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Enhancing traffic flow and congestion management in smart cities utilizing SVM-based linear regression approach

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ABSTRACT

With the development of smart cities, it is essential to monitor traffic flow and manage congestion effectively to ensure smooth movement for people and address their social and economic needs. As these needs continue to change, roadside infrastructure faces challenges in meeting the demands of citizens in smart cities. Traffic congestion is a major issue in road networks and occurs when the number of vehicles exceeds the capacity of the roads. Emerging technologies like Vehicular Networks (VN) and Support Vector Machine (SVM)-based linear regression offer promising solutions for vehicle-to-vehicle communication and managing autonomous roadside infrastructure. SVM-based linear regression is a well-known and effective method for addressing various issues related to roadside infrastructure, traffic management, data integration, analytics, and environmental monitoring. The main goal of using SVM-based linear regression in this research is to help citizens and city authorities make informed decisions and better understand and control traffic. This study demonstrates the application of SVM-based linear regression in integrating autonomous roadside infrastructure, achieving a high accuracy rate of 92% and reducing errors by 8%, showing a notable improvement compared to previous methods.

1. Introduction

In recent years, metropolitan regions have adopted the "smart city" initiative to adopt advanced technologies and improve the sophisticated lives of the people (Sharma and Kanwal, 2023). The people are eager to make use of contemporary advancements in network connectivity, waste management, transport, traffic control, city monitoring, surveillance, irrigation, and autonomous roadside infrastructure. Electric vehicles, interconnected vehicles, and autonomous roadside infrastructure are revolutionizing the automotive sector (Zaino et al., 2024).

Autonomous roadside infrastructure helps manage traffic congestion in cities and provides important updates during emergencies. Interconnected vehicles use internet connections to access cloud-based data for regional traffic and navigation. These benefits are made possible by placing smart devices throughout the city. However, these advanced technologies rely on sensors, transducers, and high-speed wireless connections to function. With the support of autonomous roadside infrastructure, city traffic can be managed more efficiently by making automatic decisions based on real-time data. To build effective traffic management systems, smart cities depend on foundational technologies such as self-driving systems, Vehicle-to-Vehicle (V2V), and Vehicle-to-Infrastructure (V2I) communication (Seth et al., 2024).

A smart city uses a variety of smart appliances as well as sensors to collect data from various nodes.

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The transportation system may interface with the various organizations that are a component of the proposal for a digital city. The smart city (Atta et al., 2020) concept and 5G network connection are promoting social transformation. The population and economic well-being of the country have an impact on the deployment of the 5G network. As modern linked automobiles receive and send information from their surroundings, the automobile industry is likewise affecting the use of advanced-level technologies.

Sensors, Internet of Vehicles (IoV) devices, and wireless networks are effectively applied in smart city data sharing on roadside infrastructure. The vehicles are equipped with sensors that collect data on the road. Drivers are provided real-time information on vehicle location, navigation, and speed using instant message services. The movement of automobiles on the road is accomplished without the intervention of humans. Real-time information is provided through smartphones linked to vehicle networks. To collect information regarding the movement of vehicles in that region, a roadside sensor is set up at a consistent distance (Miller, 2008). The IoV sensors can automatically build connectivity with adjacent devices.

Vehicles need to communicate with one another, and roadside infrastructure acts as an intermediary to facilitate this communication within a specified range. Roadside devices play a key role in connecting vehicles and managing this interaction. When unauthorized access to a vehicle occurs, the owner receives an alert with specific vehicle details. City traffic is managed effectively through roadside infrastructure, with the registration of vehicle information serving as an initial step in traffic management. The vehicle's intended destination is also identified. Devices at one location are networked with others to gather traffic data. A primary route for the vehicle is assessed for traffic conditions. If the route is feasible, it is provided to the driver; if not, alternative routes are considered until the best path is identified to reduce traffic congestion in urban areas. IoV devices send messages to share information on the optimal route. This technology helps create a better transit environment in metropolitan areas and provides effective transport solutions for emergency vehicles. Access to traffic data improves safety and supports parking space management, reducing unnecessary travel time and easing traffic congestion (Mostowfi and Buttlar, 2020).

For many years, Artificial Intelligence (AI) has been used in traditional roadside infrastructure to enhance road and urban traffic efficiency. Decision support systems within roadside infrastructure have evolved to better assist operators in making effective decisions (Borst et al., 2017). Different analytics and reasoning methods are necessary for various tasks because each roadside infrastructure system has unique needs and limitations. However, the use of advanced AI with "black-box" behavior can reduce transparency and lead to a loss of trust and responsiveness among drivers. A black-box approach offers a complete solution but without explaining its reasoning (Hagras, 2018), which makes it difficult for humans to monitor and understand the solution. This verification is especially important in safety-critical scenarios where systems need to be understandable and transparent. To address this issue, new roadside infrastructures are working towards more reliable solutions by providing clear explanations. This helps establish the right level of trust among operators, avoiding both excessive trust and mistrust.

