Smart Traffic Management System Using Internet of Vehicles

by

Abdulrahman Mohammed Alotaibi

A Thesis Submitted in Partial Fulfillment of the Requirements for the Degree of Doctor of Philosophy in Information Systems

Faculty of Computing and Information Technology
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Dedication

First and foremost, I want to express my deepest gratitude to my parents. My happiness is rooted in you, and all the goodness in my life stems from your love and guidance. Your unwavering support and prayers have been the bedrock of my strength on this incredible journey. From the bottom of my heart, thank you for always believing in me.

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I would like to express my sincere gratitude to my supervisor, Prof. Faisal Al-Shammari, for his invaluable guidance, continuous encouragement, and unwavering support throughout every stage of this research. His expertise, insightful feedback, and commitment to academic excellence have been instrumental in the successful completion of this dissertation.

I am also deeply grateful to my co-supervisor, Dr. Hassan Al-Zahrani, for his constructive suggestions, technical advice, and constant motivation. His thoughtful guidance and willingness to share his knowledge greatly enhanced the quality of this work.

My sincere appreciation is extended to the Faculty of Computing and Information Technology for providing an inspiring academic environment and the resources necessary to carry out this research.

Abstract

Rapid urbanization and economic growth have significantly increased traffic congestion in modern cities, creating substantial challenges for transportation authorities in ensuring road safety, reducing travel delays, and optimizing traffic flow. Smart Traffic Management Systems (STMS), supported by Intelligent Transportation Systems (ITS), have emerged as essential solutions for addressing these challenges through data-driven monitoring, prediction, and decision-making. In Saudi Arabia, the continued development of intelligent transportation infrastructure plays a vital role in supporting sustainable urban mobility and the objectives of Vision 2030.

This research proposes a smart traffic management framework based on the Internet of Vehicles (IoV), which enables seamless communication among connected vehicles, roadside infrastructure, and traffic management centers. By integrating Internet of Things (IoT) technologies with advanced Artificial Intelligence (AI) techniques, the proposed framework addresses challenges related to traffic prediction, network congestion, large-scale data processing, and intelligent decision support. Machine learning and deep learning models are employed to analyze real-time and historical traffic data, predict traffic conditions, and optimize vehicle movement across urban road networks.

The proposed system incorporates multiple predictive models to improve traffic flow forecasting and enhance intersection management. Experimental evaluation demonstrates that the integrated AI-driven framework achieves high prediction accuracy, reduced traffic congestion, and improved computational efficiency compared with conventional traffic prediction approaches. The results indicate that the proposed methodology provides a scalable and reliable solution for next-generation intelligent transportation systems and contributes to the advancement of smart city infrastructure.

Keywords: *Smart Cities, Internet of Vehicles (IoV), Intelligent Transportation Systems, Artificial Intelligence, Machine Learning, Deep Learning, Traffic Prediction, Traffic Flow Optimization*

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Abbreviations

No.	Terms	Alternative
1	Information and communication technology	(ICT)
2	Traffic flow prediction	(TFP)
3	Intelligent transportation systems	(ITS)
4	Global Positioning System	(GPS)
5	Deep learning	(DL)
6	Machine learning	(ML)
7	Natural language processing	(NLP)
8	Artificial intelligence	(AI)
9	Internet of Things	(IoT)
10	Federated learning	(FL)
11	Gated recurrent unit-neural network	(GRU-NN)
12	Wavelet	(WL)
13	Empirical Mode Decomposition	(EMD)
14	Ensemble EMD	(EEMD)
15	Efficient hinging hyperplanes neural network	(EHHNN)

16	Optimal attention-based deep learning with statistical analysis for TFP	(OADLSA-TFP)
17	Attention- based bidirectional long short-term memory	(ABLSTM)
18	Artificial fish swarm algorithm	(AFSA)
19	Improved whale optimization algorithm	(IWOA)
20	Wavelet neural network	(WNN)
21	long short-term memory	(LSTM)
22	One-dimensional convolution neural network and long short-term memory	(1DCNN-LSTM)
23	Efficient hinging hyperplanes neural network	(EHHNN)
24	Moving Average	(MA)
25	Butterworth	(BW)
26	Vehicular internet of things	(V-IoT)
27	Radio-frequency identification	(RFID)
28	Real-time traffic management system	(RTMS)
29	Linear Regression	(LR)
30	Smart traffic management protocol	(STMP)
31	Deep neural networks	(DNN)
32	Recurrent Neural Network	(RNN)
33	Autoregressive integral moving average	(ARIMA)
34	Internet of Vehicles	(IOV)
35	Vehicle-to-Everything	(V2X)
36	Vehicle-to- Vehicle	(V2V)
37	vehicle-to-infrastructure	(V2I)

38	vehicular ad hoc network	(VANET)
39	Artificial intelligence	(AI)
40	Fifth-Generation Network	(5G)
41	Dedicated short-range communication	(DSRC)
42	Quality of Service	(QoS)
43	service offloading	(SOL)
44	Edge-computing-enhanced Internet of Vehicles	(EC-IoV)
45	terrestrial edge computing	(TEC)
46	edge computing	(EC)
47	Software Defined Vehicular Networks	(SDVN)
48	Deep Reinforcement Learning	(DRL)
49	Markov decision process	(MDP)
50	Adaptive Boosting	(AB)
51	The adaptive neuro-fuzzy inference system	(ANFIS)
52	The adaptive neuro-fuzzy inference system optimized by genetic algorithm	(ANFIS-GA)
53	Bidirectional Gated Recurrent Unit	(BiGRU)
54	Multilayer Perceptron	(MLP)
55	Random Forest	(RF)
56	Decision Trees	(DT)
57	K-Nearest Neighbors	(KNN)
58	Gradient Boosting	(GB)

Chapter 1

Introduction

1.1 Introduction

The Internet of Things (IoT) contributes to the concept of a smart city by enabling traffic-light regulation, smart parking, intelligent emergent assistance, and anti-theft security systems, among other applications. The IoT enables effective interactions between online devices and traffic-embedded sensors, services, actuators, and other associated networks. With powerful Machine Learning (ML) and data-driven techniques, this technology has several implementation restrictions [39].

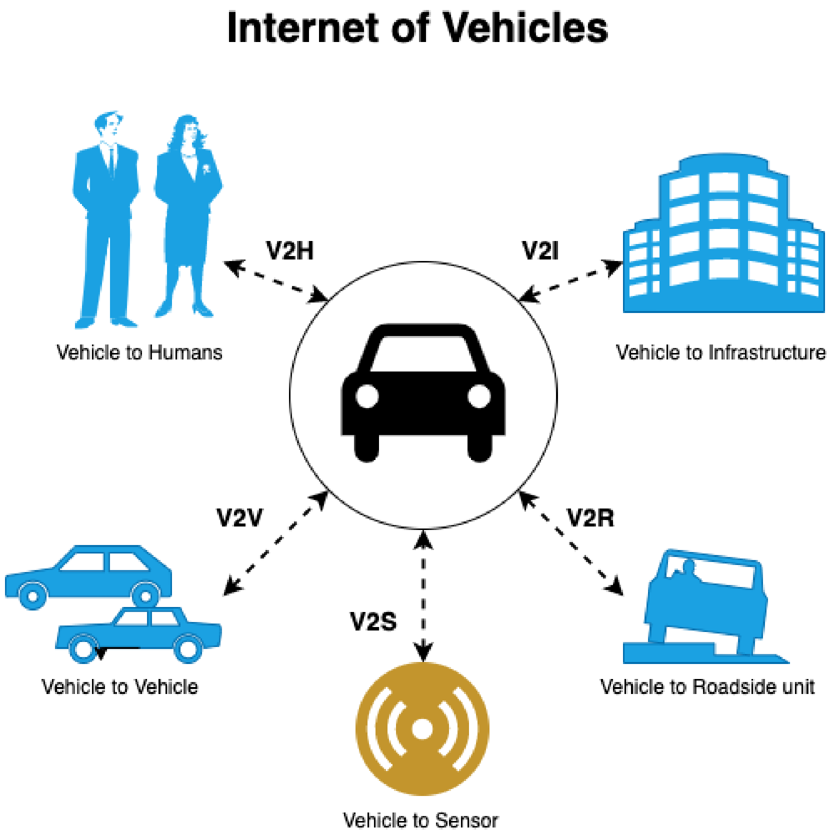

Figure 1.1: The Internet of Vehicles (IoV)

A smart city's traffic-management system innovative technologies and solutions to manage city assets, including intelligent transportation, power supply, and other critical infrastructure. Previous traffic- management methods cannot deal with the increased traffic on road networks [21]. The Internet of Vehicles (IoV) is an intelligent vehicular network model consisting of vehicles, users and other smart elements connected to network. The main objectives of IoV are to enhance and enable vehicles to communicate with human users, other vehicles, pedestrians, roadside infrastructure, and related management systems in real time.

The Internet of Vehicles (IoV) is the advanced version of Vehicular Ad hoc Network

(VANET) and considered as the latest technology being developed for smart cities in smart transportation, basically designed to provide safe driving.

Various data collected by in-vehicle devices reflect the current traffic situation in smart cities (traffic accidents, traffic jams, public transport queues, waiting, etc.) in real time. IoV not only provides users with optimal driving paths, but also enables emergency prevention and smart reactions, which can greatly improve road safety and the in-vehicle driving experience. This is considered the main contribution of IoV to smart cities. The related IoV connected graphs aims to optimize the process: accident reduction, traffic congestion relief, and the provision of additional information services. The IoV seeks to facilitate the interchange of data between a vehicle and all entities that may be associated with it.

