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Enhancing urban mobility: integration of IoT road traffic data and artificial intelligence in smart city environment

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ABSTRACT

Efficient traffic management poses a significant challenge in smart cities, requiring the integration of diverse approaches. This paper presents an artificial intelligence framework that integrates internet of things (IoT) road traffic data to optimize traffic flow in smart city environments. Real-time traffic data is collected using IoT edge sensors, processed using machine learning (support vector machines, logistic regression, k-nearest neighbors) and deep learning long short-term memory (LTSM) algorithms, and utilized to develop accurate short-term and long-term traffic forecasting models. The proposed framework showcases superior performance compared to existing approaches, making it a widely applicable solution for smart city traffic management. By leveraging IoT road traffic data and artificial intelligence (AI) techniques, real-time monitoring, proactive decision-making, and dynamic traffic control can be achieved, leading to optimized traffic flow, reduced congestion, and enhanced urban mobility. This research provides valuable insights into the potential of IoT and AI technologies in addressing urban traffic challenges and lays the foundation for intelligent transportation systems in smart city environments.

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1. INTRODUCTION

Smart cities, characterized by the integration of advanced technologies, have emerged with the goal of improving the quality of life for inhabitants and enhancing the efficiency of urban services [1], [2]. Within the realm of smart city initiatives, traffic management stands as a crucial area of focus. The rapid urbanization and technological advancements witnessed in modern cities have posed significant challenges in effectively managing traffic, primarily due to the increasing urban population and resulting traffic congestion [3], [4]. To tackle this pressing issue, emerging technologies such as the internet of things (IoT) [5]–[7] have garnered substantial interest. The interconnection capabilities offered by IoT enable cities to gather real-time data on traffic patterns, road conditions, and vehicle movements. This data, often referred to as big data, holds immense potential for developing accurate and dynamic traffic prediction models [8], [9]. However, the sheer volume, velocity, and variety of traffic-related data generated by IoT devices present both challenges and opportunities for traffic prediction [10], [11].

Traditional traffic modeling techniques struggle to effectively process and analyze such vast and diverse datasets. Nevertheless, advancements in big data analytics and machine learning algorithms have opened new avenues for extracting valuable insights and enabling precise predictions of traffic conditions. The benefits of accurate traffic forecasting and optimized traffic flow extend beyond congestion reduction [12]. By intelligently routing vehicles and predicting road conditions well in advance, cities can minimize travel times, reduce fuel consumption, emissions, and noise pollution caused by traffic crises, enhance the efficiency of public transport, and improve overall safety. Moreover, predictive traffic modeling can support emergency response planning, assist in urban infrastructure development, and facilitate effective transport demand management.

This research aims to contribute to the advancement of traffic prediction techniques in the context of smart cities. By exploring the potential of IoT [13], [14], big data analytics [15], and optimization algorithms, this study seeks to develop a comprehensive and adaptable framework for traffic prediction and flow optimization. The research will investigate the effectiveness of various machine learning algorithms in processing and analyzing large-scale traffic data. The subject of smart city traffic prediction and forecasting, particularly with a focus on machine learning and deep learning in conjunction with IoT-based data collection [16], has gained significant attention in both intervention and research domains. In this paper, articles were selected from top journals across various databases. Neelakandan *et al.* [17] reported the outcomes of a benchmarking research study on an IoT-based traffic prediction and signal management system for a smart city. Their proposed system, utilizing an Intel 286 microprocessor, encompassed data gathering via IoT, feature engineering, data separation, traffic data optimization, and traffic management. The Elman neural network method [18], was employed to classify traffic data in congested areas, demonstrating superior performance compared to existing approaches. In another study, Lilhore *et al.* [19] designed an adaptive traffic management system for smart cities using machine learning and IoT. Their work encompassed multiple scenarios addressing concerns within the city's transportation infrastructure.

The proposed system incorporated a machine learning-based clustering algorithm to detect anomalies and regularly updated traffic light schedules based on traffic movement and expected flow, considering neighboring signal junctions. Simulation results indicated that the proposed approach outperformed existing transportation strategies, reducing traffic congestion, vehicle idle times, and accidents [20]. This article is structured into distinct sections. The first section provides an overview of the project's architecture and the employed algorithms. The subsequent section delves into the implementation, providing detailed explanations of the various techniques utilized. Finally, we present the results, draw conclusions based on our findings, and discuss future perspectives.

