An artificial intelligence-based approach for avoiding traffic congestion in connected autonomous vehicles

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Abstract: The Internet of Vehicles (IoV) has led to the emergence of sustainable smart roads. Recent advancements in this field have focused on improving traffic flow and reducing congestion using intelligent systems. In this paper, we propose a novel approach called the 'Traffic Congestion Avoidance Approach (TCAA)'. Our approach leverages IoV technologies and deep learning algorithms to create a more responsive and efficient traffic management system. The IoV model facilitates communication between autonomous vehicles, allowing them to coordinate movements and optimise traffic flow seamlessly. Additionally, deep learning algorithms analyse real-time data, to predict and mitigate congestion dynamically. The performance evaluation of TCAA demonstrates the potential of intelligent traffic regulation systems. The union of IoV and deep learning technologies provides a robust solution to contemporary traffic challenges, paving the way for smarter, more sustainable urban mobility. This research underscores the transformative potential of AI-powered IoV systems in creating the smart roads, ultimately enhancing the quality of life in smart cities.

Keywords: internet of vehicles; artificial intelligence; traffic regulation; avoidance congestion; smart roads.

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1 Introduction

Road transportation plays a crucial role in the social and economic development of a country. The concept of a smart city has gained popularity as a vision for future urbanism that proposes smart solutions to deep-seated problems. A smart city utilises big data technology, Artificial Intelligence (AI), cloud computing and the Internet of Things (IoT) to integrate urban resources. This digital environment encourages learning and creativity, which contributes to a more sustainable and healthy living situation. IoT technologies provide communications among heterogeneous devices to enable smart services in different contexts. IoT technology is increasingly being used to improve the efficiency of a variety of industries and businesses, including smart cities, healthcare, transportation and logistics. However, traffic congestion remains a major issue in many cities worldwide. This has led to the development of new traffic control techniques and new technologies to improve road management. The question then arises: why do we need smart roads? The advancements in IoT, AI and centralised control systems have enabled governments to save energy and improve traffic management. These technologies have also been successfully implemented in other areas, such as the environment, agriculture, finance, healthcare and education. To address the challenge of traffic congestion, innovative approaches are needed, such as leveraging deep learning and the Internet of Vehicles (IoV). Deep learning, a subset of AI, is capable of analysing complex data patterns, while the IoV enables seamless communication between vehicles and infrastructure. In this article, we explore the contributions of deep learning and IoVto regulating traffic congestion and improving urban mobility. These technologies have also been applied in other areas, such as smart grids for managing electrical networks, providing information on energy consumption patterns and using smart metres to improve energy efficiency. Modern applications also help in avoiding traffic congestion, improving traffic flow and monitoring pollution levels. There is also a trend towards developing autonomous car fleet networks for on-demand personal transportation and providing secure electronic financial services, especially through the most secure block chain technology.

The rest of the article is organised as follows: Section 2 discusses the problem statement and related work, while Section 3 describes the various traffic congestion models. Section 4 describes our congestion traffic avoidance approach, which is followed by a scenario description in Section 5. Section 6 presents the simulation results and performance evaluation. Finally, Section 7 summarises the paper and discusses potential future work.

2 Related works

Methods for traffic flow avoidance have received significant attention in recent years due to the exponential development of intelligent cities and transportation systems. In order to create an effective traffic schedule for the entire road network, Younes and Boukerche (2015) suggested a smart traffic light-control algorithm for arterial streets that should be placed at each road intersection. Recent studies have integrated deep learning and IoV technologies to develop more effective traffic congestion regulation methods. Deep Learning (DL) has been recognised as an advanced development pillar of traditional machine learning methods, allowing for the analysis of spatial-temporal characteristics of traffic flow. For example, Zhang et al. (2016) developed a deep learning-based model that utilises historical traffic data and external factors such as weather conditions and events to forecast traffic flow. Other researchers have also applied deep learning techniques, such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), to accurately predict traffic patterns. Chen et al. (2019) proposed a deep learning framework that combines vehicle trajectory data with traffic flow data to predict congestion levels on road networks. Additionally, deep learning models have been used to predict real-time traffic congestion by incorporating data from IoV devices. These technologies enable the development of intelligent traffic management systems that can dynamically adjust traffic flow. Several studies have explored the use of IoV technologies for traffic light optimisation and intersection management. For instance, Li and Ban (2020) proposed an IoV-based traffic light control system that utilises vehicle trajectory data to optimise signal timing and reduce congestion at intersections**.** The emergence of autonomous vehicles also presents new opportunities for traffic congestion regulation. Tran et al. (2018) developed a distributed control framework by creating cooperative driving algorithms for autonomous vehicles to navigate complex traffic scenarios efficiently, merge into traffic flow, and mitigate congestion. Short-term traffic flow prediction, which refers to a few minutes into the future, has also been a topic of interest in recent studies. Researchers have explored the integration of deep learning and IoV technologies to develop more effective traffic congestion prediction methods. These methods can be divided into two categories: statistical and artificial prediction methods. For example, Du et al. (2018) proposed a hybrid multimodal deep learning strategy for short-term traffic flow prediction that takes into account the dependencies between traffic predictors. Similarly, Abdelatif et al. (2020) created a vehicular-cloud simulation framework that uses a learning algorithm to tackle the regression problem by forecasting the values of a continuous measure. Dependency can be recorded using one-dimensional Convolutional Neural Networks (CNNs) and Gated Recurrent Units (GRUs). The performance of this prediction architecture has shown promising results in terms of accuracy. Additionally, Boukerche and Wang (2020) described a new hybrid deep learning model that integrates GCN with an attention-based sequence-to-sequence model with a bi-directional GRU kernel. Sun et al. (2019, 2020) also proposed a new Selected

Stacked Gated Recurrent Units model (SSGRU) based on a machine learning model. Most research in this field focuses on predicting traffic congestion rather than avoiding it. For example, Yao and Qian (2021) developed a traffic prediction model based on tweet information collected before midnight to make accurate predictions for the next morning's traffic. In the following, we review previous research across several themes related to the context discussed earlier.