1.2 Problem Statement

Rapid economic growth has increased the size and population of cities and the number of motor vehicles in major cities, leading to traffic congestion [57]. The government may now incorporate smart traffic management systems into traffic cabinets and junctions for rapid, cost-effective safety and traffic flow improvements on their local streets. Moreover, upgrades to Saudi Arabia's current Intelligent Transportation Systems (ITS) infrastructure can result in significant cost savings and efficiency gains while significantly increasing system dependability. In today's smart city setting, particularly in industrial and market zones, the traffic situation is extremely crowded, particularly during business hours [41]. Vehicular traffic also has a significant negative impact on people's quality of life. Thus, predicting vehicular traffic has become an important step in the government's decision- making process. Also, the elements contributing to vehicle traffic must be ascertained. The Internet of Vehicles (IoV) is a model for an intelligent vehicular network consisting of network-connected vehicles, users, and other smart elements. Various data collected by IoV reflect the current traffic situation in smart cities.

Research challenges:

- Conflict while collecting information: There are several national and state-specific information requirements that are often used to collect administrative data and information. Although these guidelines are not always followed, they may have a significant impact on the compatibility of the data set.
- Inadequate information: Inadequate knowledge is one of the encountered obstacles that may face. The research will incorporate a variety of keywords pertinent to the topic. the result in several responses, on the basis of which the research will able to link two or more tools.
- Lack of quality: Inadequate information quality can result in a poorly prepared project or report. The accuracy of the information is dependent upon the research conducting an accurate search. A limited amount of time may prevent the research from evaluating the completeness of the information and acquiring the missing data.

1.3 Research Aim and objectives

The research goals are as follows:

1. To present an appropriate overview of IoV system models and discuss related strategies for simulating vehicle traffic in Smart environment.
2. To analyze the needed performance variables, parameters, attributes, standards and various indicators affecting vehicular traffic in smart cities.
3. To predict these characteristics and anticipate which of the required vehicular traffic indicators has the most influence, supporting decision-makers.
4. To provide solutions for various challenges and opportunities of the IoV technology that are still not clear so far.

Research Questions:

1. How can we employing IoV to provide safe driving in smart cities?
2. How can findings be effectively and engagingly predicted while including the capability of a big data analytics tool?
3. How can the elements affecting vehicle traffic be analyzed?
4. What are the technical solutions that should be addressed in IoV?

1.4 Research Contributions

- A prediction model to improve vehicle traffic performance.
- An analysis of vehicle traffic in smart cities.

1.5 Thesis Organization

The thesis is structured as follows:

Chapter 2 Provide an overview of the Internet of Vehicles and its Challenges and Solutions—Artificial Intelligence and Traffic Flow Prediction Applications in Smart Traffic Systems.

Chapter 3: This chapter offers a comprehensive account of its methodology, including the dataset used, the data mining tool employed in the proposed model, and an overview of traditional machine learning and ensemble methods. Evaluation measures were employed for assessing the model.

Chapter 4: The experiment's outcomes and findings are presented, together with an explanation of the evaluation measurements used to determine the model's effectiveness.

Chapter 5: Presents a complete thesis assessment, stressing its limits and proposing ideas for future research attempts.

1.6 Conclusion

This thesis aims to investigate proper models for predicting traffic-impact factors by using the IoV and ML techniques to enhance a network of information interactions between vehicles. This proposal provides in details the IoV characteristics to support road infrastructure and the related environment through optimal communication. Furthermore, this proposal outlines the IoV technical limitations that must be addressed.

Chapter 2

Literature Review

2.1 Introduction

Implementing Internet of Things (IoT) in-vehicle networks has resulted in a new vehicular communication technology-themed vehicular internet of things (V-IoT). For various tasks, prototypes of low-cost IoT devices have been constructed and tested in urban contexts. Devices are implemented at each tier of the IoT architecture and evaluated on a web-based IoT front-end application, utilizing various protocols such as LoRaWAN.

The authors create and install several IoT solutions for vehicular applications. The esp32 IoT camera module with the system-on-a-chip wifi is used at a low cost. Lora sensors are used to detect the level of pollution in intra-vehicular settings. A loRaWAN-based gateway was created and tested for usage in IoT-enabled vehicle communications at the network layer [54]. Initial car ad hoc network concepts are maturing into the Internet of Vehicles (IoV).

Another paper aims to develop a smart traffic management system that uses the Internet of Things (IoT) and a decentralised approach to optimise road traffic. The system receives traffic density data from cameras and abstracts it using Digital Image Processing techniques and sensor data, resulting in a signal management output. An algorithm is employed to forecast traffic density to decrease traffic congestion in the future. Radio-frequency identification (RFID) is also utilised to prioritise emergency vehicles such as ambulances and fire trucks by incorporating RFID tags inside these vehicles. Additionally, a web application delivers graphical representations to the smart city's higher authorities [21].

Furthermore, rapid urbanization has resulted in a rise in personal transport vehicles. However, road infrastructure has not kept pace with this expanding traffic congestion. This issue may be handled by either enhancing the road infrastructure or boosting the efficiency of existing roadways. The authors suggest a simple solution that, by utilizing RFID technology, promises to alleviate traffic congestion while also saving significant amounts of time [43].

In India, the authors suggest a real-time traffic management system (RTMS) that consists of a real-time monitoring system comprised of a small network of roadside units, junction units, and mobile units designed to prevent gridlock development. The RTMS is connected with a web-based application for vehicle drivers that uses real-time analysis to provide information about local traffic flow.

Vehicle-to-infrastructure (V2I) connection is frequently used in wireless technology as a bi-directional communication system comprised of hardware, software, and firmware supporting lane signs, road signs, and lighting systems. The research analyzed V2I performance by examining running time, data rate, and resource management. This paper investigates the comprehensive, intensive neighbourhood analysis of V2I communication. This will increase the safety and quality of transportation while also providing new adaptable solutions for entertainment. This paper discusses the applications of V2I-based wireless technology.

Moreover, the IoT is gaining importance in our daily lives. Especially the Internet of Vehicles (IoV). Wireless supply may be accomplished using lane signs, road signs, and lighting technologies. Vehicle-to-vehicle communication minimizes accidents between automobiles and road access points. Vehicles that have been a long-held desire become reality [23].

Nallaperuma's et al., (2019) paper presents a framework for the smart traffic management protocol (STMP) based on unsupervised online incremental machine learning, deep learning, and deep reinforcement learning. The STMP combines disparate large data sources, such as those from the IoT, smart sensors, and social media, to detect idea deviations in 190 million traffic data records from Victoria, Australia.

The primary advantage of the proposed platform is that its Artificial intelligent AI modules are optimised to address the critical difficulties inherent in future transportation systems where IoT devices are widely deployed. Additionally, the platform overcomes the constraints of existing algorithms and technologies, which rely mainly on sparsely labelled data and stringent assumptions about data and traffic behaviour. Additionally, the studies demonstrate that impact propagation and traffic flow prediction modules can accurately predict the short-term effects of events [32].

Deep neural networks (DNNs) have recently shown the capacity to forecast traffic flow using massive amounts of data. This work provides a DNN based traffic flow prediction model DNN-BTF that exploits the spatial-temporal properties of traffic flow to its fullest extent. The experimental findings demonstrated that the researchers' solution outperformed the current best practices [58].

This study suggests a unique Multisensor Data Correlation Graph Convolution Network (MDCGCN) model. It consists of three components: current, daily period, and weekly period components, each of which is comprised of two components: an adaptive benchmark mechanism and a multisensor data correlation convolution block. The first component may significantly enhance the quality of data input by eliminating the disparities between periodic data. The second section can adequately capture the dynamic temporal and spatial correlation induced by the shifting interaction between road traffic patterns. This might considerably increase the accuracy of medium- and long-term traffic forecasts for networks of varying sizes [26].

Based on an autoregressive integral moving average (ARIMA) model and long short-term memory (LSTM) neural network, a technique for predicting short-term traffic flow has been developed. By using previous traffic data, the approach might estimate the traffic flow in the future. Backpropagation was utilized to extract the nonlinear characteristics of the traffic flow data. The results demonstrate that the dynamic weighted combination model has a superior predictive capability [28].

Table 2.1: Five research that using machine learning algorithms for traffic flow prediction.

Researchers	Machine learning algo-rithms	The objectives	Advantages	disadvantages	Future work
Du, W., Zhang, Q., Chen, Y. and Ye, Z., 2021	IWOA-WNN model	An urban short-term traffic flow prediction model based on wavelet neural network with improved whale optimization algorithm	The paper proposes a network based on the IWOA-WNN Traffic prediction model by enhancing the whale optimization method and integrating it with a neural network.	The accuracy of short-term urban traffic flow forecasts must be improved.	To forecast short-term traffic lulls, the authors believe that future researchers will need to

					create matching mathematical models for different road segments in different cities. This can significantly reduce the urban traffic congestion problem.

Qiao, Y., Wang, Y., Ma, C. and Yang, J., 2021	1DCNN-LSTM model	Short-term traffic flow prediction based on 1DCNN-LSTM neural network structure	The predicted value derived from the forecasting model utilised in this study has a minimal deviation from the actual value, and the model's forecasting accuracy is excellent.	Long-term prediction does not produce optimum results.	After considering weather conditions and other aspects, the next stage will be to develop a more effective deep learning model.

Chen, X., Chen, H., Yang, Y., Wu, H., Zhang, W., Zhao, J. and Xiong, Y., 2021.	LSTM + EEMD scheme	Traffic flow prediction by an ensemble framework with data denoising and deep learning model	The experimental findings demonstrated that the LSTM+EEMD algorithm achieved a greater degree of precision when the average Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE)	evaluated model performance regardless of the effect of traffic parameter,complex model	undertake further tests to evaluate the performance of the model under a variety of environmental interferences (e.g., weather, emergency incidents, etc.)

			values are 0.79, 0.60, and 2.14, respectively.		Exploring temporal and geographical connections to improve the accuracy of traffic flow prediction is yet another intriguing expansion.