2. METHOD AND IMPLEMENTATION

The proposed architecture for collecting data from IoT devices on the road in this paper comprises three key components: the highway setup IoT router, the IoT platform, and the data center. Figure 1 visually represents the architecture and its components for collecting data from IoT devices on the road. The IoT router acts as a gateway, ensuring smooth connectivity and efficient transmission of data from the IoT devices. The IoT platform plays a vital role in managing and analyzing the collected data, employing advanced data ingestion techniques and robust security measures. Finally, the data center is responsible for processing the data using artificial intelligence (AI) algorithms, extracting valuable insights that contribute to effective traffic management and optimization. By seamlessly integrating IoT road traffic data with AI, this architecture holds immense potential for enhancing urban mobility in smart cities.

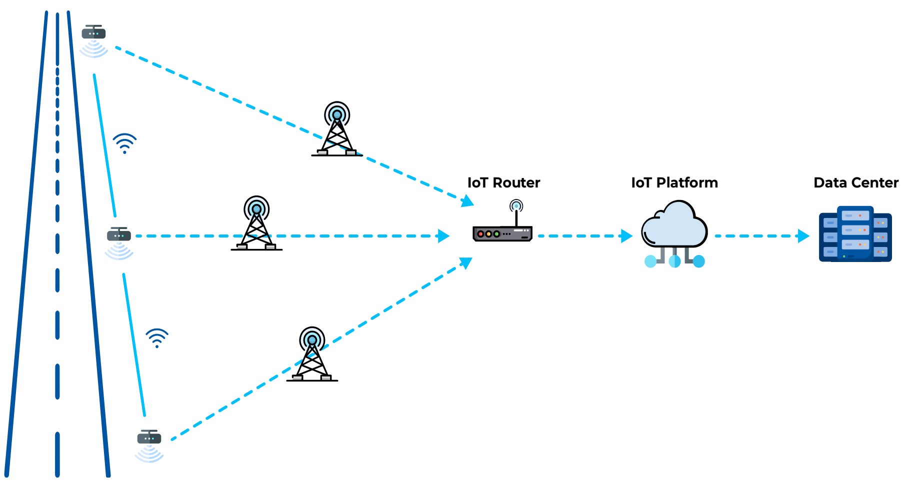

Figure 1. IoT architecture for SC traffic data collection

In this study, our focus lies on a valuable collection of datasets pertaining to vehicle traffic, which have been graciously provided by the City of Aarhus in Denmark. These datasets are generated through careful observation of vehicle traffic between two specific points, namely the start and end of a road. To ensure the collection of accurate and uninterrupted data, sensors are strategically positioned at a distance from intersections, thereby eliminating interference caused by vehicles halting at red lights. This meticulous setup enables a comprehensive analysis of traffic flow and patterns along the road segment, thereby offering valuable insights into the dynamics of vehicle movement.

Beginning our analysis with exploratory data analysis is consistently a wise decision as it helps us understand important dataset properties such as data format, number of samples, and data types. In this case, the dataset we are working with contains a total of 25,092,093 data points with 9 attributes. Figure 2 illustrates a sample of the data, providing a visual representation. The sensor connection component plays a vital role in collecting sensor readings by establishing a network connection through a RESTful endpoint. While the data wrapper model is responsible for semantically annotating the data, our specific focus is solely on the raw data itself, without requiring the semantic annotations provided by the data wrapper model. The dataset comprises two types of files: raw data and metadata. The raw data files contain measurements recorded by the deployed sensors in the area of interest. These sensors continuously capture and record various traffic-related metrics at regular intervals, typically every 5 minutes. The measurements encompass information such as the number of vehicles passing through, average vehicle speed, and the time taken for each measurement interval. In addition to the raw data files, the dataset includes metadata that provides essential contextual information. The metadata files contain details about the position of each of the two sensors used for data collection, the distance between these sensors, and their corresponding geographical coordinates. These specifics contribute to establishing a clear understanding of the physical layout and placement of the sensors along the road segment, enhancing our comprehension of the dataset, and its spatial context.

