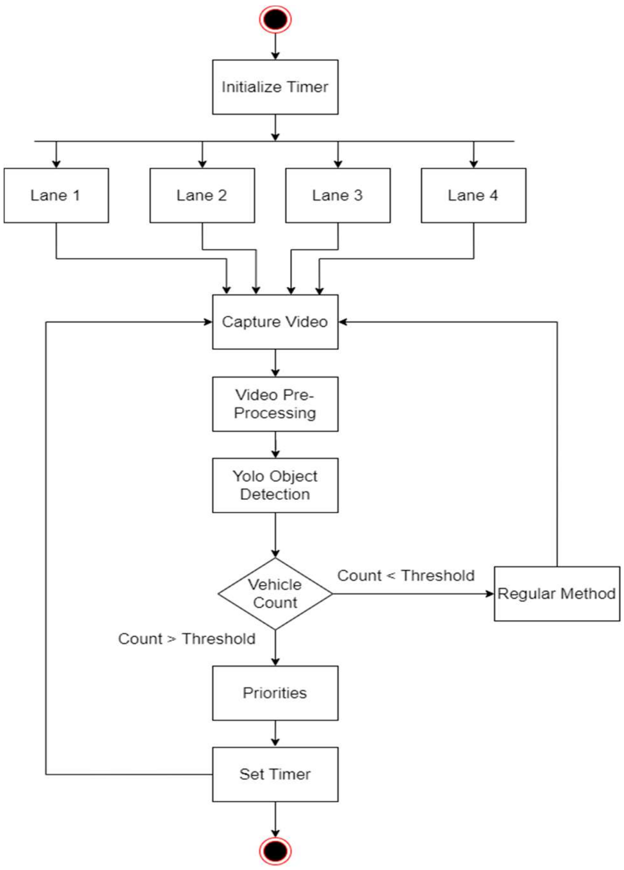


Figure 3. Flow diagram of adaptive traffic control system.

3.1.1. Model preparation

A pre-trained CNN is fine-tuned using transfer learning for vehicle detection. We used YOLO v4 as a pre-trained model trained to recognize approximately. eighty objects of different classes from the Common Objects in Context (COCO) dataset. YOLO v4 is designed to be rapid and efficient and enables real-time vehicle detection in real-world traffic situations where the ability to instantly notice and respond to changes in traffic patterns is vital. YOLO uses a convolutional neural network to swiftly detect objects in real time. The training of YOLO only requires one forward propagation through the network to detect objects. In comparison to the early version of YOLO, we got an improvement of more than 10% in the mean Average Precision (mAP) in vehicle detection to 41.46% using YOLO v4.

3.1.2. Vehicle detection

The obtained frame from live video is processed by the pre-trained CNN model, which counts the number of Jeeps, cars, buses, bicycles, trucks, and bikes on the road. Once the total number of vehicles present in a single frame of the video is found, the next step is to generate an array with vehicle counts with category, time, color of signal, and camera ID. When an object of a specified vehicle class is found, then the respective bounding box is identified. The algorithm usually divides the input image into grids up to 13 × 13 or 19 × 19. Every grid can detect either the complete bounding box or parts of bounding boxes. Every object has a bounding box associated with it, and every bounding box has a center (x, y) coordinate. The model will predict the object where the (x, y) center is located. **Figure 4** shows a sample output of the vehicle detection module of the adaptive traffic control system.

Figure 4. Vehicle detection.

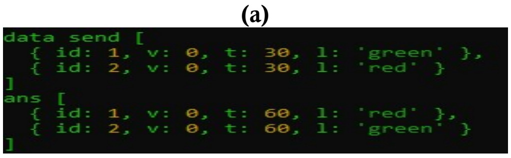
3.1.3. Signal generation

Finally, the timer value is calculated based on the vehicle count received from the vehicle detector module. After every fifty seconds elapsed, the server collects the frames from the scheduled camera to get current data of a particular traffic lane whose signal is red currently. The generated array in array form, like [{cam id: 1, vehicles: 10, time: 20, signal light: green}], from all four cameras together is sent to the main server. **Figure 5** illustrates the sample arrays received on the server. The timer is set as per the number of vehicles on the given lane to generate the signal. The following equation has been used to calculate the green signal time for each lane:

$$\text{Signal\_time} = 2 \times \text{no. of vehicles} + \text{remaining\_time}$$

where 2 secon+ds have been given to each vehicle for time to cross the signal and remaining_time denotes the previous remaining time in case of low traffic.

