Elevating smart city mobility using RAE-LSTM fusion for next-gen traffic prediction

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ABSTRACT

The burgeoning demand for efficient urban traffic management necessitates accurate prediction of traffic congestion, spotlighting the essence of time series data analysis. This paper delves into the utilization of sophisticated deep learning methodologies, particularly long short-term memory (LSTM) networks, convolutional neural networks (CNN), and their amalgamations like Conv-LSTM and bidirectional-LSTM (Bi-LSTM), to elevate the precision of traffic pattern forecasting. These techniques showcase promise in encapsulating the intricate dynamics of traffic flow, yet their efficacy hinges upon the quality of input data, emphasizing the pivotal role of data preprocessing. This study meticulously investigates diverse preprocessing techniques encompassing normalization, transformation, outlier detection, and feature engineering. Its discerning implementation significantly heightens the performance of deep learning models. By synthesizing advanced deep learning architectures with varied preprocessing methodologies, this research presents invaluable insights fostering enhanced accuracy and reliability in traffic prediction. The innovative RD-LSTM approach introduced herein harnesses the hybridization of a reverse AutoEncoder and LSTM models, marking a novel contribution to the field. The implementation of these progressive strategies within urban traffic management portends substantial enhancements in efficiency and congestion mitigation. Ultimately, these advancements pave the way for a superior urban experience, enriching the quality of life within cities through optimized traffic management systems.

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1. INTRODUCTION

Modern urban environments grapple with a significant obstacle: the prevalence of traffic congestion, causing widespread inconvenience and imposing substantial economic burdens on countless commuters. Deep learning, as a novel paradigm, emerges as a promising solution to address this challenge [1]. It distinguishes itself by its dynamic, data-centric approach to traffic prediction, diverging from traditional methodologies reliant on historical data and statistical models [2], [3]. The rapid advancement in data accessibility and efficient processing of extensive datasets has propelled the evolution of deep learning theories, exploring their potential in predicting urban traffic dynamics, including indicators such as speed, throughput, and accident risk [4], [5]. Recent investigations have underscored the indispensable role of deep learning in managing burgeoning vehicle volumes within intelligent transportation systems, diverging significantly from conventional machine learning models like support vector machines (SVM) and artificial neural networks (ANN) [6], [7]. Deep learning models utilize multi-layer structures to uncover intricate traffic patterns, employing architectures such as convolutional neural networks (CNN) [8], recurrent neural network (RNN), long short-term memory (LSTM) [9]–[11], restricted Boltzmann machine (RBM), and stacked AutoEncoder (SAE), shedding light on their efficacy across diverse traffic forecasting scenarios [12], [13].

This work chronicles the methodical development of an intelligent short- and long-term urban traffic prediction system [14], [15], encompassing various mobility data types, traffic modeling techniques, and critical traffic indicators such as speed, flow, and accident risk [16], [17]. Special emphasis is placed on time series analysis and the pivotal role of data preprocessing, encompassing normalization, transformation, outlier handling, and feature engineering, crucial in enhancing the predictive accuracy of deep learning models [18]. Notably, LSTM demonstrates remarkable proficiency in handling prolonged time series data [19], [20]. Additionally, novel hybrid methodologies like RD-LSTM, a fusion of reversed AutoEncoder and LSTM models [21], [22], show promise in surpassing conventional methods. This article documents the comprehensive process involved in developing this approach, commencing with an overview, dataset exploration, methodological descriptions, results, and future prospects for enhancement [23], [24]. Recent advancements have resulted in precision improvements, evident in reduced mean squared errors (MSE) and the evolution of methodologies like the NTP method based on Conv-LSTM models for traffic synchronization [22], [25]. The innovative RD-LSTM methodology, combining reversed AutoEncoder and LSTM models, emerges as a pioneering contribution. Its application in urban traffic management promises significant efficiency enhancements and congestion mitigation, paving the way for an elevated urban experience and improved quality of life through optimized traffic management systems.