	status	avgMeasuredTime	avgSpeed	extID	medianMeasuredTime	TIMESTAMP	vehicleCount	_id	REPORT_ID
0	OK	66	56	668	66	2014-02-13T11:30:00	7	190000	158324
1	OK	69	53	668	69	2014-02-13T11:35:00	5	190449	158324
2	OK	69	53	668	69	2014-02-13T11:40:00	6	190898	158324
3	OK	70	52	668	70	2014-02-13T11:45:00	3	191347	158324
4	OK	64	57	668	64	2014-02-13T11:50:00	6	191796	158324
...	...	...	...	...	...	...	...	...	...
25097088	OK	1798	2	623	1798	2014-11-13T10:20:00	0	32507360	210199
25097089	OK	1798	2	623	1798	2014-11-13T10:30:00	0	32507801	210199
25097090	OK	1798	2	623	1798	2014-11-13T10:35:00	0	32508244	210199
25097091	OK	1798	2	623	1798	2014-11-13T10:40:00	0	32508648	210199
25097092	OK	1798	2	623	1798	2014-11-13T10:45:00	0	32509519	210199

25097093 rows x 9 columns

Figure 2. Sample data illustration and dataset overview

2.1. Feature engineering

When constructing a model, it is crucial to conduct a comprehensive data analysis to ensure the suitability of the data for model input. In the dataset under consideration, the date time column contains valuable information, but its current string format is suboptimal for effective analysis. Treating time as a linear input may not adequately capture the underlying patterns, especially when considering the smooth transition between 23:00 and 00:00. Given the clear daily periodicity of time, addressing this periodic nature becomes essential. One effective approach to handle this periodicity is by utilizing sine and cosine transforms, which extract meaningful signals representing the "time of day" and "time of year." By applying these transforms, the representation of time-related patterns is enhanced, enabling the model to better capture the temporal dynamics present in the data.

Figure 3 showcases the representation of time in its original form, depicted by the green plot, which denotes hours ranging from 0 to 23. Conversely, the remaining plots exhibit time after applying sinusoidal and cosine transformations. In order to effectively predict long-term traffic patterns, it proves advantageous to aggregate the data from 5-minute intervals into larger time intervals, such as one hour. This aggregation process involves consolidating 12 rows of data into a single row, resulting in a new dataset where each row represents one-hour intervals. By reducing the overall data volume through aggregation, subsequent analysis becomes more manageable and efficient, especially when dealing with extensive datasets spanning extended time periods.

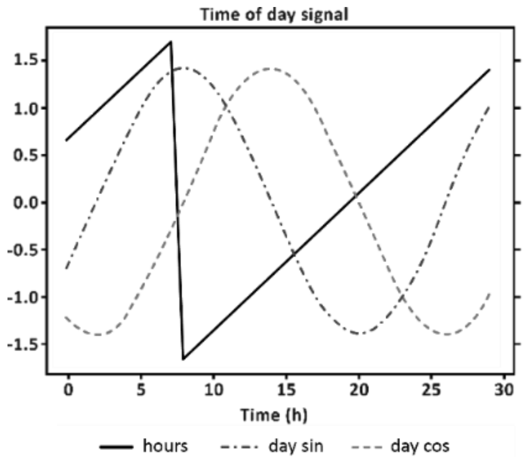

Figure 3. Transformation of time intervals for long-term traffic pattern prediction

2.2. Machine learning methods

In this study, a variety of models were utilized to predict traffic patterns using the collected data. The models employed encompassed both traditional statistical approaches and advanced deep learning techniques. This diverse selection of models allowed for a comprehensive exploration of different modeling paradigms and their effectiveness in capturing the complexities of traffic patterns.

2.3. Linear regression

Linear regression is a statistical model that analyzes the linear relationship between a dependent variable and a set of independent variables. It seeks to establish a linear equation that best fits the data, enabling predictions of the dependent variable based on the independent variables [21], [22]. In the context of traffic prediction, linear regression can help identify how changes in independent variables, such as time of day or weather conditions, impact traffic patterns.

2.4. K-nearest neighbors

K-nearest neighbors is a popular machine learning algorithm used for classification and regression tasks. It operates by finding the k-nearest neighbors to a given data point and making predictions based on their characteristics. In the case of traffic prediction, k-nearest neighbors can be applied to identify similar traffic patterns and make predictions based on the behavior of nearby instances [23], [24].