Tao, Q., Li, Z., Xu, J., Lin, S., De Schutter, B. and Suykens, J.A., 2022.	EHHNN	Short-Term Traffic Flow Prediction Based on the Efficient Hinging Hyper-planes Neural Network	Different traffic parameters, including their spatial-temporal information, are integrated into the inputs. Beyond the goal of precision	addressing improved short-term TF prediction in-terpretability	-

Tang, J., Chen, X., Hu, Z., Zong, F., Han, C. and Li, L., 2019.	EMD, EEMD, MA, BW, WL	Traffic flow prediction based on combination of support vector machine and data denoising schemes	The prediction results of the model with the denoising method are superior than those of the model alone.	did not take into account other variables that may affect the accuracy of the forecast, such as weather, road rankings, or spatial correlation between various detectors.	Combining many sources of traffic flow data, such as GPS trajectories, meteorological information, and video data, can significantly improve the accuracy of predictions.

Short-term urban traffic flow is characterized by a high amount of time variation, nonlinearity and unpredictability. To overcome the problem of urban traffic congestion, the author of this research come up with an improved whale optimization algorithm (IWOA) and tried to include it in the wavelet neural network (WNN). The experimental findings demonstrate that an absolute error has substantially improved compared to the pure WNN and WOA-WNN models [13].

Accurate and efficient traffic flow prediction, as the heart of Intelligent Traffic Systems (ITS), can effectively solve the issues of traffic travel and management in China. This research offers a short-term traffic flow forecasting approach based on a one-dimensional convolution neural network and long short-term memory (1DCNN-LSTM). The geographical information in traffic data is collected using 1DCNN, and LSTM retrieves the temporal information [37].

Considering the necessity for past data in traffic flow prediction, the Recurrent Neural Network (RNN) is inspired by the attention mechanism. The authors offer an enhanced method for linking the high-impact value of lengthy sequence time steps to the present time step. The experimental findings demonstrate that the suggested model for predicting short-term traffic flow is competitive [61].

Other disturbances may corrupt raw data on traffic flow acquired by inductive detectors. As a solution, we implemented data denoising algorithms. Afterwards, the (LSTM) neural network was implemented to complete the task of traffic flow prediction. The experimental findings demonstrated that the LSTM+EEMD method achieved greater precision [10].

Five denoising techniques, including EMD (empirical mode decomposition), EEMD, MA (moving average), BW filter (butterworth), and WL (wavelet), are contenders in the prediction performance comparison. The prediction results demonstrate that the model with the ensemble-empirical mode decomposition method produces more accurate predictions than a model without the denoising process. This research offers helpful advice for determining the optimal method for traffic flow forecasting [52].

Predicting traffic flow (TF) is an important yet difficult problem in transportation systems. In this study, the authors seek to improve the interpretability of short-term TF prediction while maintaining high accuracy. The suggested technique employs the efficient hinging hyperplane neural network (EHHNN) to filter out more significant traffic characteristics for dimensionality reduction [53].

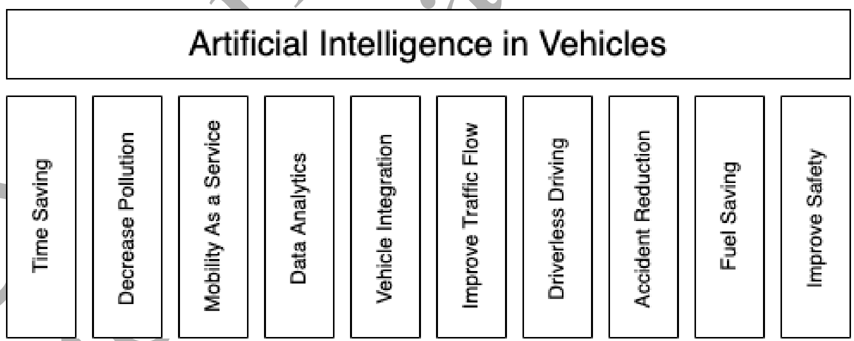

Figure 2.1: Role of Artificial Intelligence in Vehicles

According to [3], the optimal attention-based deep learning with statistical analysis for traffic flow prediction (OADLSA-TFP) model given aims to accurately predict the volume of environmental traffic. Traffic flow is predicted using an attention-based bidirectional long short-term memory (ABLSTM) model. In order to improve the performance of the ABLSTM model, the artificial fish swarm technique is used to optimise the hyperparameters.

2.2 Internet of Vehicles (IOV)

IoV stands for "Internet of Vehicles." The idea behind it is that every vehicle should be equipped with computers, control units, and sensing platforms [47]. The Internet of Vehicles (IoV) is an emerging topic within the broader field of the Internet of Things (IoT). Through IoV, we can develop intelligent transportation systems (ITS). Devices connected within the IoV transmit a vast amount of data, which imposes costs on the IoV network [35].

Although the Vehicular Ad Hoc Network (VANET), an application of mobile ad hoc networking, is widely employed in the automobile industry, the Internet of Things (IoT) serves as the driving force behind transforming the current Internet into a fully integrated version of the future Internet. IoV is built upon this context and aims to facilitate information exchange between vehicles and all associated entities, with the goal of reducing accidents, alleviating traffic congestion, and providing additional information services. This article presents a new network architecture for the future network, designed to achieve increased data throughput, reduced latency, enhanced security, and improved connectedness [22].

The Internet of Vehicles (IoV) is a rapidly evolving technology that enables communication between vehicles, infrastructure, and other devices by connecting them to the internet. In order for IoV to operate efficiently, several technological issues need to be addressed. Some of the most important technical challenges that IoV should tackle include the following: communication protocols, Vehicle-to-Everything (V2X) communication, cybersecurity, data management, edge computing, and artificial intelligence (see Figure 2.2). The authors classified the Internet of Vehicles into three main categories: communication management, data management, and Artificial intelligence. Each subject includes issues that could be a research contribution, such as Fifth-Generation Network 5G, Vehicle-to-Everything (V2X), Edge computing (EC), Cybersecurity, and Machine Learning (ML). Furthermore, Artificial intelligence (AI) Methods have been focused on in detail.

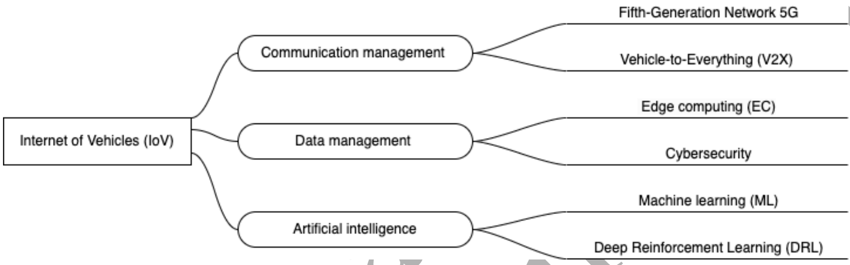

Figure 2.2: The Internet of Vehicles (IoV) Classification.

The authors reviewed the recent papers has been published recently in the field of IoV. The Internet of Vehicles (IoV) uses various wireless technologies to connect vehicles to their surroundings and share data. To ensure secure data sharing, blockchain technology can be used to mitigate IoV architecture vulnerabilities. The research examined outlines of security requirements and countermeasures, addressing severe attacks, and introducing countermeasures [14][24].

Moreover, Edge computing is essential for intelligent transportation systems, as it enables pervasive data processing and content sharing between vehicles and terrestrial edge computing infrastructures. However, it depends on connections and interactions between vehicles and technology infrastructures, which can fail in remote locations [63][29].

Combining AI and Machine Learning, IoV technology is revolutionizing the development of smart vehicles. It enables vehicles to communicate with public networks, share data, and interact with their surroundings. However, obstacles like big data connection, cloud networks, data processing, and effective vehicle-to-vehicle communication remain. AI and ML can increase the efficacy of IoV networks by addressing issues such as time, energy, rapid topology, optimization of user experience quality, and channel modelling [2].

Table 2.2: Studies related to The Internet of Vehicles (IoV).

Paper	Main Topic	Publication year
[6]	VEHICLE BLACK BOX IMPLEMENTATION FOR INTERNET OF VEHICLES BASED LONG RANGE TECHNOLOGY	2023
[40]	Improved Artificial Rabbits Optimization with Ensemble Learning-Based Traffic Flow Monitoring on Intelligent Transportation System	2023
[34]	Comparative Study Analysis of ANFIS and ANFIS-GA Models on Flow of Vehicles at Road Intersections	2023
[15]	Intelligent Slime Mould Optimization with Deep Learning Enabled Traffic	2022
[20]	Multisource Data Integration and Comparative Analysis of Machine Learning Models for On-Street Parking Prediction	2022

[33]	Traffic Flow Prediction for Smart Traffic Lights Using Machine Learning Algorithms	2022
[63]	Edge-Computing-Enhanced Space–Air–Ground-Integrated Networks for Internet of Vehicles	2021
[14]	Using Blockchain Technology for the Internet of Vehicles	2021
[2]	Machine Learning Technologies for Secure Vehicular Communication in Internet of Vehicles: Recent Advances and Applications	2021
[64]	A Decentralized Location Privacy-Preserving Spatial Crowdsourcing for Internet of Vehicles	2021
[24]	Blockchain application in internet of Vehicles: Challenges, contributions and current limitations	2021
[8]	A Probabilistic City Model Generation for Application in Internet of Vehicles Technology	2021
[38]	Internet of Vehicles: Key technologies, network model, solutions and challenges with future aspects	2020
[20]	Diversified technologies in Internet of Vehicles under intelligent edge computing	2020
[65]	Evolutionary V2X technologies toward the Internet of vehicles: Challenges and opportunities	2020
[62]	Research on the Development of Internet of Vehicles Technology	2019

[55]	An improved authentication scheme for Internet of Vehicles based on blockchain technology	2019

Figure 2.3: Represents selected publishers such as IEEE, MDPI (Multidisciplinary Digital Publishing Institute) and Wiley with paper numbers per publisher and year. They are the most significant databases and have numerous publications, and researchers are always seeking to publish their work on them and provide a citation. The papers were selected according to their related to the topic of the Internet of Vehicles, and research was excluded based on the following: First: the title of the research does not cover Internet of Vehicles technologies, second: reading the abstract, and finally: reviewing and reading the research in detail.