2. METHOD

The precise anticipation of traffic congestion, particularly within the domain of time series data, has gained paramount importance in urban planning and transportation governance. Deep learning algorithms have emerged as a robust tool to address this challenge, adept at capturing the intricate temporal patterns inherent in traffic datasets [26], [27]. However, the efficacy of these models is intricately linked to the quality of the input data. Essential to this optimization are preprocessing techniques that refine and enhance raw data, encompassing vital processes such as data cleansing, feature engineering, and normalization. These techniques ensure that the model effectively assimilates time series data, facilitating accurate predictions [28], [29]. The RD-LSTM model proposed in this study stems from the fusion of two disparate model architectures: AutoEncoder and LSTM, both renowned for their adeptness in learning and extracting features from target data. This amalgamation forms a potent synergy, notably proficient in the specific task of predicting road congestion. This prowess is conspicuous in comparative evaluations against alternative algorithms and when subjected to rigorous testing for prediction accuracy. Subsequent sections elaborate extensively on the operational mechanics of this approach.

Figure 1 represents the proposed architecture governing the functionality of the RD-LSTM. Herein, the data flow stemming from the encoder output of the reverse AutoEncoder serves as the input to the LSTM. This fusion facilitates the utilization of the enhanced features derived by the AutoEncoder while leveraging the LSTM's adeptness in capturing intricate temporal configurations. Consequently, the RD-LSTM model demonstrates an enhanced capacity to comprehend data, particularly within the domain of time series, offering a resilient and high-performance framework adaptable for diverse machine learning endeavors.

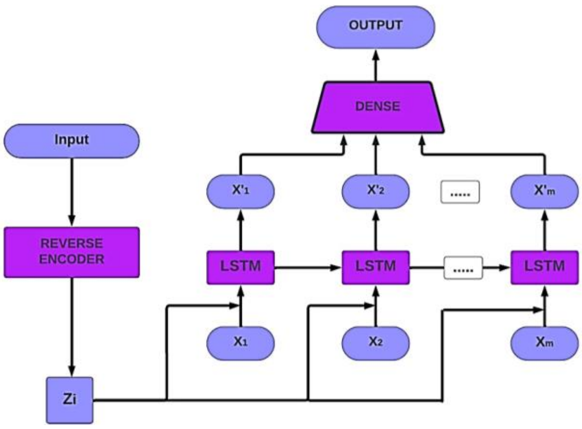


Figure 1. Proposed RD-LSTM architecture

2.1. Data collection

Moumen *et al.* [30], we extensively explored the intersection between the internet of things (IoT) and artificial intelligence (AI) within the context of smart cities, focusing on a case study. In our current research, we utilize data sourced from IoT sensors deployed in the Smart City of Aarhus, Denmark. The dataset comprises 9 columns of numeric and categorical data, totaling 25,097,093 rows. Our primary focus centers on determining the average speed of vehicles over specific time intervals, making 'avgSpeed' our target variable. To refine the dataset for this scientific inquiry, an exhaustive data inspection and cleansing process were executed. This rigorous procedure significantly reduced the dataset's volume. The primary aim was to isolate and extract the pertinent target data and their relevant intersections. Figure 2 illustrates a sample of the data, providing a visual representation. This endeavor was facilitated by integrating meteorological metadata with the proprietary dataset, aiding in pinpointing and extracting precise intersection points related to the primary target. Through the elimination of extraneous information and irrelevant variables, the resultant dataset retained only the essential components crucial for achieving our study objectives.

	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

Figure 2. Sample data illustration and dataset overview

2.2. Data preprocessing

To facilitate the prediction of traffic patterns, aggregating data from 5-minute intervals into 1-hour intervals proves advantageous. This consolidation condenses 12 rows of data into a single row, yielding a new dataset where each row corresponds to hourly intervals. Such aggregation significantly reduces data volume, enhancing manageability and analysis efficiency, a critical consideration for extensive datasets spanning prolonged periods. During the ongoing data preprocessing phase, before model construction, comprehensive analysis and data suitability checks were conducted. Notably, several crucial steps were taken to optimize model performance. Initially, we standardized the varied time series intervals (ranging from 5 minutes to 1 hour) into a unified time unit, aligning data for more efficient processing. Identifying intersection points critical to our target variable was pivotal.