Support Vector Machine (SVM) linear regression is a machine learning method that finds the line that best fits a set of data points, while minimizing the distance between the line and the data points. It is often used for prediction and modeling tasks because it can handle large datasets and complex features effectively. This technique is also being explored for its ability to support integrated and comprehensive autonomous decision-making, as well as to enhance the quality of decisions.

2. Literature survey

Many research efforts focus on improving quality of life, particularly through better access to services. However, administrators, architects, and urban planners face significant challenges due to the demands of growing industries and increasing populations in metropolitan areas. The Internet of Things (IoT) and Information and Communication Technologies (ICT) have greatly influenced how organizations drive innovation and create new opportunities in their daily operations over the past decade. These advances have become central to "smart cities," where the goal of IoT and the IoV is to use ICT to deliver better services for people while offering businesses more opportunities for innovation through advanced technology (Bresciani et al., 2018). Smart transportation is a key aspect of smart cities and has become the second largest contributor to carbon dioxide emissions due to its low efficiency. This has an impact on both smart environments and transportation systems. Therefore, improving transportation efficiency is crucial for the success of smart cities and smart transportation (Lingli, 2015).

With the rise in popularity of the IoV, applications have advanced, and interconnected devices are now widely used across various aspects of modern cities. As the amount of data collected grows, ML techniques are used to enhance the intelligence and capabilities of applications. The increasing number of vehicles on the roads, combined with the growing global population, presents greater challenges for traffic management, especially in public transportation. Moreover, the frequency of accidents and other traffic-related issues is rising. By integrating existing technology with fundamental infrastructure, the Intelligent Transportation System (ITS) addresses many of these challenges (Sutar et al., 2016). Real-time vehicle tracking is now possible, improving transportation management through mobile technology and the extensive use of cellular networks. ITS eliminates the need for long wait times for buses. Smartphones are a highly appealing option for developing IoV applications due to their accessibility, expanding features, and affordability. A system based on a combination of technologies like GPS and Android has been developed to assist public transportation users (Raad et al., 2021).

To address data vulnerability, a decentralized information management system is being developed for smart and efficient mobility, incorporating blockchain and IoT technologies within a sustainable smart city framework. In the future, electric vehicles are anticipated to be widely used in both commercial and public transportation in metropolitan areas. The growing adoption of electric vehicles will play a crucial role in the long-term environmental and economic development of cities (Cao et al., 2018). The success factor of hybrid electric automobiles through current equipment, as well as its effective method of machine control, is also discussed (Abualkishik et al., 2023; Saleem et al., 2022a; Raj and Kamaraj, 2013). The numerous electric vehicles that may be used in smart city contexts, as well as their charging procedures, are discussed (Ferrer, 2017).

In a study by Ata et al. (2019), the authors proposed a traffic congestion prediction algorithm using neural backpropagation. This system displays messages on the vehicle's LCD screen after predicting congestion and provides an alternative route using Google Maps. Tamimi and Zahoor (2010) presented a method based on Artificial Neural Networks (ANN), incorporating variables such as distance, time, wind speed, traffic flow, temperature, and humidity. The simulation results demonstrated the effectiveness of the proposed approach, confirming that the model accurately processed and learned from the data provided through an efficient system.

In a study by Li et al. (2020), the authors proposed a low-cost method for measuring vehicle speed by classifying auditory waveforms using a single roadside auditory sensor. However, the presence of extremely loud vehicles and a wide range of auditory signals can limit the effectiveness of this approach in developing countries.

Sakran developed a system (Abbas et al., 2022) that integrates the IoT with intermediary intelligence into a unified network, where agent-based expertise enables efficient communication and coordination within IoT networks involving a large number of diverse, dynamically distributed, and autonomous devices. The study introduced a real-time traffic simulation model for IoT-enabled traffic management using NetLogo, an agent-based environment, and mobile agent tools.

Sadhukhan and Gazi (2018) presented a system for real-time monitoring and controlling of road traffic using IoT. The IoT-based solution relies on cloud technology, which provides various services such as data storage and applications. An RF transmitter is used for alternative traffic control, and load cells are employed to measure the time required to optimize traffic flow. When vehicles pass over the load cells embedded in the road, their weight is converted into electrical signals, enabling precise traffic management (Sadhukhan and Gazi, 2018).