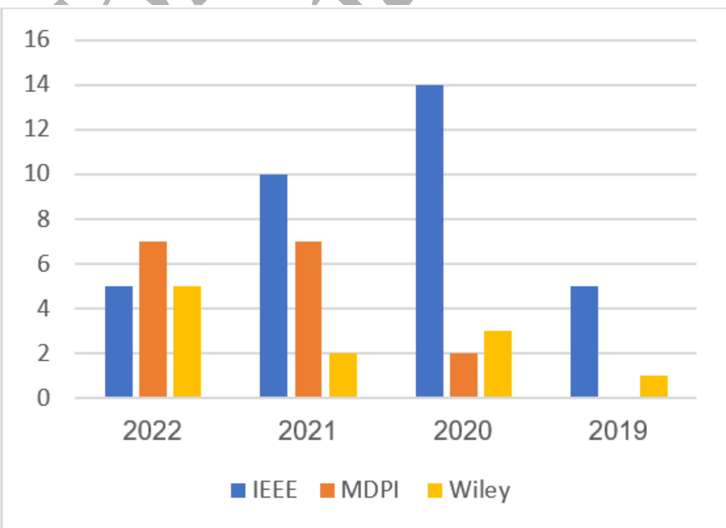

Figure 2.3: Papers per publisher and year

2.2.1 Internet of Vehicles (IOV) Technology

RQ1: What are the technical solutions that should be addressed in IoV?

This section will examine the topics researchers prefer to consider when developing technological solutions for intelligent transportation systems. Including communication protocols, vehicle-to-everything (V2X), cybersecurity, data management, edge computing and artificial intelligence (AI).

1. Communication protocols: Communication protocols specify how devices communicate within a network. In the context of IoV, communication protocols need to be developed to ensure smooth and secure communication between vehicles, infrastructure, and other devices [50].

2. Vehicle-to-Everything (V2X) communication: The term V2X refers to a collection of technologies that will be developed in the future, currently represented by Dedicated Short-Range Communication (DSRC). V2X technologies enable vehicles to communicate data with other system components, laying the groundwork for intelligent transportation systems. These technologies are considered effective means of addressing issues such as traffic accidents, congestion, and pollution [16].

3. Cybersecurity: As automobiles become increasingly connected, the importance of cybersecurity issues grows more urgent. The design of the IoV system should prioritize the security and privacy of data exchanged between vehicles and other devices [49].

4. Data management: The Internet of Vehicles (IoV) generates vast amounts of data that need to be collected, processed, and analysed to derive insights for improving safety and traffic flow. Effective data management solutions are crucial for handling the massive data volumes generated by IoV.

5. Edge computing: Edge computing refers to the practice of processing data locally instead of transferring it to a central server. By leveraging edge computing, IoV systems can achieve improved responsiveness and lower latency [59].

6. Artificial intelligence (AI): Within the Internet of Vehicles (IoV), AI can play a crucial role in analyzing data and generating insights to optimize traffic flow and enhance safety. AI systems have the potential to enable traffic signal optimization, accident detection, and traffic pattern prediction.

2.3 Artificial Intelligence methods

2.3.1 Description of Traditional AI Algorithms

Traditional AI algorithms play a crucial role in machine learning and data analysis, offering versatile tools for classifying, regressing, and predicting data. Some examples of these algorithms include Long Short-Term Memory (LSTM), Decision Tree, Random Forest, Multilayer Perceptron, K-Nearest Neighbors, Gradient Boosting, Gated Recurrent Unit (GRU), and Gradient Boosting. Linear Regression is a straightforward technique for modelling relationships between variables, while Stochastic Gradient Descent optimizes model parameters [18]. Collectively, these traditional AI algorithms form the foundation of machine learning methodologies, providing solutions to various real-world problems with their distinctive characteristics and capabilities.

2.3.2 Applications of Artificial Intelligence in Intelligent Transportation Systems

The papers reviewed in this section aim to enhance traffic flow and management in urban areas using machine learning techniques. The first paper, by Olayode et al. [34], focuses on Comparative Study Analysis of ANFIS and ANFIS-GA Models on Flow of Vehicles at Road Intersections. The second paper, by Hamza et al. [15], proposes an intelligent slime mold optimization method combined with deep learning for smart city traffic prediction. In the third paper, Inam et al. [20] compare the effectiveness of several machine learning models for on-street parking prediction using multisource data. The fourth paper, by Xu et al. [60], presents a service offloading strategy with a deep Q-network for the Internet of Vehicles (IoV) at the network's periphery. Lastly, the fifth paper, by Navarro-Espinoza et al. [33], compares the performance of different machine learning algorithms for predicting traffic flow at various intersections using two distinct datasets.

While each document focuses on a different aspect of traffic management, they all share a common goal of enhancing road efficiency and reducing congestion. These investigations employ various machine learning techniques, including the adaptive neuro-fuzzy inference system (ANFIS), deep reinforcement learning, random forest, and gradient boosting. Most studies utilize real-world datasets, such as sensor data from automobile parking, pedestrian sensor data, and traffic flow data.

The limitations of the papers differ, with some studies recommending further research on the influence of weather conditions on traffic flow and the availability of public datasets for traffic prediction models. Additionally, the traffic scenarios used to validate the models vary across the studies. [60] focus on outsourcing services in the Internet of Vehicles (IoV), while [33] predict traffic flow at various intersections.

In this study [34] aimed to compare the performance of two machine learning techniques, the adaptive neuro-fuzzy inference system (ANFIS) and the adaptive neuro-fuzzy inference system optimized by genetic algorithm (ANFIS-GA), in analyzing the flow of vehicles at road intersections. The study utilized data from Southern Africa's high traffic volume and vehicle density, with over 500,000 vehicles recorded at various times of the day. Vehicle speed, distance, and estimated time were the most important factors/variables considered in the study. Both ANFIS and ANFIS-GA demonstrated effectiveness in predicting the flow of vehicles at road intersections, with ANFIS-GA performing marginally better than ANFIS. The RTraining values were 0.8979 and 0.9709, and the RTesting values were 0.9980 and 0.9790 for ANFIS-GA and ANFIS, respectively. However, the study did not account for the influence of weather conditions on the collection of traffic datasets and the movement of vehicles. The authors suggested that future research should explore the impact of different weather conditions on traffic flow and the accumulation of traffic datasets.

Overall, the study offers valuable insights into the effectiveness of machine learning techniques in analysing traffic flow at road intersections, providing practical applications for the development of intelligent transportation systems.

In [15] the authors aims to enhance traffic prediction in smart cities through the integration of intelligent slime mold optimization and deep learning techniques. The study utilized various machine learning techniques, including in-max normalization from the scikit library, Bidirectional Gated Recurrent Unit (BiGRU), the SMO algorithm, and the SMOBGRU-TP model. The primary factor considered in the study was time duration. The dataset consisted of the preceding traffic flow data from an hour, which formed a time series of 12 data points used to forecast the traffic flow expected within the next five minutes. The data was divided into 13 sets for training and testing purposes. The proposed SMOBGRU-TP model outperformed the other models, achieving significantly lower MAPE, MSE, and RMSE values. This research demonstrates the effectiveness of the proposed machine learning techniques in enhancing traffic prediction in smart cities.

The significance of this study lies in its potential contribution to the development of intelligent transportation systems that can improve traffic flow, reduce congestion, and enhance road safety. Transportation engineering researchers and practitioners can benefit from the study's findings regarding the application of intelligent optimization and deep learning techniques to traffic prediction.

The study [20] aims to predict on-street parking availability in smart cities by integrating multisource data and conducting a comparative analysis of machine learning models. The study utilized the following models: Multilayer Perceptron (MLP), Random Forest (RF), Decision Trees (DT), K-Nearest Neighbors (KNN), Gradient Boosting (GA), Adaptive Boosting (AB), and linear SVC. Precision, recall, and F-score were the primary factors/variables considered in this study. The dataset included car parking sensor data with 35.9 million records, pedestrian sensor data with 3.09 million records, car traffic data with 60.2 K records, and meteorological data collected between January 1, 2017, and December 31, 2017. Among the models, the MLP model demonstrated the highest performance in terms of precision, recall, and F-score. The combination of parking, pedestrian, traffic, and weather data resulted in more accurate predictions of parking availability, highlighting the significance of data integration. This research can contribute to the development of intelligent parking systems, which can reduce traffic congestion, enhance the urban environment, and improve the user experience. Overall, the study provides valuable insights into the use of machine learning techniques and data integration for predicting on-street parking availability, benefiting transportation engineering researchers, practitioners, and policymakers.

The paper titled 'Service Offloading With Deep Q-Network for Digital Twinning-Empowered Internet of Vehicles in Edge Computing' by [60] presents a novel approach to the service offloading (SOL) problem within the context of the Internet of Vehicles (IoV) and edge computing devices (ECDs). With the objective of optimizing Quality of Service (QoS) in IoV scenarios, this study proposes an SOL method based on deep reinforcement learning (DRL). The study utilizes position, velocity, and vehicle spacing data to construct a digital twin of the traffic environment and a simulated testing platform. The performance evaluation involves dashcam footage collected from vehicle sensors and cameras. The results demonstrate that the proposed SOL method outperforms existing methods in terms of QoS performance, achieving lower packet loss ratio, lower latency, and higher throughput. This paper contributes to the existing body of knowledge by introducing the concept of digital twinning in the context of IoV and SOL, while showcasing the potential of DRL for optimizing QoS in edge computing.