Table 1 Review of previous research

Field	*Authors*	*Publication Year*	*Title*	*Focus*
Deep learning for traffic prediction and management	Joseph et al.	2021	A novel hybrid deep learning algorithm for smart city traffic congestion predictions.	explores the use of deep learning models to predict traffic patterns using IoV data and optimise traffic signal control for improved urban mobility.
	Zhou et al.	2020	DRLE: Decentralised reinforcement learning at the edge for traffic light control in the IoV.	present a deep reinforcement learning framework integrated with IoV for adaptive traffic signal control to reduce congestion and enhance traffic flow.
	Xiaet al.	2020	Shift control of vehicle automatic transmission based on traffic congestion identification.	The study demonstrates that the T-S fuzzy neural network and the layered correction shift control strategy effectively manage vehicle gear shifting under congested conditions. This approach reduces gear wear and braking system strain, contributing to more efficient and durable vehicle operation in traffic.
IoV and AI Integration for Smart Road	Ali et al.	2021	Machine learning technologies for secure vehicular communication in the internet of vehicles: recent advances and applications.	This paper discusses how IoV and deep learning integration can be leveraged to improve traffic management and reduce congestion in smart cities.

Table 1 Review of previous research (continued)

Field	*Authors*	*Publication Year*	*Title*	*Focus*
	Nie et al.	2020	Data-driven intrusion detection for the intelligent internet of vehicles.	The study presents a novel approach to traffic management by integrating IoV data with deep neural network models to predict and manage traffic conditions in real-time.
	Patel et al.	2022	**Traffic sign recognition using deep learning.**	This paper utilises Convolutional Neural Networks (CNNs) to recognise traffic signs using the GTSRB data set. The model, trained with the Adam optimiser, achieved optimal performance.
Sustainability in Smart Cities Using AI and IoV	Narsimhulu et al.	2024	An intelligent FL-based vehicle route optimisation protocol for green and sustainable IoT-connected IoV, the Internet of Things.	The authors explore how deep learning and IoV technologies can be integrated to promote sustainability in smart cities through efficient traffic management and reduced emissions.
	Hildebrand et al.	2023	A comprehensive review of blockchains for the Internet of Vehicles: Challenges and Directions.	This review paper discusses various AI and IoV applications, focusing on how deep learning models can be used for sustainable urban development.
Case Studies and Real-World Implementations	Bibri and Krogstie	2020	The emerging data-driven Smart City and its innovative applied solutions for sustainability: the cases of London and Barcelona.	The authors detail Barcelona's efforts to integrate deep learning and IoV technologies into its smart city initiatives, highlighting successes and lessons learned.
	Reza	2023	AI-Driven Solutions for Enhanced Waste Management and Recycling in Urban Areas.	The authors discuss the implementation of cognitive AI systems to manage dynamic urban environments, focusing on real-time analytics and predictive modelling.

Table 1 Review of previous research (continued)

Field	*Authors*	*Publication Year*	*Title*	*Focus*
AI and IoV Integration for Traffic Management	Rangari et al.	2022	Deep learning-based smart traffic light system using image processing with Yolo v7.	This study presents a deep learning framework for optimising traffic signals using IoV data, demonstrating improved traffic flow and reduced congestion.
	Koch et al.	2023	Adaptive Traffic Light Control with Deep Reinforcement Learning: An Evaluation of Traffic Flow and Energy Consumption.	The authors propose an adaptive traffic signal control system using deep reinforcement learning and IoV data, achieving significant improvements in traffic efficiency.
	Singh	2023	Deep Reinforcement Learning (DRL) for Real-Time Traffic Management in Smart Cities.	The author proposes a deep learning-based adaptive traffic signal control system that leverages IoV data to optimise traffic flow and reduce congestion.
	Rahman	2024	Deep Reinforcement Learning for Adaptive Traffic Signal Control in Smart Cities: An Intelligent Infrastructure Perspective.	This paper presents a reinforcement learning approach for real-time traffic signal control to transform urban traffic management and create a more sustainable, efficient and effective smart city.

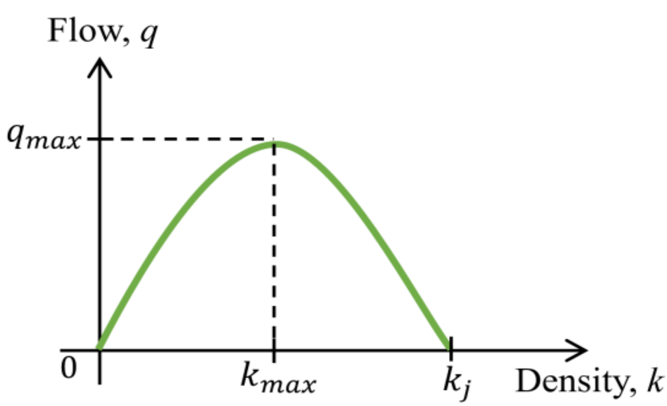
However, no avoidance methods are discussed. In the newly designed TCA model, researchers aim to develop adaptive traffic management systems that can respond to changing traffic conditions in real-time by stacking two layers and combining deep learning-based traffic prediction models with real-time data from IoV devices. In summary, the integration of deep learning and IoV technologies shows great potential for revolutionising traffic congestion regulation and improving urban mobility. By harnessing the power of AI and connectivity, researchers and practitioners can develop innovative solutions to address the challenges of congestion and pave the way for smarter, more efficient transportation systems.

3 Traffic congestion model

Traffic safety has been a pressing issue for a considerable amount of time and has garnered widespread attention. Despite efforts to address it, traffic congestion continues to significantly disrupt the well-being of citizens, transportation activities and government services. To mitigate this problem, traffic congestion models have been developed to control and manage traffic and provide effective solutions. Globally, a significant amount of work hours are lost due to traffic jams, as highlighted in a study by Faheem (2024). One potential solution to this issue is the use of connected car technologies, which utilise intelligent systems to optimise road space and reduce congestion, as suggested by Boban et al. (2018). The following are key characteristics of a macroscopic traffic congestion model:

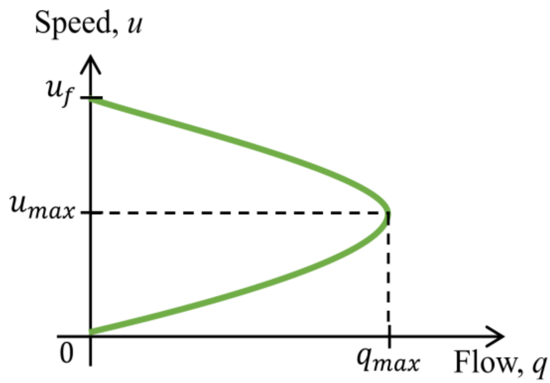
- *Flow (q):* The rate of vehicles passing a specific point within a given time period (measured in vehicles per hour).
- *Density (ρ):* The number of vehicles per unit length of roadway.
- *Speed (V):* The average speed of vehicles on the roadway (miles per hour or kilometres per hour).
- *Flow-Density Relationship:* This describes how traffic flow (the rate of vehicles passing a point per unit time) varies with traffic density (the number of vehicles per unit length of roadway). In congested conditions, flow typically decreases as density increases due to interactions between vehicles as the figure below shows.