Big data analytics are widely used in smart communities, cities, control systems, and other smart applications. A framework utilizing Hadoop and Spark for estimating transportation data was proposed to process real-time transport information efficiently. The methodology was validated using reliable transportation data from various sources, demonstrating that citizens can access real-time data processing and delivery quickly (Aujla et al., 2018). V2V and V2I communication play a crucial role in smart transportation (Agarwal et al., 2021). These methods help build the essential framework for autonomous vehicles in future smart cities.

Specifically, AI experienced significant growth during the 2010s, driven by increased access to vast amounts of data and the exceptional capabilities of computer graphics card processors, which accelerated learning processes (Muller, 2020). Certain approaches allow humans to understand (i) the AI algorithms and (ii) their explanations, which are closely linked to the systems they describe and follow similar trends. According to Mueller et al. (2019), this approach is now considered to be in its third generation.

The performance of some previous methods, in terms of accuracy, is highlighted in Table 1. There are various methods that can help develop solutions for the increasing challenges in designing smart and autonomous systems. Ensemble learning technique (Matloob et al., 2021), blockchain technology (Malik and Saleem, 2022), Machine learning (Atta et al., 2020; Ata et al., 2021; Saleem et al., 2019; 2022b; Bokaba et al., 2022; Asif et al., 2022), soft computing (Khan et al., 2020a; 2020b), Intelligence approaches (Khan et al., 2022), Particle Swarm Optimization (PSO) (Khan et al., 2019; Asif et al., 2019), as well as computational intelligence (Sajjad et al., 2023), transfer learning (Mehmood et al., 2022), and deep learning technique (Siddiqui et al., 2021) are approximate methods being applied in constructing several smart, as well as autonomous agendas.

Table 1: Performance of previous methods

Reference	Method	Accuracy
Krizhevsky et al. (2012)	AlexNet	85.33%
Szegedy et al. (2015)	GoogLeNet	87.08%
Simonyan and Zisserman (2014)	VGG-16	86.25%
Simonyan and Zisserman (2014)	VGG-19	86.58%
He et al. (2016)	ResNet 50	87.08%

3. Proposed methodology

In recent times, the worldwide transportation industry has undergone significant changes with the rise of autonomous vehicles and the implementation of smart city infrastructure. Autonomous roadside infrastructure has emerged as a promising solution for improving traffic management operations and enhancing the safety and efficiency of transportation systems. This research aims to develop a system that leverages SVM linear regression models to enable decision-making in autonomous roadside infrastructure with a better understanding. The proposed infrastructure is shown in Fig. 1.

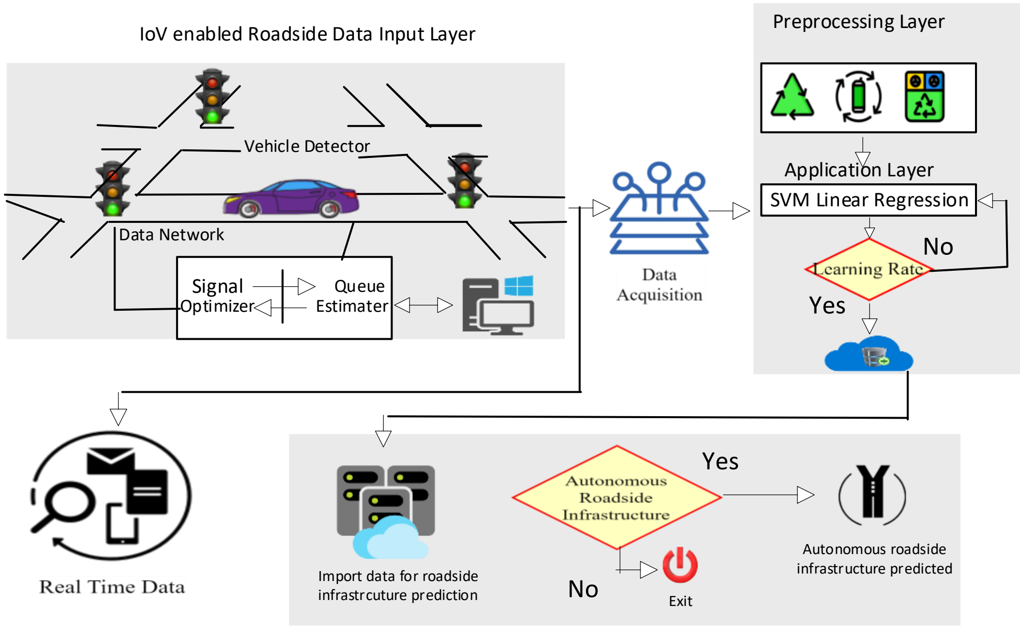

Fig. 1: Proposed model

Fig. 1 illustrates the structure of the proposed autonomous roadside infrastructure, which is evaluated using training and validation phases. The training phase consists of five layers: roadside infrastructure, data acquisition layer, preprocessing layer, application layer, and SVM linear regression. IoV-enabled devices connected to the roadside infrastructure collect data and send it to the data acquisition layer. This layer gathers data, converts it into electrical signals, and performs the necessary processing. The data is then passed to the preprocessing layer, which reduces noise generated from wireless communication. The preprocessed data moves to the application layer, where it is analyzed using a linear regression algorithm. This algorithm predicts patterns and generates reports that offer real-time insights into performance.