The paper titled "Traffic Flow Prediction for Smart Traffic Lights Using Machine Learning Algorithms" Navarro-Espinoza [33] aims to predict traffic flow and enable efficient traffic control by employing various machine learning algorithms. The study discusses and applies several machines learning algorithms, including MLP-NN, Gradient Boosting, Random Forest, GRU, LSTM, Linear Regression, and Stochastic Gradient, to two datasets. The first dataset used is the Road Traffic Prediction Dataset from the Huawei Munich Research Center, while the second dataset is compiled from the PeMS dataset, which comprises more than 15,000 sensors deployed in California.

In this study, a time sequence of 12 data points is used to predict traffic flow for the next five minutes. The main factors/variables considered include traffic flow prediction for lanes 1, 2, 3, and 4, as well as metrics such as MAE, RMSE, MAPE, and R-squared, with a desired threshold of greater than 0.90. The results of traffic flow prediction show that machine learning algorithms such as GRU, LSTM, and Random Forest outperformed the other models. However, it is important to note a few limitations of the study, including the limited availability of public datasets, the focus on short-term prediction, and the simulation restricted to only four lanes at an intersection. Overall, this study provides valuable insights into the application of machine learning algorithms for predicting traffic flow and emphasizes the significance of efficient traffic control in smart cities. The authors of this study are Navarro-Espinoza et al. [33].

Table 2.3: Papers that using AI algorithm technique.

Authors-/Date	Research Objective	ML techniques Used
Olayode et al 2023	Comparative Study Analysis of ANFIS and ANFIS-GA Models on Flow of Vehicles at Road Intersections	The adaptive neuro-fuzzy inference system (ANFIS), The adaptive neuro-fuzzy inference system optimized by genetic algorithm (ANFIS-GA)
Hamza et al 2022	Intelligent Slime Mould Optimization with Deep Learning Enabled Traffic Prediction in Smart Cities	Bidirectional Gated Recurrent Unit (BiGRU), SMO algorithm, SMOBGRU-TP model
Inam et al 2022	Multisource Data Integration and Comparative Analysis of Machine Learning Models for On-Street Parking Prediction	Multilayer Perceptron (MLP), Random Fores, (RF), Decision Tree, (DT), K-Neares, Neighbors (KNN), Gradient Boosting (GA), Adaptive Boosting (AB), linear SVC

Xu et al 2020	Service Offloading With Deep Q-Network for Digital Twinning-Empowered Internet of Vehicles in Edge Computing	Service offloading (SOL), Deep reinforcement learning
Navarro-Espinoza et al 2022	Traffic Flow Prediction for Smart Traffic Lights Using Machine Learning Algorithms	MLP-NN, Gradient Boosting, Random Forest, GRU, LSTM, Linear Regression, Stochastic Gradient

Table 2.4 shows some of the papers' results after applying the model they proposed, which was concluded using the evaluation measures (explained in the next section).

Table 2.4: shows the papers results using the evaluation measures.

Paper	ML	MAPE (%)	RMSE	R^2
[11]	ANFIS	-	-	0.9790
	ANFIS-GA			0.9980
[12]	AI-TFP	21.364	17.31	-
	SMOBGRU-TP	18.560	16.011	

[14]	MLP-NN	21.1593	15.42	0.9304
	GB	21.9493	15.41	0.9305
	RF	21.8392	15.54	0.9296
	GRU	22.8492	15.61	0.9278
	LSTM	22.3244	15.67	0.9267
	LR	24.3238	15.85	0.9263
	SG	29.0075	18.37	0.9003

The papers conclude by demonstrating how machine learning techniques have the potential to enhance urban traffic management. These studies provide valuable insights into the performance of different algorithms and models, emphasizing the importance of using specific and diverse datasets in the development of effective traffic prediction models. By addressing the challenges highlighted in these studies and validating the models across various traffic scenarios, researchers can further improve the field of traffic management.

2.4 Challenges and Solutions

RQ2: What are the challenges and solutions of Internet of Vehicles technology?

This section will review the challenges in the Internet of Vehicles and some proposed solutions to improve transportation systems in urban cities, including managing massive amounts of data, addressing data privacy and security concerns, mitigating network congestion, ensuring reliability, and achieving scalability.

Big Data: One of the major concerns in the Internet of Vehicles (IoV) is the storage of large volumes of data generated by numerous connected vehicles, including driverless automobiles, which are projected to process 1 GB of data per second. To address this challenge, effective management of big data through techniques such as big data analytics and mobile cloud computing is crucial [42].

Mobility: Maintaining continuous connectivity and ensuring real-time broadcasting and receiving of resources becomes challenging in the context of rapidly moving cars and dynamically changing network topologies [42].

The mobility of nodes in Internet of Vehicles (IoV) poses challenges in accurately analysing the number of participating nodes in the network. Even if vehicles have sufficient energy to utilize computing and communication resources when they connect with surrounding objects, maintaining a stable connection becomes difficult due to the diverse and rapid mobility of vehicles, leading to additional issues. For instance, the limited transaction times caused by vehicle mobility constraints make it challenging to deliver critical vehicle data [24].

Reliability: It is important to acknowledge that automobiles, sensors, and network hardware can experience failures. The system should be designed to handle inaccurate data and poor communications, including potential security threats like denial-of-service attacks. In general, prioritizing vehicle safety is more crucial than focusing on entertainment [42].

To support mission-critical applications, transportation systems, including first responder communication and transportation systems, require services with low communication latency and high reliability. The Internet of Vehicles (IoV) possesses various characteristics, such as limited wireless connection bandwidth, rapid vehicle mobility, rapid data transfer, and heavy computing load. These characteristics must be managed within a predetermined time frame to avoid potentially dangerous situations [24].

Security and Privacy: The Internet of Vehicles (IoV) ecosystem requires robust security and privacy solutions to mitigate the risks associated with false and malicious information exchanges between vehicles. Such exchanges can lead to accidents, data security vulnerabilities, and reliability issues. These risks can be categorized into physical, communication, and application domains. The various components of the IoV are susceptible to criminal activity and unauthorized access at a physical level, while communication-level challenges involve ensuring secure and prompt transactions and interactions. Additionally, issues with cloud services at the application level may result in data loss or insufficient storage capacities [24].

Given that IoV involves the integration of numerous technologies, services, and standards, data security becomes paramount. It is susceptible to cyberattacks and intrusions, which can lead to data breaches and physical harm [42]. In table 2.5, a summery of these papers are provided.

Table 2.5: Challenges and solutions of IoV technology.

Technological Aspects	Challenges	Solutions
Big Data	A significant number of connected vehicles generates a substantial amount of data for processing and storage.	Mobile cloud computing will manage the massive amounts of data.
Mobility	It is difficult to maintain nodes connected and to send and receive in real-time when vehicles are moving fast	Network stability for non-stop connections must be provided.
Reliability	The system must cope with both inaccurate data and faulty communications.	Priority must be given to vehicle safety
Security and Privacy	IoV could be the target of cyberattacks and incursions, resulting in data breaches and physical harm	A data security and privacy system must be effective.

This research has some limitations, such as the number of publishers that have been used, including IEEE, MDPI, and Wiley. Moreover, recent papers written five years ago have been cited in this research. Also, this research focused on AI, but communication and data management need to be explained in future work.

2.5 Traffic Flow Prediction in Smart Traffic Systems

Road traffic accidents increase dramatically each year due to the massive increasing number of vehicles on the roads. This problem is a serious risk and a major source of trouble for all people over the world and a significant global concern

[5]. Collecting and analyzing comprehensive data is essential for any initiative aimed at improving traffic safety [1]. With the increasing number of vehicles on the roads and the resulting congestion issues, optimizing traffic flow has become a pressing challenge in modern cities. Intelligent Transportation Systems (ITS) have emerged as a promising solution to alleviate traffic congestion and enhance overall transportation efficiency [45][17]. The Vehicle Ad-Hoc Network (VANET) serves as a fundamental infrastructure for the Intelligent Transport System (ITS), enabling wireless connectivity among vehicles [25][46]. Additionally, intelligent transport systems are increasingly focused on addressing traffic congestion. Researchers have employed machine learning algorithms to predict traffic flow and reduce congestion at intersections. These models were evaluated using the national road traffic dataset for the United Kingdom. An adaptive traffic light system was implemented, which adjusts green and red lights based on road width, traffic density, and vehicle categories. Simulations demonstrated a 30.8% decrease in traffic congestion [31].

Accurate prediction of traffic is crucial for enhancing the effectiveness of traffic systems and reducing energy consumption. Machine learning-based methods have become commonplace, but they often rely on historical data [56][48]. Furthermore, ML-based models are gaining popularity due to their ability to accurately forecast traffic conditions, thereby improving safety and infotainment applications. However, the effectiveness of these models in predicting real-time traffic remains a subject of investigation [51].

This paper utilizes four Machine Learning (ML) and Deep Learning (DL) models: random forest, linear regressor, long short-term memory (LSTM), and ensemble using bagging (random forest). The objective is to utilize these predictions to enhance the efficiency of traffic light controllers in the context of traffic flow prediction at intersections. Experimental results demonstrate that all models exhibit a strong predictive capacity for estimating vehicular flow, highlighting their potential utility in smart traffic systems.

Several research studies have focused on developing methods and models for traffic flow prediction and management. It was shown that [11], a framework is presented that utilizes vector autoregression (VAR) and a CNN-LSTM hybrid neural network to predict short-term traffic flow. The CNN-LSTM model outperforms other models in forecasting short-term traffic flow and demonstrates the predictive accuracy associated with spatial correlation in traffic flow. In [9], three proposed solutions are discussed to address the issue of missing data in traffic management. These solutions include a live-traffic traffic simulation, a neural network traffic prediction and rerouting system based on pheromone principles, and a Weighted Missing Data Imputation (WEMDI) approach. The integration of WEMDI into the systems yields notable improvements in various traffic factors and demonstrates efficient routing to alternative destinations.