(a)



(b)

Figure 5. (a) array generated at client side; **(b)** vehicle count data sent to the server.

We used a Python module "pygame" to showcase the working of signals at a junction using an adaptive traffic control system. **Figure 6** illustrates a virtual environment that simulates the traffic lights. The simulation shows real-time data on traffic patterns and changes in signal at each lane based on traffic conditions.

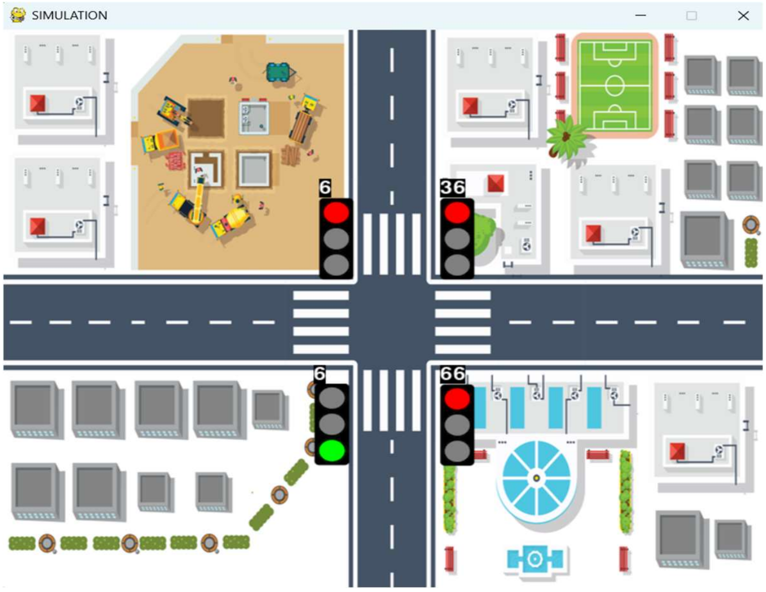


Figure 6. Simulation of the traffic junctions utilizing the proposed system.

4. Discussion and future direction

The adaptive traffic control system presented in the case study continuously analyses live video feeds from multiple surveillance cameras to provide a comprehensive understanding of traffic patterns and allows for proactive management of traffic flow. It is best suited for real-time applications that require precise and accurate object detection in images and videos, such as traffic monitoring, surveillance, and security systems. Proactive signal adjustments can be done by analyzing historical data and incorporating real-time information in the future for the implementation of congestion management strategies. This solution tackles key challenges such as traffic jams, long wait times at intersections, and wasted fuel consumption, ultimately leading to smoother traffic operations and a better commuting experience for motorists and pedestrians alike.

In the future, the system can empower citizens by providing accessible and real-time traffic information to make informed decisions about their travel routes and modes, fostering a sense of ownership and engagement in managing urban traffic. As autonomous vehicles become more prevalent, this system can be integrated with autonomous vehicles to enable smoother coordination between traffic signals and autonomous vehicles. Furthermore, this system can be expanded by integrating the traffic signal system with IoT devices and data from sensors, such as vehicle detectors, pedestrian counters, or air quality monitors, to get additional insights to enhance traffic management strategies.