$$\hat{H} = J\text{ŋ} + \bar{Æ} \tag{1}$$

In Eq. 1, 'J' denotes the slope of the line, and '$\bar{Æ}$' represents the intercept.

$$J\text{ŋ} - \hat{H} + \bar{Æ} = 0$$
$$\vec{\text{ꝑ}} . \vec{\text{ȍ}} + \bar{Æ} = 0 \tag{2}$$

The direction of a vector $\bar{\text{ȍ}} = (\text{ŋ}, \hat{H})^{T}$ is $\bar{\text{ꝑ}}$ and defined as:

$$\text{ꝑ} = \frac{\text{ŋ}}{||\text{ȍ}||} + \frac{\hat{H}}{||\text{ȍ}||} \tag{3}$$

where,

$$||\text{ȍ}|| = \sqrt{\text{ŋ}_{+}^{2}\, \hat{H}_{+}^{2} \,\dots\dots\dots\, \text{ȍ}_{\zeta}^{2}}$$

$$\cos(\theta) = \frac{\text{ŋ}}{||\text{ȍ}||} \; and \; \cos(\mu) = \frac{\hat{H}}{||\text{ȍ}||}$$

Eq. 3 can also be written as:

$$\text{ꝑ} = (\cos(\theta), \cos(\mu))$$
$$\vec{\text{ꝑ}} . \vec{\text{ȍ}} = ||\text{ꝑ}|| \; \big| |\text{ȍ}| \big| \cos(\theta)$$
$$\theta = \text{ύ} - \mu$$
$$\cos(\theta) = \cos(\text{ύ} - \mu) = \cos(\text{ύ}) \cos(\mu) + \sin(\text{ύ}) \sin(\mu)$$
$$= \frac{\vartheta}{||\text{ꝑ}||} \frac{\text{ŋ}}{||\text{ȍ}||} + \frac{\alpha}{||\text{ꝑ}||} \frac{\hat{H}}{||\text{ȍ}||} = \frac{\vartheta\text{ŋ} + \alpha\hat{H}}{||\text{ꝑ}||||\text{ȍ}||}$$
$$\text{ꝑ} . \text{ȍ} = ||\text{ꝑ}||||\text{ȍ}|| \left[\frac{\vartheta\text{ŋ} + \alpha\hat{H}}{||\text{ꝑ}||||\text{ȍ}||}\right]$$
$$\vec{\text{ꝑ}} . \vec{\text{ȍ}} = \sum_{i=1}^{\zeta} \text{ꝑ}_i \text{ȍ}_i \tag{4}$$

The dot product can be compared as Eq. 4 for ζ dimensional vectors, Let,

$$B = M\,(\text{ꝑ} . \text{ȍ} + \bar{Æ})$$
$$B_i = M_i\,(\text{ꝑ} . \text{ȍ} + \bar{Æ})$$

þ is the functional margin of the dataset:

$$\text{þ} = \min_{i=1\dots\text{ɮ}} B_i$$

While comparing hyperplanes, one with the largest þ will be chosen. þ is the geometric margin of the dataset. The goal is to find an optimal hyperplane, which means finding the values of $\vec{\text{ꝑ}}$ and b of the optimal hyperplane.

The Lagrangian function is:

$$\breve{A}\,(\text{ꝑ}, \bar{Æ}, \mu) = \frac{1}{2}\, \text{ꝑ} . \text{ꝑ} - \sum_{i=1}^{\text{ɮ}} \mu_i \,[M : (\text{ꝑ} . \text{ȍ} + \bar{Æ}) - 1]$$
$$\nabla_{\text{ꝑ}} \breve{A}\,(\text{ꝑ}, \bar{Æ}, \mu) = \text{ꝑ} - \sum_{i=1}^{\text{ɮ}} \mu_i\, M_i\, \text{ȍ}_i = 0 \tag{5}$$
$$\nabla_{\bar{Æ}} \breve{A}\,(\text{ꝑ}, \bar{Æ}, \mu) = - \sum_{i=1}^{\text{ɮ}} \mu_i\, M_i = 0 \tag{6}$$