Machine learning (ML) and neural networks play a significant role in solving traffic congestion issues. In this context, this paper proposes machine learning and deep learning algorithms for predicting intersection traffic flow [33]. The models were trained, validated, and tested using public datasets, and the Multilayer Perceptron Neural Network (MLP-NN) produced the best results. Gradient Boosting, Recurrent Neural Networks, Random Forest, Linear Regression, and Stochastic Gradient also showed promising performance.

Authors in [33] demonstrate a Mean Absolute Error (MAE) of roughly 10.83, suggesting that, on average, there is a deviation of approximately 10.83 units between the predicted values and the actual values. The Root Mean Square Error (RMSE) value of around 15.42 suggests a slightly higher average magnitude of error. The R-squared (R2) value of 0.9304 indicates that the MLP-NN model accounts for roughly 93.04% of the variability seen in the dependent variable. Additionally, Gradient Boosting performs very similarly to the Multi-Layer Perceptron Neural Networks (MLP-NN). The Mean Absolute Error (MAE) is estimated to be approximately 10.85, the Root Mean Square Error (RMSE) is approximately 15.41, and the R2 value is approximately 93.05%.

Intelligent Transportation Systems (ITS) require traffic flow monitoring for effective management and optimization. Conventional methods of data collection and analysis are being augmented with AI techniques, such as ensemble learning [40]. The IAROEL-TFMS methodology utilizes feature subset selection and optimal ensemble learning to predict traffic flow, outperforming other approaches with its low RMSE.

Authors in [40] used models Hybrid-LSSVM, AST2FP-OHDBN, and IAROEL-TFMS models for evaluation purposes, considering their respective performance indicators. Among the several models evaluated, it was observed that IAROEL-TFMS had the most superior predictive performance, as evidenced by its notably low values for both the Mean Absolute Error (MAE) at 18.1508 and the Root Mean Square Error (RMSE) at 17.8412. Furthermore, it has attained an outstanding

Equal Coefficient of 99.29%, which signifies precise predictions of class labels for a significant majority of occurrences. In close succession, the AST2FP-OHDBN model exhibited robust performance, as evidenced by its mean absolute error (MAE) of 19.7508, root mean square error (RMSE) of 23.4312, and notably high Equal Coefficient value of 98.61%. In contrast, the Hybrid-LSSVM model demonstrated a somewhat reduced level of prediction accuracy, as evidenced by a mean absolute error (MAE) of 24.4347, root mean square error (RMSE) of 28.7079, and an Equal Coefficient of 97.24%. Regarding predictive performance, the IAROEL-TFMS model had the best precision and accuracy in forecasting the target variable. The AST2FP-OHDBN model closely followed it. On the other hand, the Hybrid-LSSVM model exhibited slightly inferior predictive skills.

2.6 Summary and Conclusion

AI-powered Internet of Vehicles (IoV) technology revolutionizes traffic efficiency and promotes environmental sustainability by integrating AI methods and addressing the complexities of vehicles, transforming transportation systems. Within the IoV landscape, solutions driven by AI techniques address key concerns such as data privacy and security, network congestion, and interoperability. Through the use of deep learning algorithms, predictive analytics, adaptive routing, and reinforcement learning, AI empowers optimized traffic signal control and route planning. The transformative potential of AI-driven IoV systems calls for continuous research and innovation, aiming for a safer, more efficient, and environmentally conscious future. The synergy between IoV and AI creates a wiser and more connected world, propelling the development of a smart transportation ecosystem. This research has provided answers to two essential questions regarding the Internet of Vehicles: the technical solutions that should be addressed and the challenges that will be encountered, including dealing with a huge amount of data, nodes connected to send and receive in real-time, reliability, and cyberattacks and incursions. Thereby assisting researchers in examining the field.

Chapter 3

Research Methodology

3.1 Introduction

This chapter provides an in-depth analysis of the approach utilized for this research. It explores data processing, including data collection and preparation. In addition to elaborating on the traditional machine Learning and tools implemented in the research project, this chapter also comprehensively explains the data sources and evaluation measures. The experiments' designs are commented upon in great detail.

3.2 Data Pre-Processing

3.2.1 Data Collection

The datasets used for traffic prediction were obtained from various traffic sensors provided by the Huawei Munich Research Center. These datasets play a crucial role in predicting traffic patterns and making necessary adjustments to stop-light control settings, including cycle length, offset, and split timings.

The dataset consists of recorded data from six intersections located within an urban area, collected over a period of 56 days "Table 3.1". The data is presented as a flow time series, which indicates the number of vehicles passing through each intersection every five minutes, spanning 24 hours. This results in 12 readings per hour, 288 readings per day, and a total of 16,128 readings over the course of the 56 days. For this study, four out of the six intersections were selected to replicate a four-lane intersection scenario [7].

Table 3.1: DISPLAYS THE SIX INTERSECTIONS OF THE DATASET USING COLAB.

	Cross 1	**Cross 2**	**Cross 3**	**Cross 4**	**Cross 5**	**Cross 6**
0	105.0	48.0	30	62.0	31	110.0
1	97.0	41.0	32	55.0	42	103.0
2	76.0	47.0	44	58.0	40	100.0
3	98.0	40.0	39	59.0	43	104.0
4	87.0	41.0	47	49.0	35	112.0

3.2.2 Data Preparing

Data cleaning is a critical step in the preprocessing phase, where incorrect, incomplete, duplicate, or erroneous data within a dataset is rectified. Fortunately, the collected data for this study does not contain any missing values. The dataset has been divided into two parts: 70% for training the model and the remaining portion for testing. To ensure consistency and optimal performance during training, the data was scaled using the MinMaxScaler from the scikit-learn library. This scaler transforms the data, making it range between zero and one [36].

3.2.3 Proposed Techniques

In this experiment, four regression models from the scikit-learn module in the Python programming language are employed. The scikit-learn module is a comprehensive Python library that offers a wide range of state-of-the-art machine learning algorithms designed to tackle various supervised and unsupervised challenges [36]. The authors applied four ML/DL techniques to the dataset: random forests, long short-term memory (LSTM), linear regression, and ensemble methods (bagging). The upcoming section provides an overview of the traditional machine learning and ensemble methods utilized in the experiment.

3.3 Overview of Traditional Machine Learning

3.3.1 Random Forest

Random forests are an ensemble learning method that combines multiple tree predictors. Each tree in the forest is constructed based on the values of a random vector, sampled independently from the same distribution for all trees. Tree-based models form the core components of the random forest algorithm. A tree-based model involves iteratively dividing a given dataset into two distinct groups, guided by a specific criterion, until a predetermined stopping condition is met. The terminal nodes of decision trees are commonly known as leaf nodes or leaves [44].

3.3.2 Long Short-Term Memory (LSTM)

Long short-term memory (LSTM) networks have found extensive applications in various domains, including image processing, speech recognition, manufacturing, autonomous systems, communication, and energy consumption, for dynamic system modelling purposes.

LSTM has gained significant attention in recent years due to its effectiveness in modelling and predicting the dynamics of nonlinear time-variant systems. It incorporates the characteristics of short-term and long-term memory, the ability to make predictions several steps ahead, and the propagation of errors. Sequence-to-sequence networks with partial conditioning have been shown to outperform other techniques such as bidirectional or associative networks, making them well-suited for achieving the specified objectives [27].

3.3.3 Linear Regression

Linear regression is a widely used and straightforward machine learning algorithm. The technique, as mentioned above, is a mathematical methodology employed to do predictive analysis. Moreover, Linear regression is a statistical technique that enables the prediction of continuous or numerical variables. Linear regression is a statistical technique employed to assess and quantify the association between variables under consideration [30].

3.4 Ensemble Method (Bagging)

Bagging, short for bootstrap aggregating, is a technique that involves creating multiple iterations of a predictor and combining them to form an aggregated predictor. In the aggregation process, the mean is calculated across the iterations when predicting a numerical outcome, while a majority vote is used when predicting a class. To generate multiple versions, bootstrap copies of the original learning set are created, and these replicates are then used as new learning sets [19].

3.5 Evaluation Measures

Evaluation metrics are crucial for assessing the efficacy of machine learning models and algorithms. Accuracy, Precision, Recall, and F-Measure are four commonly used evaluation metrics. These metrics provide insights into various aspects of model performance, enabling a comprehensive understanding of its strengths and limitations.

Collectively, these evaluation measures provide a nuanced assessment of a model's prediction accuracy and are extensively used to guide model selection and optimization in numerous domains.

Accuracy: A classifier's accuracy is determined by its ability to effectively predict the effect of a predicted feature on new data.

$$1.\ \text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

Where:

- (TP) True positive cases predicted as yes.

- (TN) True negative cases that are predicted as no.

- (FP) False positive cases that are predicted yes and it is yes.

- (FN) False negative cases predicted as no but it is yes.

Precision: Precision is determined by dividing the number of accurately classified positive predictions by the total number of correctly or inaccurately classified positive predictions.

$$2.\ \text{Precision} = \frac{TP}{TP + FP}$$

Recall: The recall of a prediction is calculated by dividing the proportion of correctly classified positive predictions by the total number of positive predictions.

$$3.\ \text{Recall} = \frac{TP}{TP + FN}$$

F-Measure: The F-measure is a single measure that conveys both recall and precision, calculated using the next Equation:

$$4.\ \text{F- Measure} = \frac{2 * \text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}}$$

In model evaluation, the coefficient of determination (R-squared), root-mean-squared error (RMSE) and mean absolute error (MAE) are standard metrics [12].

$$R^2 = 1 - \frac{\sum_{i=1}^{m} (x_i - y_i)^2}{\sum_{i=1}^{m} (\bar{y} - y_i)^2} \tag{3.1}$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2} \tag{3.2}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{3.3}$$

3.6 Conclusion

This chapter presents a comprehensive examination of the methodology employed for this research. The study encompassed data processing analysis, which involved gathering and organizing data. This chapter provided detailed information on the conventional machine learning techniques and tools utilized in the study project and included a full explanation of the data sources and assessment metrics. The designs of the experiments are thoroughly analyzed and discussed.