Figure 1 Flow-density relationship (see online version for colours)



- *Speed-Flow Relationship:* This relationship illustrates how the average speed of traffic varies with flow rate. In congested conditions, average speeds typically decrease as flow decreases due to increased interactions and reduced spacing between vehicles as the Figure 2 shows.

Figure 2 Speed-flow relationship (see online version for colours)



The fundamental diagram typically relates flow (Q) to density (ρ) and speed (V) through equation (1), which can be expressed as

$$q = V . \rho \quad (1)$$

This equation represents the fundamental relationship between flow, density and speed. It states that flow is equal to the product of density and speed.

- *Congestion Formation:* The model should account for how congestion forms as traffic density approaches or exceeds the capacity of the roadway. This often involves the emergence of stop-and-go waves or queues of vehicles.
- *Capacity Constraints:* It considers the maximum flow rate that the roadway can handle under ideal conditions. Congestion occurs when demand exceeds this capacity.
- *Travel Time Estimation:* The model may provide estimates of travel times under varying traffic conditions, taking into account the effects of congestion. This is essential for effective transportation planning and management.
- *Congestion Dissipation:* The model also describes how congestion dissipates over time as flow conditions change. This can occur through the clearing of incidents, changes in demand, or improvements in roadway conditions.
- *Impact of Control Measures:* Additionally, the model can evaluate the effectiveness of different traffic management strategies, including ramp metering, variable speed limits and lane control, in reducing congestion. Many transportation communities are currently prioritising the development of Intelligent Traffic Regulation Systems (ITRS) to improve traffic safety. These systems utilise smart cities as a foundational infrastructure to make citizens' daily lives easier by addressing common issues such as traffic congestion and promoting carpooling. In this article, we will introduce the key terms used in our proposed congestion model, beginning with:
- *Congestion Description Message (CDM):* refers to a message that includes data about congestion location, which is sent out by witness vehicles or by the subject vehicle in the vicinity. This type of message contains the following fields:

Congestion Location (CL), Congestion Data Identification (CDI), Congestion Start Time (CST) and Congestion end Time (CET). The congestion location data is identified by the GPS system. The Congestion Data Identification (CDI) refers to data relating to sudden problems on the road or within the vehicle system. This data can include information about engine problems, variations in velocity and practical vehicle and drive data during and after the congestion. The Congestion short-term Period (CP) is calculated as follows:

$$CP = CET - CST \tag{2}$$

- We consider these cases based on the density of each traffic flow and the saturation density of that traffic flow, which is represented by the Saturation Density Factor (*SD-F*). Equation (3) computes the Saturation Density Factor $(SDFi)$ for each traffic flow, i.e., (*i*). *SDFi* is used to schedule the phases of each cycle at any traffic light located on an arterial street, as illustrated in Faheem et al. (2024).

Thus,

$$SDF_i = di / Sdi \tag{3}$$

where *di* represents the density of traffic flow *i*, and *Sdi* is the density required to completely saturate traffic flow *i*. The value of *SDFi* varies between 0 and 1, indicating that there are no cars on traffic flow, and a value of 1 indicates that the current traffic density (di) is equal to *Sdi*.

- *Data Collection Message (DCM):* is a tool to gather information about vehicle congestion, such as location, direction, sources and destination. Its purpose is to provide accurate information about current congestion. The collected data is transmitted to a cloud service through vehicle-to-vehicle and vehicle-to-everything communications. The cloud service uses this data to make informed decisions about vehicles.
- *Notification Decision-AI-Message-(NDM):* is a warning message generated by the AI ecosystem service and sent to drivers who are near a congested area. The NDM includes data such as new deviation, traffic velocity and estimated travel time in order to decrease the frequency and severity of road congestion, minimise driving risks and suggest alternative routes with less congestion. These notification messages are transmitted through the communication layer to all connected vehicles.