From the Eqs. 5 and 6, we get:

$$ƀ = \sum_{i=1}^{ƀ} µ_i M_i ð_i \text{ and } \sum_{i=1}^{ƀ} µ_i M_i = 0 \quad (7)$$

After substituting the Lagrangian function Ă, we get:

$$ƀ(µ, Ǣ) = \sum_{i=1}^{ƀ} µ_i - \frac{1}{2} \sum_{i=1}^{ƀ} \sum_{j=1}^{ƀ} µ_i µ_j M_i M_j ð_i ð_j$$

thus,

$$\max_{µ} \sum_{i=1}^{ƀ} µ_i - \frac{1}{2} \sum_{i=1}^{ƀ} \sum_{j=1}^{ƀ} µ_i µ_j M_i M_j ð_i ð_j \quad (8)$$

Subject to $µ_i \geq 0, i = 1 \ldots ƀ, \sum_{i=1}^{ƀ} µ_i M_i = 0$

The Lagrangian multipliers method is extended to Karush-Kuhn-Tucker (KKT) conditions because of inequalities in the constraints. KKT's complementary status states that:

$$µ_i [M_i(ƀ_i . ð^* + Ǣ) - 1] = 0 \quad (9)$$

where, $ð^*$ is the point/points where we reach the optimal; µ is the positive value and μ for the other aspects are ≈ 0, So:

$$M_i\big((ƀ_i . ð^* + Ǣ) - 1\big) = 0 \quad (10)$$
$$ƀ - \sum_{i=1}^{ƀ} µ_i M_i ð_i = 0$$
$$ƀ = \sum_{i=1}^{ƀ} µ_i M_i ð_i \quad (11)$$

To compute the value of Ǣ, we get:

$$M_i\big((ƀ_i . ð^* + Ǣ) - 1\big) = 0 \quad (12)$$

In Eq. 12, multiply both sides by M to get:

$$M_i^2\big((ƀ_i . ð^* + Ǣ) - M_i\big) = 0$$

where, $M_i^2 = 1$.

$$\big((ƀ_i . ð^* + Ǣ) - M_i\big) = 0$$
$$Ǣ = M_i - ƀ_i . ð^* \quad (13)$$

then,

$$Ǣ = \frac{1}{Ƀ} \sum_{i=1}^{Ƀ} (M_i - ƀ . ð) \quad (14)$$

where, Ƀ is the number of support vectors. On one occasion, the hyperplane will make predictions. Where the hypothesis function is:

$$c\,(ƀ_i) = \begin{bmatrix} 1 \text{ if } ƀ . ð + Ǣ > 0 \\ 0 \text{ if } ƀ . ð + Ǣ \leq 0 \end{bmatrix} \quad (15)$$

The main goal of the SVM algorithm is to identify a hyperplane that can effectively separate the data, aiming to find the optimal hyperplane. Once determined, the output from regression models is used to make predictions and generate explanations based on traffic data.

The output from linear regression is further utilized to provide predictions, offering valuable assistance to traffic management administrators in interpreting decisions, which is crucial for smooth city traffic flow.

Next, the learning criteria are evaluated. If the criteria are not met, the linear regression algorithm is retrained; if the criteria are met, the predicted outcome is stored in a cloud database. During the validation phase, trained patterns are imported from the cloud dataset and compared with real-time data from IoV-enabled roadside infrastructure to determine whether the prediction for the autonomous roadside system is accurate. If not, the process terminates; if accurate, a message confirms that the autonomous roadside infrastructure prediction has been achieved.

4. Results and simulation

This research aims to explore the integration of autonomous roadside infrastructure into smart cities using SVM linear regression. Integrating this infrastructure has the potential to transform urban mobility, making it more efficient and sustainable. However, several challenges must be addressed to ensure successful implementation. To address these challenges, simulation environments can be used to test the effectiveness of SVM linear regression techniques on datasets, with 70% of the data used for training and 30% for validation. This approach can contribute to the development of more efficient and sustainable smart cities, ultimately enhancing the quality of life for residents.

Table 2 presents the results for training (70% of the data) and validation (30% of the data) for supervised learning algorithms. The training results show an accuracy of 93%, a miss rate of 4.42%, a mean absolute error of 5.3%, a root mean squared error of 51.54%, a median absolute error of 4.14%, and an explained variance score of 93%. The validation results indicate an accuracy of 92%, a miss rate of 16.67%, a mean absolute error of 5.5%, a root mean squared error of 55.8%, a median absolute error of 4.31%, and an explained variance score of 93%. This suggests that the algorithms may have overfit during training and may require further tuning to improve their performance on unseen data.