2.5. Support vector regression

Support vector regression is a variant of the support vector machine algorithm, specifically designed for regression tasks [25]. Its objective is to find a function that maps input data to output values while minimizing prediction error. By constructing a hyperplane in a high-dimensional feature space defined by a subset of training samples called support vectors, support vector regression aims to capture the underlying patterns in the data and make accurate predictions.

2.6. Long short-term memory

LSTM is a type of recurrent neural network (RNN) specifically designed to address the vanishing gradient problem that occurs in traditional RNNs. The vanishing gradient problem refers to the difficulty of learning long-term dependencies when the gradients used for weight updates become very small. LSTMs overcome this challenge by introducing a memory cell and gating mechanisms that allow for better information flow and retention over time [26], [27]. They are widely used in various applications, including traffic prediction, due to their ability to capture and model complex temporal relationships.

The implementation of these models was carried out using popular deep learning frameworks, namely TensorFlow and PyTorch, which offer efficient tools for constructing and training neural networks [28]. By adopting a combination of traditional statistical models and advanced deep learning techniques, this research aimed to harness the respective strengths of each approach and develop traffic prediction models that are both accurate and robust. This hybrid approach sought to capitalize on the interpretability and domain knowledge offered by statistical models while harnessing the predictive power and ability to capture complex patterns provided by deep learning techniques.

3. RESULTS AND SIMULATION

The obtained results from our study on enhancing urban mobility through the integration of IoT road traffic data and artificial intelligence are promising. We employed a (70%, 20%, and 10%) split for training, validation, and test sets, without random shuffling. This approach ensures the feasibility of dividing the data into consecutive samples and evaluates the validation and test results on data collected after the model was trained. In our initial task of predicting traffic three hours into the future based on the current values of all features, we applied supervised machine learning algorithms such as linear regression, k-nearest neighbor's algorithm, and support vector machines. The models' performance in this task was as follows: linear regression achieved 41% accuracy, support vector regression achieved 46% accuracy, and k-nearest neighbors achieved 43% accuracy. It is important to note that these models may perform less effectively when predicting further into the future. For deep learning, we opted to work with an RNN, specifically a layer called LSTM, which is well-suited for handling time series data. RNNs process time series data sequentially, maintaining an internal state from one time-step to the next. Before training our LSTM model, we employed the technique of data windowing to prepare the dataset. This involved partitioning the data into smaller, sequential subsets called windows, on which the models would make predictions. We used a window width of 24 hours as input and an offset of eight hours for predictions. Figure 4 presents a graph comparing the performance results.

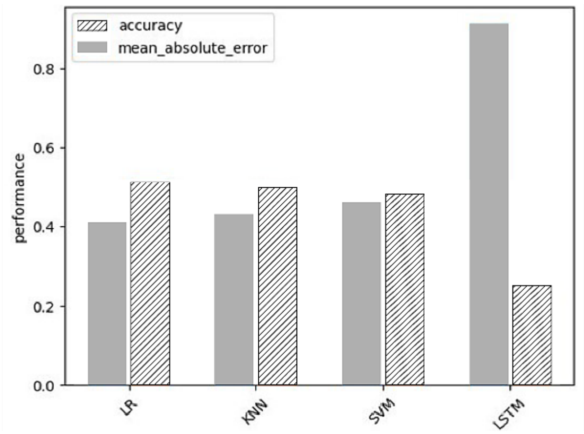

Figure 4. Performance comparison of predictive models for traffic forecasting

After conducting multiple iterations and refining the deep learning model, we obtained an impressive accuracy score of 91%. This noteworthy enhancement in performance demonstrates the efficacy of the LSTM model in accurately forecasting real-time vehicle count and future traffic patterns. The LSTM model, renowned for its capability to capture temporal dynamics and dependencies, emerged as a potent tool for improving urban mobility. In contrast, the machine learning models displayed lower accuracy, implying their shortcomings in comprehending the intricate nature of traffic patterns. The superior performance of the LSTM model emphasizes the significance of employing deep learning techniques for precise traffic prediction.