4 Traffic congestion avoidance approach (TCAA)

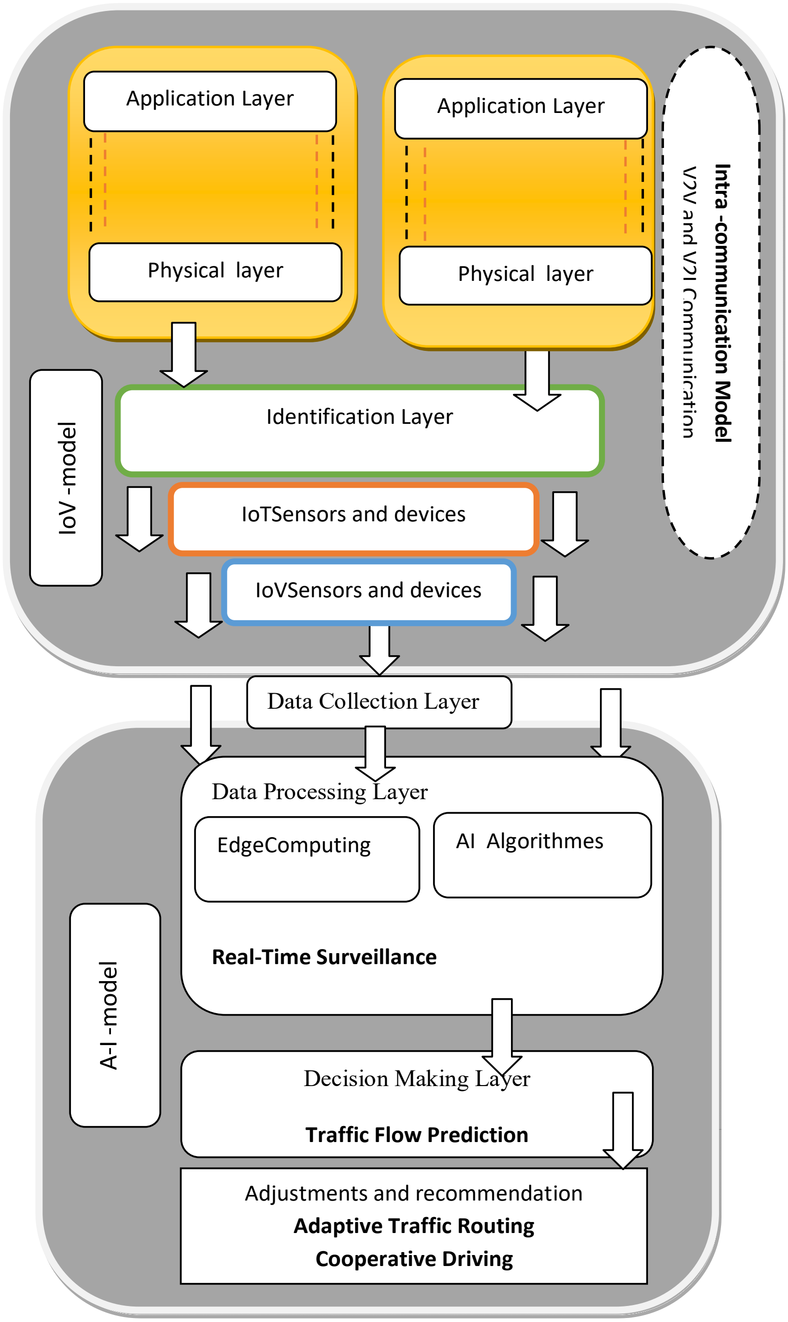
This section presents the main elements of the new architecture called the '*Traffic Congestion Avoidance Approach*'. The following diagram illustrates the elements of the Traffic Congestion Avoidance Approach (TCAA-IoV) and the components of its layered structure. Our approach is divided into two main sections: the IoV model, which consists of seven layers, and the AI module, which includes four layers: the traffic data collection layer, the traffic data processing layer, the traffic flow prediction layer and the decision-making layer.

4.1 IoV architecture part

In a smart road scenario, many physical objects or more precisely, 'smart' objects with their own processors, computing power and communication capabilities, can interact with each other. These smart things, also known as the Internet of Things (IoT), contribute to a safer and more intelligent environment by increasing interconnection and interoperability. As part of the IoT, many objects will be connected vehicles or cars that can communicate and interact wirelessly with different types of devices connected to the internet, both inside and outside the car. This is known as V2V and V2I, which leverage traffic management systems with data related to the speed and position of every vehicle, efficiently controlling the flow of traffic (Boban et al., 2018). This data significantly reduces the time involved in urban congestion, finding parking spots and fuel consumption. This leads to a specific and personalised type of IoT called the Internet of Vehicles (IoV), which enables unified management in intelligent transportation. Digital technology plays a pivotal role in shaping the development and functioning of smart roads in numerous ways. Digital sensors, IoT devices and other data-gathering technologies allow roads to collect vast amounts of data from various sources, such as traffic cameras, environmental sensors and public infrastructure. This data is then analysed in real-time to derive valuable insights into urban dynamics, allowing for informed decision-making by city officials. It can also track environmental indicators such as air quality, temperature and pollution levels, informing environmental management strategies, supporting sustainability initiatives and helping roads mitigate the impacts of climate change. Digital platforms and applications facilitate smarter transportation systems, including real-time traffic management, public transit tracking and ride-sharing services.

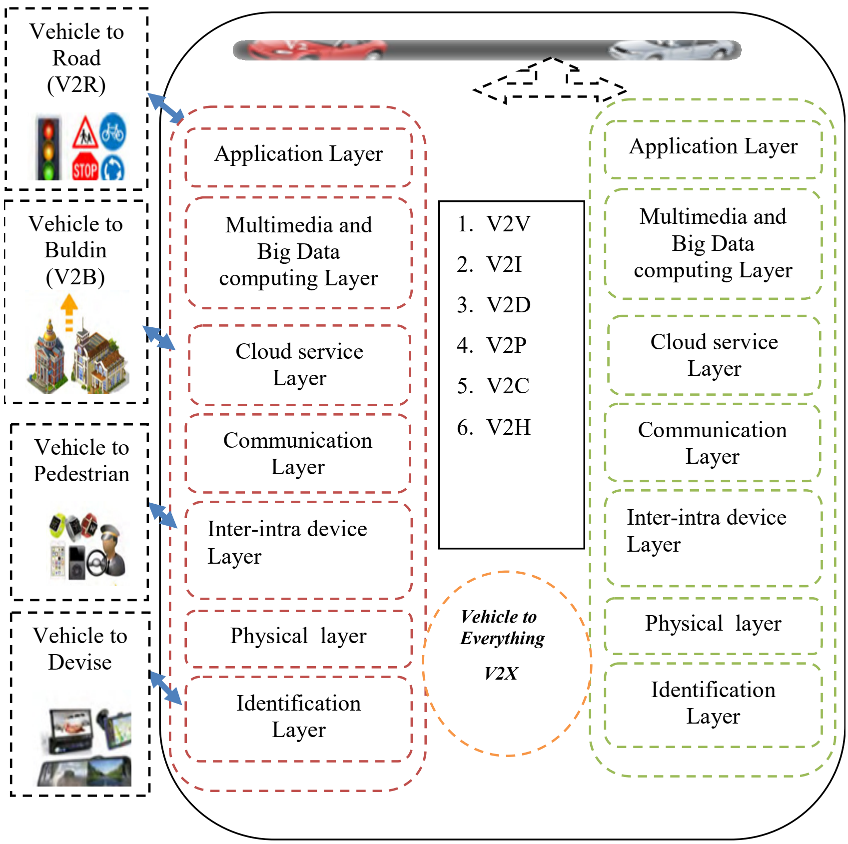
By integrating data from various transportation modes, cities can improve mobility, reduce congestion and enhance accessibility for residents. Digital tools like Geographic Information Systems (GIS) and Building Information Modelling (BIM) enable urban planners and architects to visualise, simulate and optimise urban designs. These technologies enhance the efficiency of infrastructure development, streamline permitting processes and foster sustainable urban growth. Additionally, the various data collected by connected vehicles allow citizens to better understand the state and evolution of the road. The Internet of Vehicles (IoV) is a subset of the Internet of Things that focuses on systems related to transportation and vehicles. In this case, the object of interest is a vehicle. IoV stands for 'internet of vehicles', a massive network of interactions that describes dynamic mobile communication networks that facilitate communication between vehicles and any other object, as shown in Figure 3. These networks can use a variety of communication types, including vehicle-to-vehicle, vehicle-to-infrastructure and vehicle-to-road. They can also use vehicles to connect to smart homes, buildings, devices or anything else. Additionally, it permits data transfers from the vehicle to the sensor. The deployment of IoV in smart roads enables information sharing and collection of big data from vehicles, roads, infrastructure, buildings and their environment (Ang et al., 2019). The IoV architecture can provide smart services for transport applications to guide and supervise vehicles and provide various multimedia and mobile Internet application services, as Figure 4 shows.