Moreover, the integration of traffic analytics and air quality monitoring systems allows for real-time tracking and analysis of pollutants across different traffic junctions. Continuous monitoring and data analysis of environmental sensors placed strategically across a city can provide valuable insights to uncover pollutant factors and locate congestion hotspots. This information can help transportation authorities implement targeted strategies to mitigate air pollution, such as promoting electric vehicles, implementing low-emission zones, or adjusting traffic patterns to reduce emissions hotspots. By combining congestion management and air pollution reduction strategies, efficient transport systems can foster sustainable urban mobility and improve the overall liability of cities. Integrating live video feed analytics into smart city traffic control systems holds immense promise for optimizing traffic flow and enhancing safety. However, this path is paved with its own set of issues, challenges, and recent hiccups. Let's delve into each:

4.1. Issues

1) Data privacy concerns: Public surveillance through cameras raises concerns about data privacy and potential misuse. Balancing traffic management benefits with individual privacy requires robust regulations and ethical frameworks.
2) Algorithmic bias: AI-powered video analytics algorithms can inherit biases from training data, leading to unfair or discriminatory traffic management decisions. Mitigating bias requires diverse datasets and careful algorithm design.
3) Technical hurdles: Live video analytics require robust infrastructure, including high-bandwidth networks, edge computing capabilities, and reliable data storage. Scalability and cost effectiveness can be hurdles.
4) Interoperability issue: Integrating video analytics with existing traffic control systems and software can be complex, requiring interoperability and data standardization across different platforms.

4.2. Challenges

1) Weather and lighting conditions: Rain, fog, and low-light conditions can significantly impact the accuracy of video analytics algorithms, posing challenges in dynamic weather environments.
2) Occlusions and object complexity: Complex traffic scenes with occluded vehicles, pedestrians, and diverse object types can confuse algorithms, requiring advanced computer vision techniques.
3) Cybersecurity threats: Video analytics systems are vulnerable to cyberattacks, potentially compromising traffic data and disrupting control systems. Robust cybersecurity measures are crucial.
4) Public acceptance and trust: Gaining public trust in video analytics-based traffic management requires transparency, clear communication, and demonstrably positive outcomes.

4.3. Opportunities

1) Real time traffic insights: Live video analytics provides real-time data on traffic volume, speed, violations, and incidents, enabling dynamic adjustments to traffic signals and routing strategies.
2) Improved safety and emergency response: Early detection of accidents, congestion, and hazardous events through video analytics can improve emergency response time and prevent accidents.
3) Reduced emissions and fuel consumption: Optimized traffic flow through video analytics-driven control can lead to shorter travel time, reduced congestion, and lower emissions.
4) Smarter parking management: Video analytics can automate parking space detection, optimize parking utilization, and implement dynamic pricing for efficient parking management.

4.4. Recent problems

1) Bias in pedestrian detection algorithms: Recent studies have highlighted biases in pedestrian detection algorithms, raising concerns about fairness and inclusivity.
2) Data breaches and privacy violations: Several high-profile data breaches involving traffic camera

footage have underscored the need for stronger data security measures and transparency practices.

3) Public backlash against surveillance: Concerns about overreach and lack of transparency in video surveillance programs have led to public backlash in some cities, prompting calls for stricter regulations and community oversight.
4) Maintenance and calibration: Regular maintenance and calibration of cameras and analytics systems are crucial to ensure accurate results. Failure to perform these tasks can lead to false readings and decreased system reliability.

5. Conclusion

Enhancing traffic control systems with live video analytics presents a powerful opportunity for smarter and safer cities. However, navigating the issues, challenges, and recent problems requires a nuanced approach that prioritizes data privacy, algorithmic fairness, robust infrastructure, and public trust. By addressing these concerns and harnessing the technology's potential responsibly, we can pave the way for a future where traffic flows smoothly, efficiently, and safely in our smart cities. This paper presents valuable insights to urban planners, policymakers, and technocrats of intelligent traffic control systems in the evolving landscape of smart cities. The detailed literature survey can provide a foundation for the continued development and implementation in the field of smart transportation.

Furthermore, we have presented a case study to showcase a novel framework for enhancing traffic control using live camera feeds and pre-trained convolutional neural networks. This system is capable of detecting vehicles in real time and making intelligent decisions based on the detected traffic patterns. The system employs a pre-trained CNN for vehicle detection and counting and a real-time traffic control algorithm for manipulating signal timers to achieve adaptive signal control. Furthermore, the proposed system provides a cost-effective and efficient solution to the problem of traffic congestion in urban areas. The experimental results show that convolutional neural network-based traffic video processing is a useful tool to control road congestion. It envisions reality, so it works far superior to existing systems.