Table 2: Performance measures of training and validation

Supervised learning algorithms	Training results parameters					
	Accuracy	Miss rate	Mean absolute error	Root mean squared error	Median absolute error	Explain variance score
Training	93	4.42	5.3	51.54	4.14	93
Validation	92	16.67	5.5	55.8	4.31	93

In Fig. 2, the graph shows a linear trend model of a variable over time, where the predicted value is represented by the red line. The red line is constant at a value of 60, indicating that there is an overall trend of the variable being stable over time. However, fluctuations in the data points are shown by the scattering of points around the red line. These fluctuations are quite significant, with the variable values ranging between 20-140, and they occur almost on a monthly basis. This means that the variable has a lot of variability or volatility, which may be due to various factors, such as external conditions that may affect the variable.

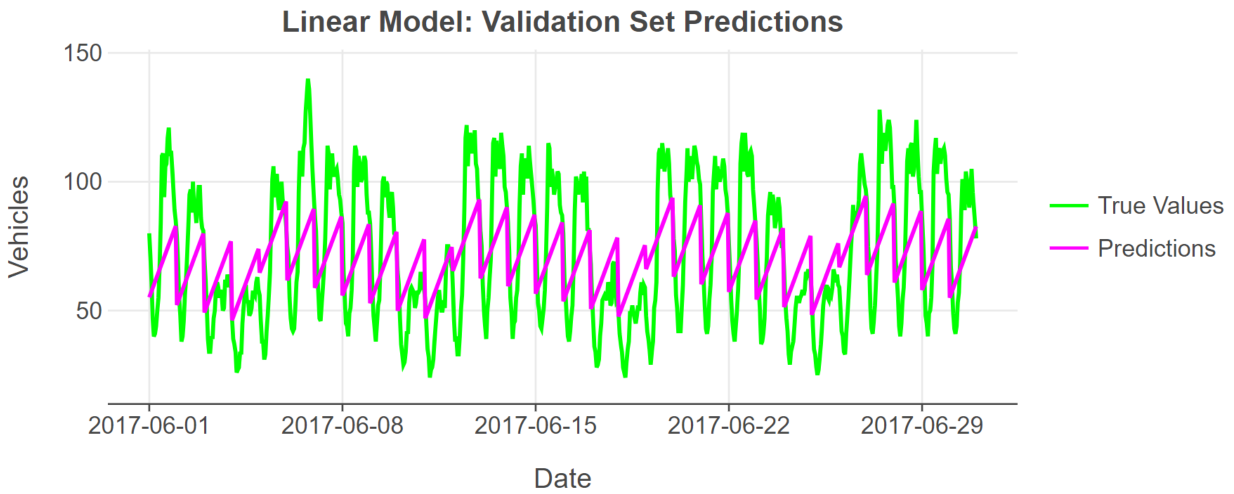

Fig. 2: Linear trend model

In Fig. 3, the graph represents a linear model for a validation set of predictions. The predicted values are represented by the pink line, which is between 50-85, and the true values by the green line are represented by the scatter of points around the pink line. The true values fluctuate between 20-140, and these fluctuations occur almost monthly. These fluctuations in the true values can have a significant impact on the variable and cannot be ignored. Therefore, it is crucial to understand the underlying factors that are causing these fluctuations and to take them into account when making predictions or decisions based on this data. This understanding can help improve the accuracy of the model and help make more informed decisions based on the data.