Figure 3 Architecture of our approach TCAA (see online version for colours)



- *Identification layer:* Every object in our suggested ecosystem is regarded as an autonomous vehicle, and the identification layer in our suggested method (TCAA-IoV) helps to give each vehicle a unique, unambiguous identity. Two crucial characteristics that each vehicle's identification layer must provide are naming and addressing methods. The identities of vehicles can also be uniquely identified using addressing schemes (such as IPv4 and IPv6). Nevertheless, the name cannot be globally unique, and multiple cars may share the same ID number within the network. The Vehicle Identification Number (VIN), a special code used by the automotive industry to identify individual motor vehicles, or a serial number, must be used to identify the ID of the vehicle.

Figure 4 IoV-model in a smart road (see online version for colours)



- *Physical vehicles layer*: The Physical Objects Layer collects data from all objects, including vehicles and non-vehicles, within the TCAA-IoV ecosystem. This data is then transmitted to the intra-device layer for further processing. In this layer, the focus is on AI-IoV, where objects are classified as either non-vehicle objects or vehicle objects.
- *Layer inter-intra devices*: Traditionally designed IoV architectures do not include this layer; AI-IoV architecture allows for various types of communication models, such as vehicle-to-vehicle, vehicle-to-road, vehicle-to-everything. In the TCAA-IoV architecture, we have merged the inter-internal devices layer and the communication layer to connect different objects and heterogeneous networks to provide specific services.

- *Communication layer:* Its goals are to achieve low-power communications in noisy communication channels and multi-hop networks, as well as to connect various and heterogeneous devices or vehicles within the network to provide specific services.
- *Cloud service layer:* A private or public cloud can form this layer, which supplies client IoV systems with hardware computing platforms, infrastructure and software services. The scalability of IoV patterns is made possible by the parallel computing environment that cloud virtualisation technology offers. Scalable servers and storage are part of the hardware infrastructure, which provides high reliability and quick computing response. A crucial part of the software services offered to regulate access by authorised users and guarantee IoV system security is the access centre cloud.
- *Multimedia and big data computing layer*: Three components make up this layer: intelligent transport, big data and multimedia computing and data pre-processing. Large amounts of multimedia data produced by sensors, cameras and other IoV ecosystem sources are handled by this layer. Big data must be processed, stored and analysed in order to provide insightful information and aid in decision-making. Distributed computing, cloud computing and edge computing are some of the technologies that are used to effectively manage and process multimedia data in real time. In order to detect objects, identify patterns and extract pertinent information for a variety of applications, including traffic monitoring, behaviour analysis and anomaly detection, Artificial Intelligence (AI) algorithms are applied to analyse multimedia data, which includes images, videos and audio.
- *Application layer:* This layer encompasses a variety of applications tailored to meet the needs of users and stakeholders in the IoV ecosystem, such as intelligent navigation systems, predictive maintenance tools, driver assistance programmes and smart traffic management solutions. The Application Layer is responsible for delivering valuable functionalities to users, enhancing convenience, safety and efficiency in connected vehicle environments.

4.2 AI architecture part

In a smart road, IoT sensors are deployed across the road to collect real-time data on various aspects of urban life, such as traffic congestion data, incidents and road risk. The integration of Artificial Intelligence (AI), the Internet of Things and the Internet of Vehicles (IoV) into smart road infrastructure requires a comprehensive architectural framework that facilitates seamless communication, data exchange and decision-making across interconnected systems. The data collected by IoT or IoV sensors is then analysed by AI algorithms to extract useful insights and make smart decisions, such as using machine learning algorithms to analyse traffic data and predict congestion patterns, ultimately recommending alternative routes. Xiong et al. (2023) addressed abnormal IoT traffic classification, indicating that their strategies have significantly enhanced the efficiency and precision of the proposed schemes. Additionally, AI systems can analyse weather data and energy consumption to optimise operations of smart electrical grids, while AI models can predict air pollution peaks and recommend mitigation measures to protect public health. The second part of our approach will be described in the following section.