These results showcase the potential of integrating IoT road traffic data and artificial intelligence to optimize urban mobility. By harnessing the power of data and advanced modeling techniques, we can make informed decisions, plan efficient routes, and improve the overall transportation experience for individuals within smart city environments. To evaluate the performance of machine learning algorithms, we focused on two key metrics: accuracy (R2) and mean absolute error (MAE) [29], [30]. They are defined as:

$$\mathrm{MAE}(y,\hat{y}) = \frac{1}{n}\sum_{i=0}^{n-1}|y_i - \hat{y}_i| \quad (1)$$

$$R^2(y,\hat{y}) = 1 - \frac{\sum_{i=1}^{n}(y_i-\hat{y}_i)^2}{\sum_{i=0}^{n}(y_i-\bar{y})^2} \quad (2)$$

where: n: number of samples, y: observed traffic flow, $\hat{y}$: predicted traffic flow, $\bar{y}$: mean.

The MAE and the coefficient of determination (R^2) are two important metrics used in evaluating machine learning models. The MAE measures the absolute prediction error and provides an indication of how close the predicted values are to the actual values. A smaller MAE value indicates better prediction performance. On the other hand, R^2 quantifies the goodness-of-fit of the regression model and ranges from 0 to 1. A higher R^2 value signifies a stronger relationship between the variables and suggests that the model captures a larger portion of the variation in the data.

Table 1 provides a comparison of these algorithms, highlighting their accuracy and prediction error rates. It is evident from the results that machine learning algorithms are not sufficiently reliable and efficient in predicting traffic. However, the LSTM model, a deep learning algorithm, demonstrated outstanding performance with a minimal error rate, making it the ideal choice for traffic prediction and simulation.

Table 1. Comparison of machine learning and deep learning models performance metrics

Model	Predict N hours in advance	R2	MAE
Linear regression	3	41%	0.595
K-nearest neighbor's	3	43%	0.577
Support vector machines	3	46%	0.570
LSTM	8	91%	0.285

Figure 5 visually presents the outcomes of three distinct tests that were conducted to determine the most accurate LSTM model for our simulation. The objective of these tests was to identify the model that offers the highest level of reliability and precision in its predictions. This rigorous evaluation process ensures that the selected LSTM model is well-equipped to simulate real-world traffic scenarios effectively, thereby contributing to the enhancement of urban mobility. By integrating IoT road traffic data and leveraging the capabilities of artificial intelligence, our study provides valuable insights into the seamless integration of these technologies to improve transportation systems in smart city environments.

In this paper, we developed a simulation using the pygame framework [31], [32] to demonstrate our work and bridge the gap between our results and real-world scenarios. The primary objective of this simulation was to accurately predict the number of vehicles passing through a specific road segment in real-time and provide forecasts for the next hour. To visually represent the traffic conditions within the simulation, we adopted a color-based visualization approach. Specifically, congested scenarios were depicted by representing affected vehicles in red Figure 6, while non-congested situations were represented in green Figure 7. This color-coded visualization method facilitated a clearer understanding and differentiation of various traffic conditions within our simulation, bringing us closer to reality and providing valuable insights for enhancing urban mobility in smart city environments.