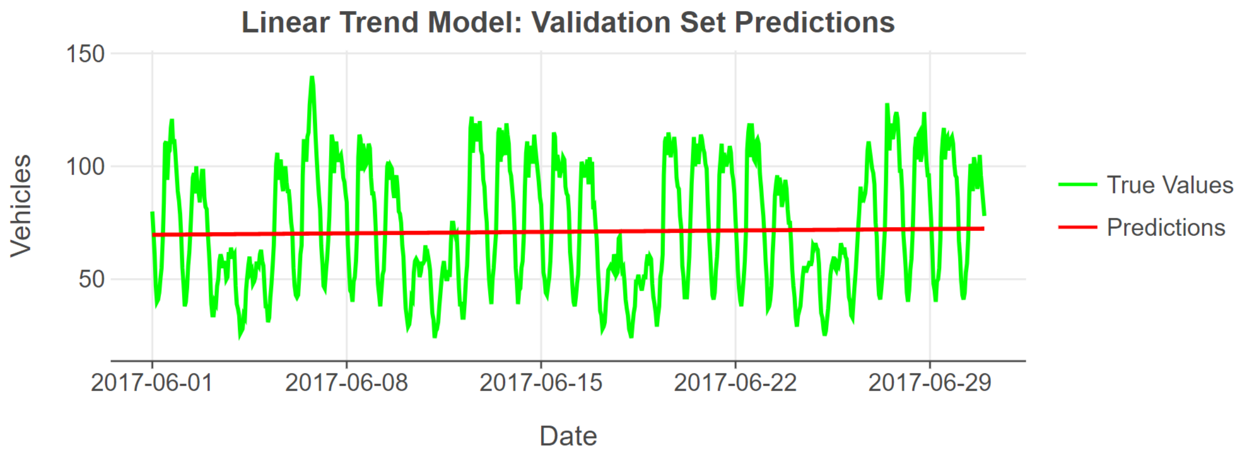

Fig. 3: Linear model for the validation set predictions

This graph in Fig. 4 represents an XGBoost model for a validation set of predictions. The predicted values are represented by the pink line, which is between 30-125, and the true values are represented by the scatter of green points around the pink line. The true values fluctuate between 20-140, and these fluctuations occur almost monthly. It is important to understand the underlying factors that are causing these fluctuations and to take them into account when making predictions or decisions based on this data. This understanding can help improve the accuracy of the XGBoost model further and make more informed decisions based on the data.

Fig. 5 shows the graph of the trend model and an XGBoost model applied to a validation set of predictions. The models are depicted by a blue line, covering values between 20 and 130. The true values are represented by green scatter points around the lines, ranging between 15 and 140, with fluctuations that occur almost on a monthly basis. These fluctuations are influenced by underlying factors that must be considered when making predictions or decisions based on this data. Understanding these factors can help improve model accuracy and enable more informed decision-making based on the data.