- *Data collection layer:* The first layer of the smart transportation system is the data collection layer, which consists of IoT and IoV sensors. These sensors, such as GPS, cameras and LiDAR, are installed in vehicles to collect real-time data on traffic flow, road conditions and vehicle status. Additionally, smart infrastructure, including roadside sensors, traffic cameras, and environmental monitors, captures data on urban conditions such as air quality and weather.
- *Data processing layer:* The collected data is then sent to a centralised AI system, which uses machine learning algorithms to process it. In addition, distributed edge computing nodes are used to process data locally, reducing latency and enhancing scalability for time-sensitive applications. The AI algorithms analyse the incoming data to extract insights, predict traffic patterns, optimise routes and detect anomalies.
- *Decision-making layer:* Based on the analysis, the AI system determines the optimal adjustments needed to alleviate congestion. This could include changing traffic light timing, adjusting signal priority for different traffic lanes or recommending alternative routes.
- *Centralised AI platform:* The centralised AI platform aggregates and analyses data from various sources to generate actionable insights and make informed decisions. This platform plays a crucial role in the smart transportation system by providing a centralised hub for data processing and decision-making.
- *Traffic management system:* One of the key components of the smart transportation system is the AI-powered traffic management system. This system uses real-time data to dynamically adjust traffic signals, reroute vehicles and optimise traffic flow. This helps reduce congestion and improve overall traffic efficiency. Another important application of AI in the smart transportation system is predictive maintenance. By using AI algorithms, maintenance needs for infrastructure and vehicles can be predicted, optimising maintenance schedules and reducing downtime.
- *Adjustments recommendation:* The AI system generates recommendations for adjusting traffic lights along the congested artery to improve traffic flow. These recommendations take into account the current traffic conditions, anticipated traffic patterns and potential impacts on surrounding areas. These recommendations can be applied to various management systems, from basic ones like automotive navigation and traffic signal control to more advanced systems that integrate live data and feedback from multiple sources, such as guidance and parking information systems. In order to accurately predict collective traffic behaviour, it is crucial to consider interaction-based multi-vehicle predictions. In their study, Wei et al. (2024) introduced a novel model called the Knowledge-Informed Generative Adversarial Network (KI GAN) that incorporates both traffic signal information and multi-vehicle interactions to accurately predict vehicle trajectories. André (2017) suggested a differentially confidential estimation algorithm. The differentially private mechanism publishes a density map that is usable by any third-party application.

5 Scenario description proposed

Our scenario uses IoT sensors to detect heavy congestion on a major city artery. The data is transmitted to a centralised AI system, which analyses real-time information and recommends adjustments to traffic lights to alleviate congestion. Simultaneously, vehicles equipped with IoV technologies receive notifications about traffic conditions and receive instructions to follow alternative routes.

1 ***InitialiseTrafficLightController***:

Variable keys

intVeh_density: represent(veh_density)

ConstTh_Cong= 100 represents the congestion threshold.

- Set the congestion threshold to 100 (Th-cong = 100)
- Create an AIController instance.
- Create a TrafficControlCenter instance.

2 ***Begin monitoring traffic***.

1. Repeat the following steps indefinitely:

a.i. Collect (**veh_density)** from IoT sensors.

a.ii. If (veh_density> 100),

a.ii. Wait for 5 seconds. Then go to step b **Else**, go to a.Analysetraffic:

b.1. Call AIController'sanalyze_traffic function with vehicle_density.

b.2. Proceed to step 3.

3 ***AIControlleranalyze_traffic(vehicle_density)***:

If (**veh_density**>=100):

a.1. Recommend adjustments by calling recommend_adjustments (vehicle_density).

2. Proceed to step 4.

4 ***TrafficControlCenteradjust_traffic_lights(adjustments)***:

1) ***Update traffic light timings based on adjustments***.
2) Set the green light duration to adjustments [green_duration'].
3) Set the yellow light duration to adjustments [yellow_duration'].
4) Display the updated durations for green and yellow lights.

6 Simulation results

We consider that each infrastructure (road, traffic sensors, lights, etc.) is equipped with IoT sensors, communication hardware and wireless protocols such as GPS and DSRC, which broadcast GPS location, speed and direction avoidance systems, as well as collision warning algorithms. Such tools are important to build and show the concept of AI a realistic traffic avoidance scenario. Thereby, each vehicle may use the threshold congestion fix of 100 in order to trigger a possible traffic congestion and warn its driver, which is subsequently processed by AI algorithms to make intelligent decisions.

To simulate and analyse the performance of our model, we used the traffic simulator SUMO 1.5.0 and the network simulator OMNET++ 5.6.1. The choice of the OMNET++ network simulator is due to the many advantages it presents compared to the NS2 simulator. The evaluation of the behaviour of road traffic entities (flow, density) with the OMNET++ simulator requires the use of a Veins Framework (vehicles in network simulation), which allows bidirectional coupling and makes it work in parallel with the SUMO traffic simulator, which generates significant simulation results close to the real environment. In the simulation section, we used various tools and described simulation parameters in the table below.

Table 2 Tools and parameters of simulation

Parameters	*Value*
Map realistic	OpenStreetMap 300*200
Traffic model (roads, vehicles junction traffic light)	Sumo Simulator 1.5.0
Networks Simulator	Omnet++ 5.6.1
Coupling platform (SUMO&Omnet++)	Veins2.0 et TraCI protocol.
Number of Segments	07
Number of vehicles	250
Number of traffic light	5
Interval speed	5 to 15 m/s
Transmission rang (m)	250
Simulation tame (s)	7000 s

6.1 Traffic network (generate vehicle routes)

The first step of the simulation is to define our mobility and traffic model on a realistic map downloaded from the OpenStreetMap site (see Figure 5). The test road map was captured from the Cnep of Souk Ahras city. Design the road network layout using a SUMO scenario file (.net.xml). Use a route file (.rou.xml) to define vehicle routes within the network. This file specifies the road topology, junctions, traffic lights, lanes and connections between different segments of the network.

Our simulation is divided into two parts: the first part does not use an AI algorithm and instead analyses congestion as an abnormal situation. We used a traffic flow model to evaluate the avoidance model of Cnep-Souk Ahras city and tested its performance during peak hours of the day, from 15:30 to 17:00. Figure 6 show the performance of the traffic flow avoidance during peak hours of the test. The results show that the application of AI methods produces data that closely matches real-time traffic flow. It is also worth noting that the regression analysis improves short-term predictions, resulting in better performance during the peak hour of the test.