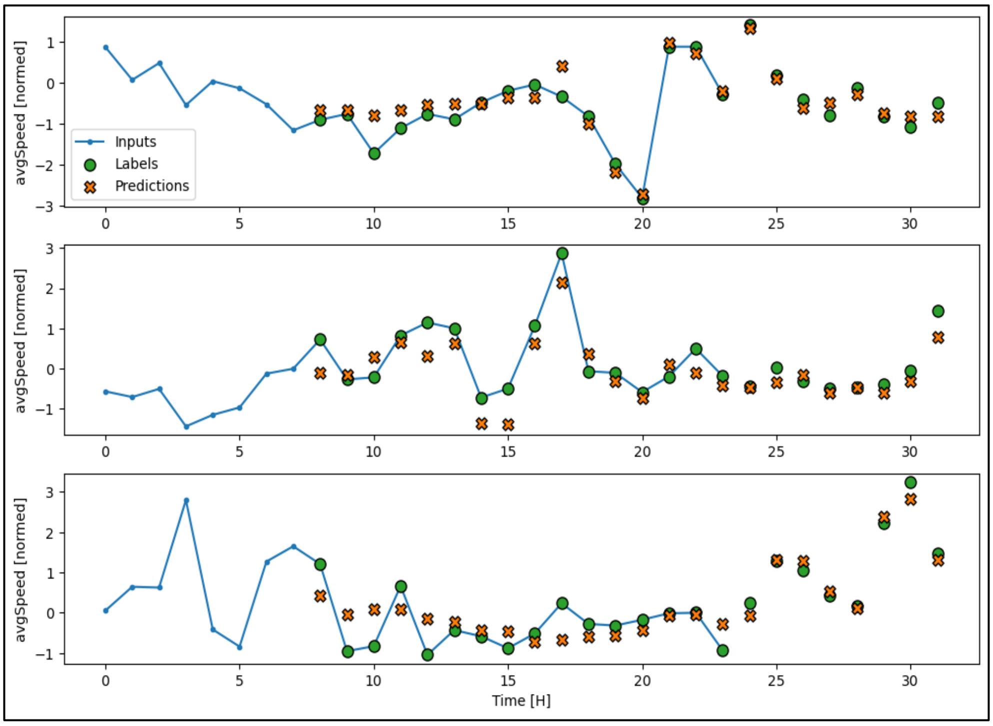

Figure 5. Comparative analysis of LSTM models for traffic prediction accuracy

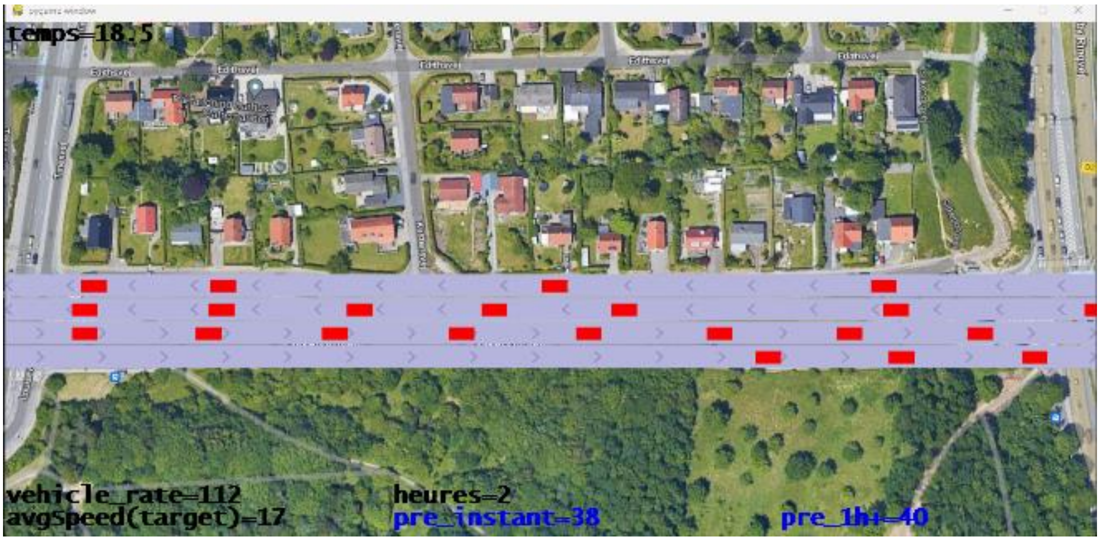

Figure 6. Visualization of congested traffic scenario in the simulation

Figure 7. Visualization of non-congested traffic scenario in the simulation

4. CONCLUSION

In conclusion, the integration of IoT road traffic data and artificial intelligence in smart city environments has the potential to greatly enhance urban mobility. Through our study, we have demonstrated the effectiveness of leveraging IoT sensors and deep learning algorithms, specifically LSTM, for accurate traffic flow prediction. Machine learning algorithms, despite initial exploration, fell short of meeting the desired standards for accuracy in traffic prediction. This realization prompted us to explore alternative approaches, leading us to the LSTM model. The implementation of LSTM allowed us to achieve significant improvements in real-time vehicle count estimation and forecasting future traffic patterns. This valuable insight empowers individuals to make informed decisions regarding their routes, whether for short-term commuting or long-term planning. It is important to acknowledge that our model has its limitations. Further enhancements can be made to improve its performance and applicability in various contexts. Ongoing research and development in this field are crucial for continuously refining traffic prediction models, ultimately leading to enhanced traffic conditions and improved quality of life for city dwellers. The integration of IoT road traffic data and AI holds immense promise for smart cities. As we continue to advance our understanding and implementation of these technologies, we can pave the way for efficient traffic management, reduced congestion, optimized transportation systems, and ultimately, enhanced urban mobility. By harnessing the power of data-driven insights, we can create more sustainable and livable cities for the benefit of all citizens.

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