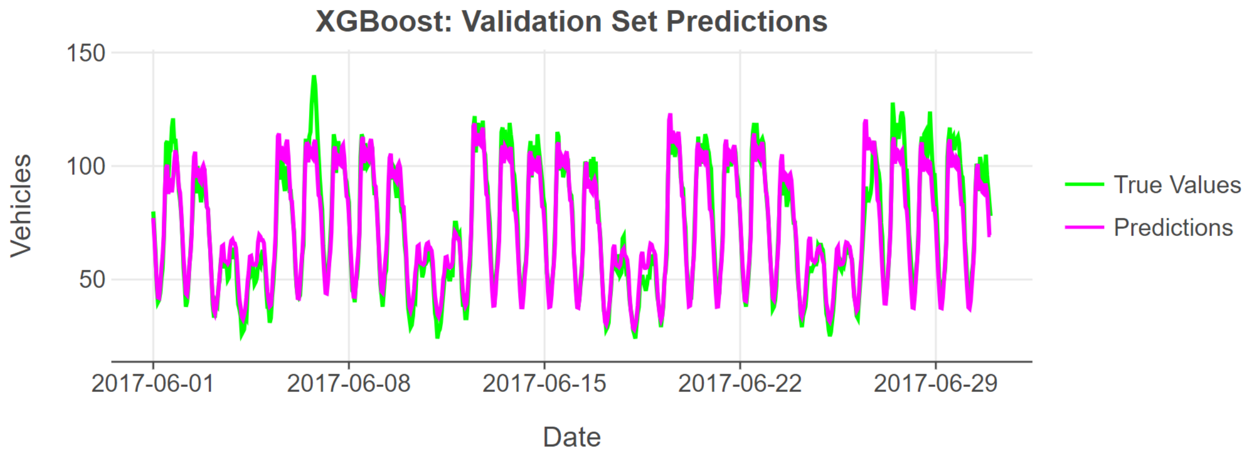

Fig. 4: XGBoost for the validation set predictions

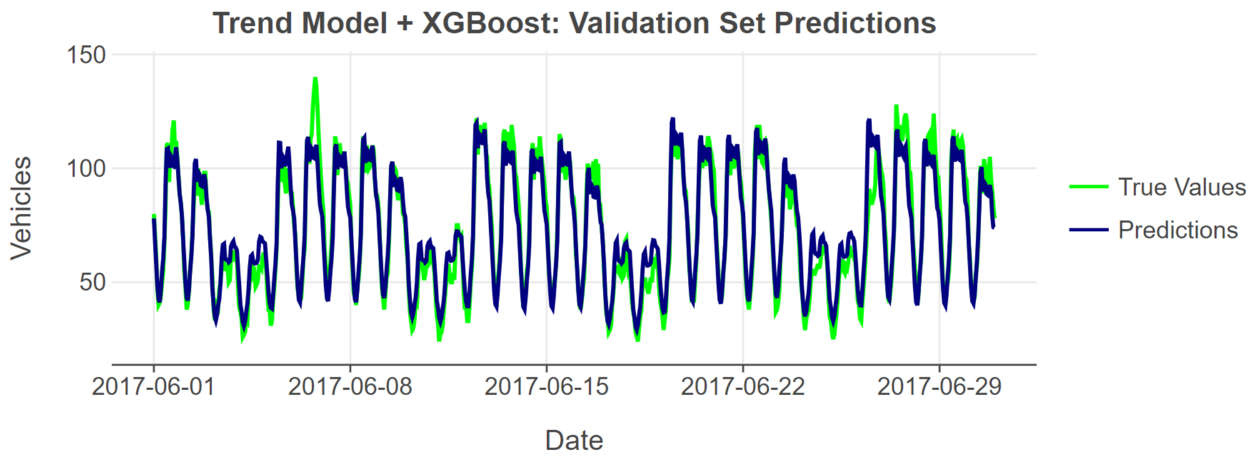

Fig. 5: Trend model and the XGBoost model for the validation set predictions

Fig. 6 illustrates an XGBoost model with lagging variables applied to a validation set of predictions. The predicted values are shown by a pink line, ranging between 15 and 120, while the true values are depicted as green scatter points around the pink line, fluctuating between 15 and 135. These fluctuations occur almost monthly and may be influenced by various factors that need to be considered when making predictions or decisions based on this data. Understanding these factors can help improve the accuracy of the XGBoost model with lagging variables and enable more informed decision-making based on the data.

According to Table 3, the proposed model shows better performance than the previous published approaches, with an accuracy of 92% and an 8% miss rate.

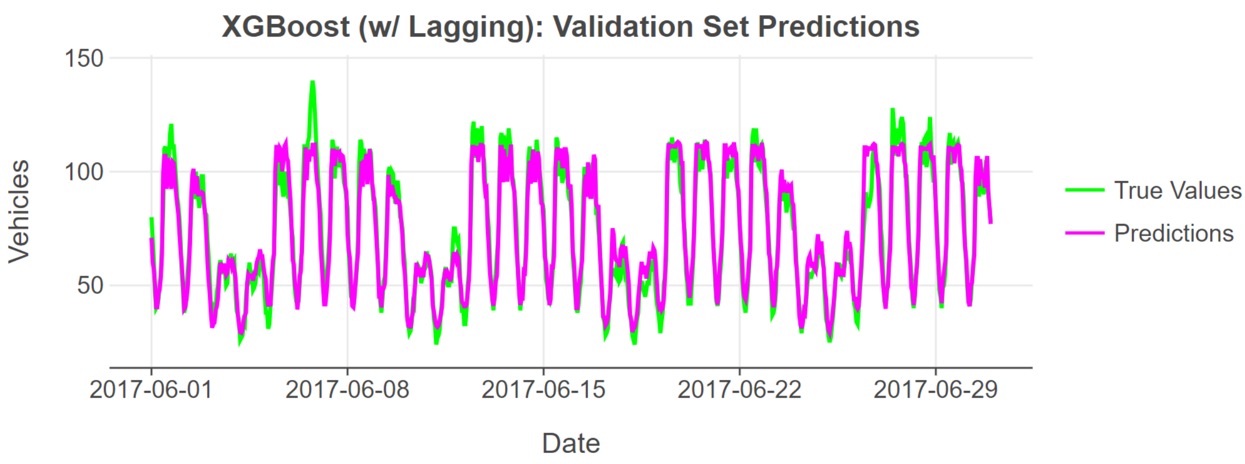

Fig. 6: XGBoost (w/Lagging) for the validation set predictions

Table 3: Comparison of the proposed model

Method	Accuracy	Miss rate
AdaBoost (Model 9) (Bokaba et al., 2022)	52.1%	47.9%
RF (Al Mamlook et al., 2020)	85.1%	14.9%
RF (Bharadwaj et al., 2019)	75.5%	24.5%
DT (Al Mamlook et al., 2020)	80.7%	19.3%
MLP (Wang et al., 2019)	71.4%	28.6%
Proposed model	92%	8%

5. Conclusions

The primary motivation for this research is to improve traditional traffic management systems through automation and machine learning techniques. As cities expand, traffic congestion has become a significant problem, negatively impacting citizens' quality of life, causing delays, and increasing pollution levels. To address these challenges, innovative solutions are needed to optimize traffic flow and enhance road safety. Smart city traffic management aims to optimize traffic signals, predict congestion, integrate transportation systems, and improve safety, thereby promoting efficient and congestion-free urban mobility.

Autonomous roadside infrastructure offers a promising approach to improving traditional traffic management. This research proposes a system that utilizes SVM linear regression models to enable autonomous decision-making and enhance the decision-making processes within smart city roadside infrastructure. The proposed system demonstrates better results compared to previous methods, achieving 92% accuracy and an 8% miss rate. In the future, this work could be further refined to improve decision-making transparency through explainable AI approaches.

Compliance with ethical standards

Conflict of interest

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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