Chapter 4

Experiment Work

4.1 Introduction

Due to the tremendous growth of road traffic accidents every year, Intelligent Transportation Systems are becoming ever more important. To prevent road traffic accidents in the long term, it is necessary to find new vehicles flow management techniques in order to optimize traffic flow. Recently, with high growth of deep learning and machine learning they are increasingly being used in Intelligent Transportation Systems. This experiment provides a novel conceptual model for intelligent traffic systems (ITS) that aims to predict vehicle movement through the use of collective learning to anticipate intersections. The proposed approach consists of three main stages: data collection through cameras and sensors, implementation of machine learning and deep learning algorithms, and evaluation of results using the coefficient of determination (R-squared), root-mean- squared error (RMSE), and mean absolute error (MAE). To accomplish this, various machine learning and deep learning algorithms, such as Random Forest, LSTM, Linear Regression, and ensemble methods (bagging), were incorporated into the model. The comprehensive results stated the betterment of proposed method in a significant performance improvement of 93.52% compared to recent approaches.

4.2 Proposal Model

This experiment has developed a model for monitoring traffic flow. The primary objective of this model is to predict traffic movement. To achieve this objective, the model operates in three distinct stages. Firstly, data collection can be accomplished using cameras or sensors. Secondly, machine learning and deep learning technologies are applied. Thirdly, the outcomes are evaluated using the mean absolute error (MAE), root-mean-squared error (RMSE), and the coefficient of determination (R-squared). The workflow of the suggested approach is illustrated in Figure 1. Overall, the proposed model aims to monitor traffic flow by predicting its movement. It involves data collection through cameras or sensors, the application of machine learning and deep learning technologies, and the evaluation of outcomes using specific error metrics. "Figure 4.1" provides a visual representation of the workflow.

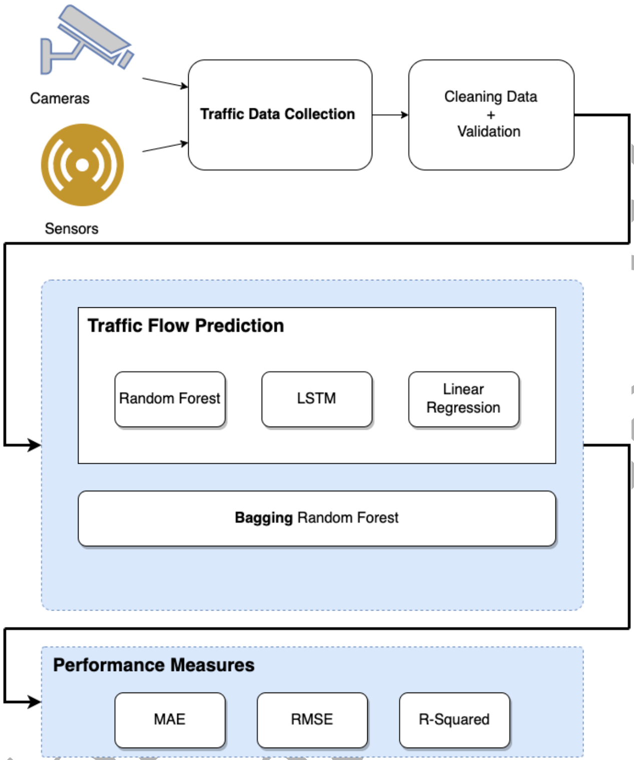

Figure 4.1: The workflow of the model.

4.3 Experimental Results and Discussion

"Table 4.1" presents the results of the model using various machine learning and deep learning algorithms. From the table, it can be observed that Random Forest achieved an MAE of 13.76, while LSTM and Linear Regression achieved 14.74 and 17.80, respectively. When Bagging (Random Forest) was applied, the minimum MAE obtained was 13.69. In terms of RMSE, the models achieved values of 22.39, 23.50, and 27.04, while the Bagging model achieved a lower RMSE of 22.21. In terms of R-squared, the experimental results for the models were 0.9341, 0.9275, and 0.9040, respectively. The best R2 value was obtained by the Bagging model, which achieved a value of 0.9352.

These results indicate that the Random Forest model and the Bagging model (using Random Forest as the base model) outperformed the LSTM and Linear Regression models in terms of both MAE and RMSE. Additionally, the Bagging model showed the highest R2 value, suggesting a better fit to the data. Overall, these findings demonstrate the effectiveness of the Random Forest algorithm and the potential benefits of using ensemble methods like Bagging for traffic flow prediction.

Table 4.1: THE RESULTS USING PYTHON.

ML/DL Model	MAE	RMSE	R2
Random Forest	13.76	22.39	0.9341
LSTM	14.74	23.50	0.9275
Linear Regression	17.80	27.04	0.9040
Bagging (RF)	13.69	22.21	0.9352

"Figure 4.2" presents the numerical values representing the mean absolute error (MAE) measurements for various machine learning (ML) and deep learning (DL) models. MAE is a commonly used metric for evaluating the performance of regression models. It measures the average absolute deviation between the predicted and observed values within a given dataset. From the figure, it can be observed that the LSTM model has a slightly higher MAE (14.74) compared to the Random Forest (13.76) and Bagging (Random Forest) models (13.69). This suggests that the LSTM model may not perform optimally in this particular scenario. On the other hand, the linear regression model has the highest MAE score (17.80) among all the models. This indicates that it may not excel at accurately predicting the target variable.

These results suggest that the Random Forest and Bagging models (using Random Forest as the base model) perform better than the LSTM and linear regression models in terms of MAE. It is important to consider these findings when selecting the most suitable model for traffic prediction in this context.

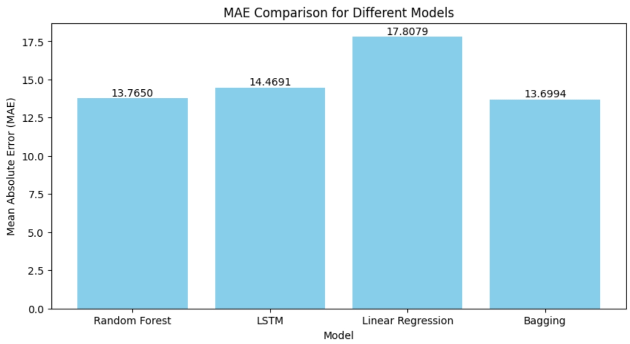

Figure 4.2: MAE comparison for different models.

The figures presented in “Figure 4.3” illustrate the Root Mean Square Error (RMSE) metrics associated with machine learning (ML) and deep learning (DL) models. RMSE is a commonly used statistic for evaluating the performance of regression models. It measures the average magnitude of the discrepancy between predicted and actual values within a dataset. From the figure, it can be observed that the Bagging (Random Forest) model has the lowest RMSE score (22.21), indicating that, on average, its predicted values deviate the least from the actual values. This suggests that the model exhibits strong predictive accuracy. The Random Forest model also performs well, although it has a slightly higher RMSE (22.39) compared to Bagging (Random Forest).

On the other hand, the LSTM model shows a larger RMSE (23.50) compared to both the Random Forest and Bagging (Random Forest) models, indicating potentially inferior performance in terms of predictive accuracy. Among the mentioned models, the linear regression model has the largest RMSE value (27.04), suggesting a potentially lower level of accuracy in predicting the target variable compared to the other models.

These findings suggest that both the Bagging (Random Forest) and Random Forest models perform well in terms of RMSE, indicating their ability to provide accurate predictions. However, the LSTM and linear regression models may have limitations in accurately predicting the target variable based on their higher RMSE values.

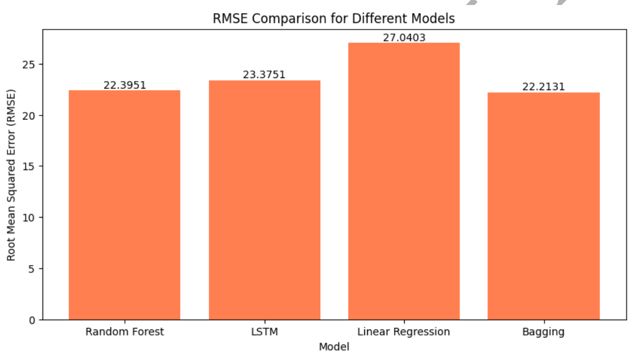

Figure 4.3: RMSE comparison for different models.

The numbers provided in the "Figure 4.4" represent the R2 values for different machine learning (ML) and deep learning (DL) models. The R2 coefficient is a statistical metric that quantifies the extent to which the independent variables can explain the variability observed in the dependent variable. It ranges from 0 to 1, with a value of 1 indicating a perfect fit. Among the models presented, it is evident that the Bagging (Random Forest) model shows the highest R2 value (0.9352), indicating its superior ability to fit the data accurately. The Random Forest (0.9341) and LSTM (0.9275) models also demonstrate high R2 values, suggesting their effectiveness in explaining a significant proportion of the observed variability in the dependent variable. While Linear Regression still performs satisfactorily (0.9040), its R2 value is slightly lower compared to the alternative models. Overall, it can be observed that all of the models exhibit strong performance in elucidating the variability in the dependent variable. However, it is noteworthy that Bagging (Random Forest) emerges as the most prominent performer among them.