Author contributions

Conceptualization, DKS, PS and AG; methodology, DKS, PS and AG; software, DKS; validation, DKS, PS and AG; formal analysis, DKS; investigation, DKS; resources, DKS; data curation, DKS; writing—original draft preparation, DKS, PS and AG; writing—review and editing, DKS, PS and AG; visualization, DKS; supervision, AG; project administration, DKS; funding acquisition, DKS and PS. All authors have read and agreed to the published version of the manuscript.

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Conflict of interest

The authors declare no conflict of interest.

References

1. Afrin T, Yodo N. A Survey of Road Traffic Congestion Measures towards a Sustainable and Resilient Transportation System. Sustainability. 2020; 12(11): 4660. doi: 10.3390/su12114660
2. Aleko DR, Djahel S. An Efficient Adaptive Traffic Light Control System for Urban Road Traffic Congestion Reduction in Smart Cities. Information. 2020; 11(2): 119. doi: 10.3390/info11020119
3. Fattah MdA, Morshed SR, Kafy AA. Insights into the socio-economic impacts of traffic congestion in the port and industrial areas of Chittagong city, Bangladesh. Transportation Engineering. 2022; 9: 100122. doi: 10.1016/j.treng.2022.100122
4. Chakraborty P, Adu-Gyamfi YO, Poddar S, et al. Traffic Congestion Detection from Camera Images using Deep Convolution Neural Networks. Transportation Research Record: Journal of the Transportation Research Board. 2018; 2672(45): 222-231. doi: 10.1177/0361198118777631
5. Chin J, Callaghan V, Lam I. Understanding and personalising smart city services using machine learning, The Internet-of-Things and Big Data. In: Proceedings of the 2017 IEEE 26th International Symposium on Industrial Electronics (ISIE); 19-21 June 2017; Edinburgh, UK. pp. 2050-2055. doi: 10.1109/isie.2017.8001570
6. Kleine Deters J, Zalakeviciute R, Gonzalez M, et al. Modeling PM2.5 Urban Pollution Using Machine Learning and Selected Meteorological Parameters. Journal of Electrical and Computer Engineering. 2017; 2017: 1-14. doi: 10.1155/2017/5106045
7. Ameer S, Shah MA, Khan A, et al. Comparative Analysis of Machine Learning Techniques for Predicting Air Quality in Smart Cities. IEEE Access. 2019; 7: 128325-128338. doi: 10.1109/access.2019.2925082
8. Srivastava S, Divekar AV, Anilkumar C, et al. Comparative analysis of deep learning image detection algorithms. Journal of Big Data. 2021; 8(1). doi: 10.1186/s40537-021-00434-w
9. Bahiru TK, Kumar Singh D, Tessfaw EA. Comparative Study on Data Mining Classification Algorithms for Predicting Road Traffic Accident Severity. In: Proceedings of the 2018 Second International Conference on Inventive Communication and Computational Technologies (ICICCT); 20-21 April 2018; Coimbatore, India. pp. 1655-1660. doi: 10.1109/icicct.2018.8473265
10. Athiappan K, Karthik C, Rajalaskshmi M, et al. Identifying Influencing Factors of Road Accidents in Emerging Road Accident Blackspots. Advances in Civil Engineering. 2022; 2022: 1-10. doi: 10.1155/2022/9474323
11. Katuk N, Wan Abdullah WAN, Sugiharto T, et al. Smart technology: Ecosystem, impacts, challenges and the path forward. Information System and Smart City. 2023; 3(1). doi: 10.59400/issc.v3i1.63
12. Saleem M, Abbas S, Ghazal TM, et al. Smart cities: Fusion-based intelligent traffic congestion control system for vehicular networks using machine learning techniques. Egyptian Informatics Journal. 2022; 23(3): 417-426. doi: 10.1016/j.eij.2022.03.003
13. Anwar AHMM, Oakil AT. Smart Transportation Systems in Smart Cities: Practices, Challenges, and Opportunities for Saudi Cities. In: Belaïd F, Arora A (editors). Smart Cities: Social and Environmental Challenges and Opportunities for Local Authorities. Cham: Springer International Publishing; 2024. pp. 315-337.
14. Oladimeji D, Gupta K, Kose NA, et al. Smart Transportation: An Overview of Technologies and Applications. Sensors. 2023; 23(8): 3880. doi: 10.3390/s23083880
15. Mahdavinejad MS, Rezvan M, Barekatain M, et al. Machine learning for internet of things data analysis: a survey. Digital Communications and Networks. 2018; 4(3): 161-175. doi: 10.1016/j.dcan.2017.10.002
16. Sharma P, Raglin A. Iot in smart cities: Exploring information theoretic and deep learning models to improve parking solutions. In: Proceedings of the 2019 IEEE SmartWorld, Ubiquitous Intelligence & Computing, Advanced & Trusted Computing, Scalable Computing & Communications, Cloud & Big Data Computing, Internet of People and Smart City Innovation (SmartWorld/SCALCOM/UIC/ATC/CBDCom/IOP/SCI); 19-23 August 2019; Leicester, UK. pp. 1860-1865.
17. Aboualmal A. Artificial Intelligence for IoT & Smart Cities. Available online: https://www.itu.int/en/ITU-T/Workshops-and-Seminars/201812/Documents/S3-Pres2-Abdulahhi%20AI%20for%20IoT%20and%20Smart%20City_v3.pdf (accessed on 12 December 2023).
18. Jan MA, He X, Song H, et al. Editorial: Machine Learning and Big Data Analytics for IoT-Enabled Smart Cities. Mobile Networks and Applications. 2021; 26(1): 156-158. doi: 10.1007/s11036-020-01702-4
19. Prasad MVD, Kumar EK, Krishna SVNPV, et al. Detection of two wheelers helmet using machine learning. Turkish Journal of Physiotherapy and Rehabilitation. 2021; 32(2): 1-8.
20. Hilmani A, Maizate A, Hassouni L. Automated Real-Time Intelligent Traffic Control System for Smart Cities Using Wireless Sensor Networks. Wireless Communications and Mobile Computing. 2020; 2020: 1-28. doi: 10.1155/2020/8841893