Figure 5 Integration of the map of simulation in SUMO (see online version for colours)

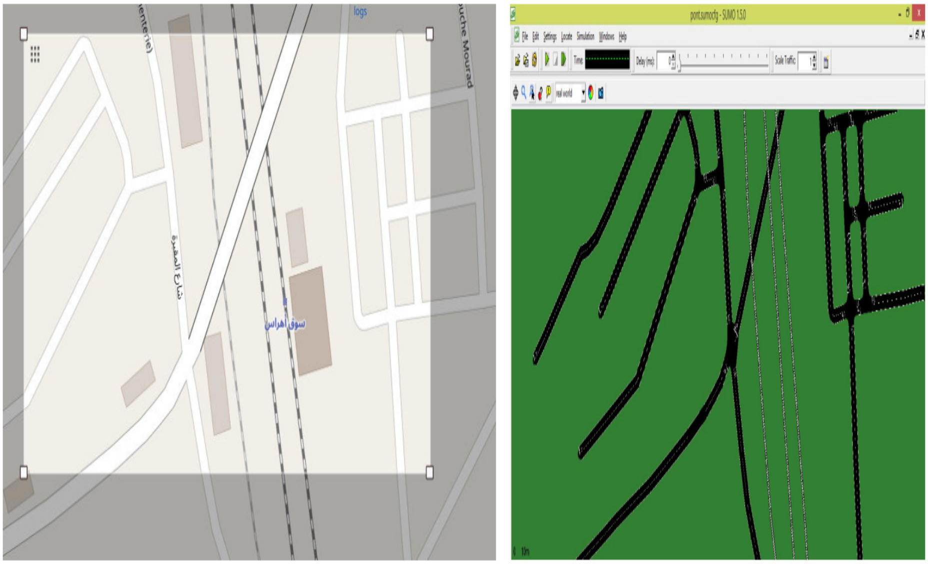
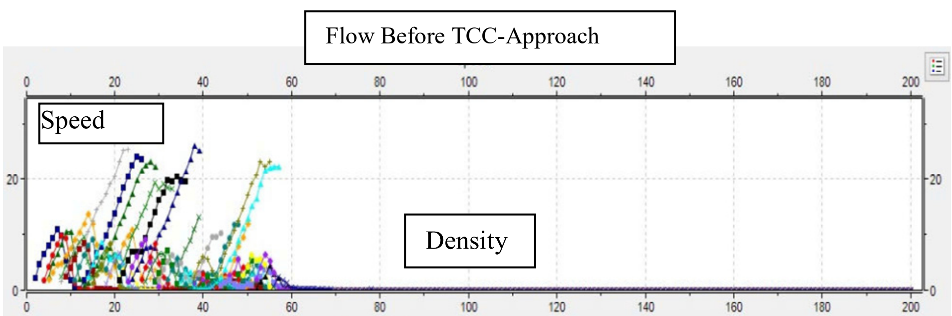


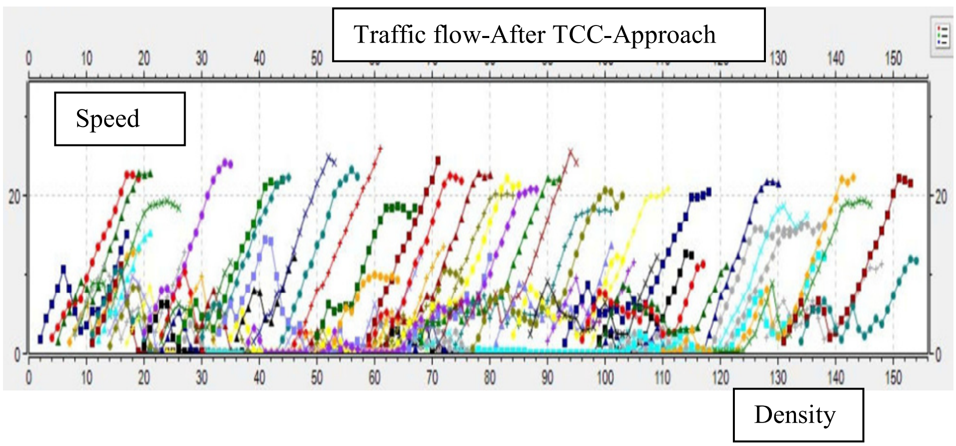
Figure 6 Simulation result of congestion traffic before the TCA approach (see online version for colours)



After integrating the traffic light programmes proposed in Section 5 into a SUMO traffic light model, we created an OMNeT++ simulation model to interact with the SUMO simulation using the TraCI protocol. This model is responsible for controlling vehicles and traffic lights according to the scenario. It is important to ensure that the OMNeT++ simulation model is properly connected to the SUMO simulation using the TraCI protocol. The figure below represents the results of the simulation for congested traffic lights before the application of the AI algorithm. In the first simulation phase, we removed the AI model and the IoV communication. This showed that the number of vehicles in full congestion increased over time, reaching a maximum of 200 vehicles. The traffic flow was also too heavy compared to the speed of the vehicles, which had a maximum speed of 20 km/h on the 07 test segments.

The Figure 7 below represents the simulation results of the traffic congestion light after implementing an AI algorithm. Initially, we ran the simulation without the AI model to establish a baseline. In the second phase, we integrated the AI model along with IoV (Internet of Vehicles) communication for each vehicle. This advanced setup allowed vehicles to share real-time data regarding their speed, location and traffic conditions.

Figure 7 Simulation result of congestion traffic after the TCA approach (see online version for colours)

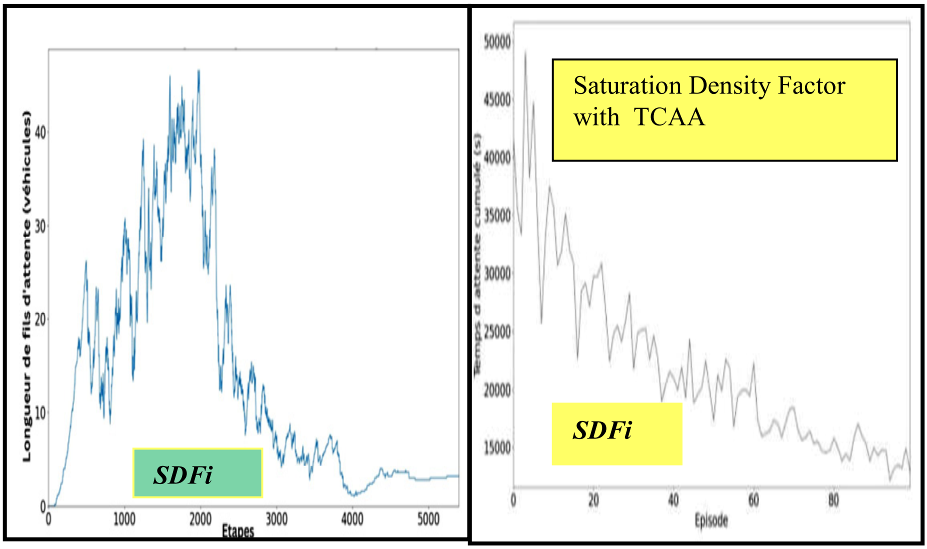


The results were significant: the number of vehicles experiencing full congestion decreased dramatically, with a reduction of 50 vehicles compared to the initial phase. Additionally, traffic flow began to improve noticeably across the seven test segments. This improvement was observed as vehicles adjusted their routes and speeds in real-time based on the AI's predictions and recommendations, demonstrating the potential of AI and IoV integration in alleviating urban traffic congestion. This phase of the simulation highlights the effectiveness of leveraging cutting-edge technology for smarter and more efficient traffic management systems.