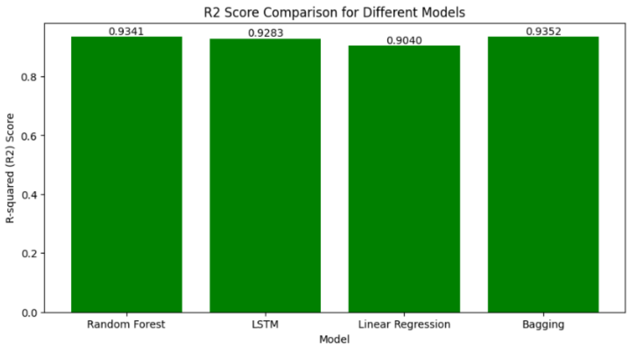

Figure 4.4: R- squared comparison for different models.

Compared to the previous study, this research has improved the results by More than 0.5%. It was shown that [12], the researchers used the same dataset and applied five machine learning methods; gradient boosting was the most performed, with 93.05%. The proposed model gets 93.41% by using a random forest. Bagging (random forest) has the highest results, 93.52%. In the future, researchers in this field could use a combination of ML and DL to improve model performance [4].

4.4 Conclusion

The authors mainly presented a new model to enhance intelligent traffic systems. The main purpose of this method is to recognize the traffic flow prediction or vehicle movement at intersections using an ensemble learning technique. The proposed framework consisted of three primary phases: data collection through cameras and sensors, implementation of machine learning and deep learning algorithms, and evaluation of the outcomes using metrics such as R-squared, RMSE, and MAE. The model utilized various machine learning (ML) and deep learning (DL) algorithms, including Random Forest, LSTM, Linear Regression, and ensemble methods (bagging), to achieve its objectives. To safeguard the better performance of the proposed procedure, a series of tests were involved. The comprehensive results stated the betterment of proposed method in a significant performance improvement of 93.52% compared to recent approaches. The obtained values highlighted that the proposed technique reaches significant performance. As a future work, combining multiple ML and DL algorithms could be explored to further enhance the performance of this model for more effective intelligent traffic systems.

Chapter 5

Conclusion, Discussion, and Future Work

5.1 Introduction

This chapter serves to elaborate on the findings and contributions of this dissertation while also aiming to consolidate and summarize them. Furthermore, it seeks to identify the limitations of the current research and provide avenues for future investigation. Divided into four parts, this chapter encompasses Section 5.2, which offers a summary of the thesis, Section 5.3.1, which discusses the contributions and limitations of the present study, Section 5.3.2, which explores potential future work, and Section 5.4, where the conclusion is presented.

5.2 Summary of the thesis

The Internet of Vehicles (IoV) enables uninterrupted communication and data exchange among pedestrians, infrastructure, and vehicles. By harnessing the potential of artificial intelligence, IoV can be transformed into a transportation system that is safer, more efficient, and environmentally friendly, effectively addressing these challenges. This thesis contributes to the field of "Traffic Flow Prediction in Smart Traffic Systems." The model integrates a diverse range of machine learning and deep learning techniques, resulting in a significant performance enhancement.

Chapter 1 discusses the problem statement, the purpose of the thesis, and the research objectives, highlighting the scientific contributions.

Chapter 2 defines the term "Internet of Vehicles" and categorizes the associated technologies. It also explores artificial intelligence technologies and their applications in intelligent transportation systems. Additionally, it presents the challenges and solutions in the field of the Internet of Vehicles, along with a review of previous research on traffic flow prediction in intelligent traffic systems.

Chapter 3 focuses on data preprocessing, encompassing data collection, preparation, and proposed techniques. The chapter also discusses the proposed model, which integrates traditional machine learning approaches such as Random Forest, Long Short-Term Memory (LSTM), and Linear Regression with ensemble methods like Bagging (Random Forest). Each method is briefly described, and measurement indices such as Accuracy, Precision, Recall, F-measure, the coefficient of determination (R-squared), root-mean-squared error (RMSE), and mean absolute error

(MAE) are explained in detail.

Chapter 4 presents the results generated using machine learning techniques and ensemble methods on our dataset. The primary objective was to enhance the predictability of traffic flow. Three key parameters, namely the coefficient of determination (R-squared), root-mean-squared error (RMSE), and mean absolute error (MAE), were utilized to evaluate the performance of various models. These metrics provide a comprehensive assessment of the model's performance and aid in identifying the optimal approach for the dataset. A thorough analysis was conducted to compare the results of conventional machine learning approaches with ensemble methods. The main finding was that integrating conventional machine learning approaches with ensemble methods significantly improved accuracy. This outcome supports the notion that ensemble approaches enhance prediction performance by leveraging collective strengths and minimizing individual flaws. To validate the results, the author compared them with previous studies that employed similar datasets to forecast traffic flow.

5.3 Discussion

Section 5.3 Discussion is divided into two parts. The initial part highlights the contributions made by the thesis, while the subsequent part focuses on the future work that the thesis will undertake.

5.3.1 Contributions of the Thesis

The primary objective of this research is to elucidate the technical aspects, challenges, and solutions related to the Internet of Vehicles (IoV) technology. In order to conduct thorough research and analysis, two key questions were formulated:

Q1: What are the technical solutions that need to be addressed in the context of IoV?

Q2: What are the challenges and solutions associated with IoV technology?

The main focus of this thesis was to propose a novel model that enhances intelligent traffic systems. This approach employs an ensemble learning technique to accurately predict traffic flow and vehicle movements at intersections.

Furthermore, several articles have been published in conjunction with this thesis. One of them, titled "Using Ensemble Learning-Based Algorithms for Traffic Flow Prediction in Smart Traffic Systems," was published in the Engineering, Technology & Applied Science Research journal in 2024. Another paper, titled "The Internet of Vehicles (IoV) Technology: Challenges and Solutions," was published in the Journal of Theoretical and Applied Information Technology in 2023.

5.3.2 Future Work

In future work, several concepts for future projects will be reflected upon. The suggested model will utilize various methodologies to examine potential ensemble combinations and improve performance. The results of these trials will be compared to the findings reported in the thesis, contributing to the advancement of the suggested model. Furthermore, a thorough analysis will be carried out to compare the outcomes derived from different data mining methods in order to determine the most advantageous ones. This will facilitate a more comprehensive comprehension of the variables that influence vehicle movement at intersections.

5.4 Conclusion

Our primary focus was to develop a new model aimed at enhancing intelligent traffic systems. The main objective of this approach, which utilizes ensemble learning, is to accurately predict traffic flow and vehicle movement at intersections. The suggested framework consists of three phases: data collection through cameras and sensors, deployment of machine learning and deep learning algorithms, and evaluation of results using metrics such as R-squared, regression mean square error, and mean absolute error. To achieve its goals, the model incorporates various machine learning (ML) and deep learning (DL) techniques, including Random Forest, LSTM, Linear Regression, and ensemble approaches (bagging). Several tests were conducted to ensure the effectiveness of the proposed procedures. Through comprehensive comparisons with contemporary approaches, the findings demonstrated a significant performance improvement of 93.52% for the suggested method. These results highlight the proposed technique's ability to achieve a high level of performance. In future studies, exploring the combination of different ML and DL algorithms could further improve the model's performance, ultimately leading to more efficient and intelligent traffic systems.

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نظام ذكي لإدارة حركة المرور باستخدام إنترنت المركبات

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رمضان ١٤٤٧ هـ - شره ٢٠٢٦ م

المستخلص

يشهد العالم توسعاً حضرياً متسارعاً أدى إلى زيادة الكثافة المرورية وتعقيد إدارة شبكات النقل داخل المدن الحديثة، الأمر الذي يتطلب حلولاً ذكية قادرة على تحسين انسيابية الحركة المرورية وتعزيز سلامة مستخدمي الطرق. ويُعد إنترنت المركبات (يط) أحد أهم التقنيات الحديثة التي تُمكّن المركبات والبنية التحتية المرورية من تبادل البيانات بصورة مستمرة، مما يساهم في بناء أنظمة نقل ذكية تعتمد على البيانات في اتخاذ القرارات.

تهدف هذه الدراسة إلى تطوير نظام ذكي لإدارة حركة المرور يعتمد على تقنيات إنترنت المركبات والذكاء الاصطناعي، وذلك من خلال دمج خوارزميات تعلم الآلة والتعلم العميق لتحليل البيانات المرورية والتنبؤ بحالة الطرق والازدحام قبل حدوثه. كما يعتمد النظام المقترح على معالجة البيانات الواردة من المركبات وأجهزة الاستشعار وإشارات المرور بهدف تحسين توزيع الحركة المرورية وتقليل زمن الرحلات واستهلاك الوقود والانبعاثات البيئية.

تم تقييم النموذج المقترح باستخدام مجموعة من البيانات المرورية الواقعية والمحاكاة، حيث أظهرت النتائج قدرة النظام على تحقيق دقة مرتفعة في التنبؤ بحركة المرور وتحسين أداء إدارة التقاطعات مقارنةً بالأساليب التقليدية. كما أثبتت النتائج فعالية دمج تقنيات الذكاء الاصطناعي مع إنترنت المركبات في دعم أنظمة النقل الذكية وتحقيق مستوى أعلى من الكفاءة والموثوقية.

وتؤكد نتائج هذه الدراسة أن النظام المقترح يمثل خطوة مهمة نحو تطوير حلول نقل ذكية تدعم مستهدفات المدن الذكية ورؤية المملكة العربية السعودية ٠٣٠٢ من خلال تحسين جودة خدمات النقل، وتعزيز السلامة المرورية، والاستفادة المثلى من التقنيات الرقمية الحديثة.

الكلمات المفتاحية: المدن الذكية، إنترنت المركبات، أنظمة النقل الذكية، الذكاء الاصطناعي، تعلم الآلة، التعلم العميق، التنبؤ بحركة المرور، إدارة المرور. ععع