21. Rachmadi MF, Al Afif F, Jatmiko W, et al. Adaptive traffic signal control system using camera sensor and embedded system. In: Proceedings of the TENCON 2011 - 2011 IEEE Region 10 Conference; 21-24 November 2011; Bali, Indonesia. pp. 1261-1265. doi: 10.1109/tencon.2011.6129009
22. Fedorov A, Nikolskaia K, Ivanov S, et al. Traffic flow estimation with data from a video surveillance camera. Journal of Big Data. 2019; 6(1). doi: 10.1186/s40537-019-0234-z
23. Asha CS, Narasimhadhan AV. Vehicle Counting for Traffic Management System using YOLO and Correlation Filter. In: Proceedings of the 2018 IEEE International Conference on Electronics, Computing and Communication Technologies (CONECCT); 16-17 March 2018; Bangalore, India. pp. 1-6. doi: 10.1109/conecct.2018.8482380
24. Iwasaki Y, Misumi M, Nakamiya T. Robust Vehicle Detection under Various Environments to Realize Road Traffic Flow Surveillance Using an Infrared Thermal Camera. The Scientific World Journal. 2015; 2015: 1-11. doi: 10.1155/2015/947272
25. Terven J, Cordova-Esparza D. A Comprehensive Review of YOLO: From YOLOv1 and Beyond. Available online: https://www.researchgate.net/publication/369760111_A_Comprehensive_Review_of_YOLO_From_YOLOv1_to_YOLOv8_and_Beyond (accessed on 12 December 2023).