It is evident that real-time traffic flow benefits significantly from the application of AI-driven data analysis. The AI method enhances congestion analysis, particularly during peak hours, thereby increasing the accuracy of short-term congestion avoidance strategies. This improvement in performance underscores the capability of AI to dynamically adapt to fluctuating traffic conditions.

Figure 8 below illustrates the simulation results of traffic flow saturation density across seven segments, considering the previously described simulation time. Initially, as a large number of vehicles enter the system, congestion is triggered when the vehicle count reaches 100. At this critical point, the AI module and Internet of Vehicles (IoV) communication are activated. Figure 8 shows a noticeable decrease in saturation density and an improvement in traffic fluidity starting at a simulation time of 2500 seconds.

Figure 8 Simulation result of saturation density (see online version for colours)



The deployment of the proposed avoidance approach demonstrates how AI and IoV technologies can effectively manage and mitigate congestion. By dynamically adjusting to real-time traffic conditions, the system ensures smoother traffic flow and reduces the overall congestion levels. This highlights the transformative potential of integrating AI and IoV in urban traffic management, leading to more efficient and responsive transportation networks.

We can conclude that the proposed integration of AI and IoV in smart city development offers a transformative improvement over traditional approaches, leveraging real-time data, predictive analytics and adaptive control to create more efficient, sustainable and liveable urban environments. This innovative approach not only addresses current traffic management challenges but also paves the way for future advancements in smart city infrastructure. We present in the following table the novelty of our proposed approach as compared to other studies and the difference between the previous works and the present work.

Table 3 Comparison between previous works and our proposed approach

Previous works	*Our proposed approach*
Traditional traffic management systems relied on historical data and static traffic signals, which were unable to adapt to real-time conditions effectively.	The use of AI algorithms and IoV devices allows for real-time data collection and analysis, enabling dynamic adjustments to traffic signals and route recommendations based on current conditions. This leads to more responsive and efficient traffic management.
Earlier systems lacked the predictive capabilities to foresee traffic congestion and other urban mobility challenges.	AI models, especially those leveraging machine learning and deep learning techniques, can predict traffic patterns and potential congestion points. This predictive capability allows for proactive measures to be implemented, preventing congestion before it occurs.

Table 3 Comparison between previous works and our proposed approach (continued)

Previous works	*Our proposed approach*
Precision-making in traffic management was often manual and based on limited data, leading to suboptimal outcomes.	The integration of AI provides city planners and traffic managers with actionable insights derived from vast amounts of data. These insights facilitate informed decision-making, optimising traffic flow and improving urban mobility.
Static traffic signal systems were not capable of adjusting to changing traffic conditions throughout the day.	AI-driven adaptive traffic signal control can adjust signal timing in real-time based on current traffic conditions, reducing wait times and improving overall traffic efficiency.
Conventional traffic management systems do not effectively prioritise safety, particularly for emergency vehicles.	The integration of IoV allows for real-time communication between vehicles and traffic management systems. AI algorithms can prioritise the movement of emergency vehicles, reducing response times and improving overall safety.
Driver experiences were often hampered by a lack of real-time information and inefficient traffic management.	Real-time route recommendations and traffic updates provided by AI systems enhance the driving experience, reducing frustration and improving journey times.

7 Conclusions

In order to enhance the quality-of-life for residents, a smart city project must prioritise optimising city management. Transportation is one of the many stakeholders who must actively participate in this. A smart road would be the central component of a smart city design, incorporating components like data management (using big data, cloud and storage technologies), data acquisition (through sensors), data transmission (via wireless networks, etc.) and the optimisation of city activities (through artificial intelligence and analysis). In order to enable intelligent road traffic management, especially in congested situations that call for intelligent and immediate management, we propose in this paper to integrate Artificial Intelligence (AI) and the Internet of Vehicles (IoV) technologies. The integration of Artificial Intelligence (AI) and the Internet of Vehicles (IoV) represents a transformative leap in the development of smart cities. The Traffic Congestion Avoidance Approach (TCAA) demonstrates how leveraging these advanced technologies can address the persistent issue of urban traffic congestion. By utilising IoV for real-time communication between autonomous vehicles and incorporating deep learning algorithms for dynamic traffic analysis, the TCAA provides a robust framework for managing traffic flow more effectively. Our simulations have shown that this approach can significantly reduce congestion and improve the overall efficiency of urban traffic systems. The adaptability of AI allows the system to respond to changing traffic conditions instantaneously, making real-time adjustments that traditional traffic management systems cannot achieve. This not only enhances the flow of traffic but also contributes to environmental sustainability by reducing idle times and emissions from vehicles. Implementing TCAA in urban environments can lead to safer, more efficient roadways and a better quality of life for city residents. The reduction in traffic congestion also has economic benefits, such as decreased fuel consumption and reduced travel times, which contribute to the overall productivity of the city. The Traffic Congestion Avoidance Approach exemplifies the potential of AI and IoV in revolutionising traffic management. By harnessing the power of real-time data and advanced algorithms, we can create smarter, more sustainable cities. Future research and development in this field hold promise for even greater advancements, ultimately leading to urban spaces that are more liveable, efficient and environmentally friendly.

In the future, the integration of IoV and AI paves the way for future innovations in smart city infrastructure. As these technologies continue to evolve, we can anticipate even more sophisticated solutions that will further optimise urban mobility and resource management. The insights gained from this research can serve as a foundation for policymakers and urban planners aiming to design more resilient and responsive urban environments.

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I acknowledge the use of ChatGPT [https://chat.openai.com/] to enrich the introduction and conclusion then rephrase a few sentences. I entered the following prompts: 'enrich the following text [x]'. I used the responses as a starting point for further reformulation.

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