Analysis of diverse characteristics around these points, especially average speeds on the left and right paths, highlighted influential features. This exploration led to the strategic introduction of two new features: "avgspeed on the left" and "avgspeed on the right." These features aimed to enhance model performance by offering critical insights into average vehicle speeds preceding and succeeding intersection points, refining our understanding of traffic dynamics in these key locations. This meticulous preprocessing, creating informative features, constitutes a vital stride towards optimizing our prediction model. The objective was to provide the model with informative, relevant data to facilitate more efficient training and achieve superior prediction accuracy, thus optimizing traffic management and future analysis precision.

Recognizing the limitations of the date time column's string format and linear time treatment, we sought to address the daily periodicity in time-related patterns. Employing sine and cosine transformations allowed for the extraction of meaningful signals representing "time of day" and "time of year." Incorporating these components for each day improved the model's ability to capture temporal dynamics. Graphical representations demonstrated the positive impact of these transformations on the model's performance, showcasing improved correlation for both short- and long-term predictions compared to the initial version. Figure 3 visually represents the time in its original form (green plot), ranging from 0 to 23 hours, contrasted with plots reflecting the effects of sinusoidal and cosine transformations.

Improving functionalities stands as a crucial precursor to training deep learning models. Normalization, a prevalent technique, contributes to this enhancement. Through normalization, the DataFrame data is scaled using scikit-learn's MinMaxScaler, resulting in a new DataFrame that accommodates scaled data within a standardized range from 0 to 1. This step assures data comparability, a fundamental aspect aiding model preparation. The normalization phase holds paramount importance in model development, exerting a substantial positive influence on performance. Its role is pivotal in aligning the model's outcomes with real-world scenarios. Figure 4 illustrates a sample of the data after preprocessing. By evaluating the model on data collected post-training, normalization ensures that validation and test results reflect the model's efficacy in handling unseen chronological data, thereby bolstering its adaptability to real-world contexts.

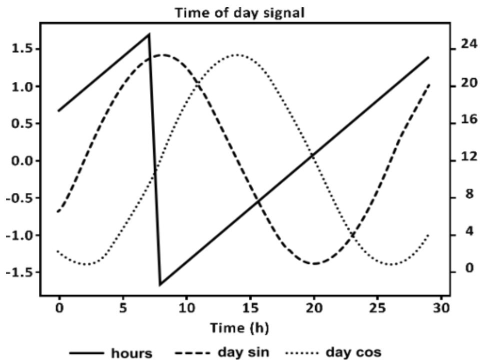


Figure 3. Plot of the time according to time-of-day signal

	avgMeasuredTime	avgSpeed	vehicleCount	mean1	mean2	yearcos	yearsin	Day sin	Day cos	Year sin	Year cos
0	0.375394	0.554945	0.216216	0.705098	0.841610	1.000000	0.750000	0.629410	0.982963	0.842018	1.000000
1	0.409306	0.641941	0.283784	0.727451	0.808362	1.000000	0.750000	0.500000	1.000000	0.842279	0.999703
2	0.447161	0.727106	0.378378	0.607843	0.866010	1.000000	0.750000	0.370590	0.982963	0.842540	0.999406
3	0.384464	0.539377	0.216216	0.871373	0.830337	1.000000	0.750000	0.250000	0.933013	0.842801	0.999108
4	0.249606	0.325092	0.108108	0.839608	0.873858	1.000000	0.750000	0.146447	0.853553	0.843062	0.998811
...	...	...	...	...	...	...	...	...	...	...	...
4805	0.468454	0.810989	0.216216	0.578353	0.773116	0.788675	0.066987	0.933013	0.750000	0.123405	0.956621
4806	0.279968	0.419414	0.054054	0.697255	0.822489	0.788675	0.066987	0.853553	0.853553	0.123640	0.956948
4807	0.484753	0.765568	0.189189	0.730458	0.777017	0.788675	0.066987	0.750000	0.933013	0.123876	0.957274
4808	0.214826	0.349451	0.054054	0.306353	0.564897	0.788675	0.066987	0.146447	0.146447	0.126486	0.960853
4809	0.000000	0.000000	0.000000	0.000000	0.109018	0.788675	0.066987	0.500000	0.000000	0.121525	0.954000

4810 rows × 11 columns

Figure 4. Dataset overview after preprocessing

2.3. Model evaluation

To assess the effectiveness of machine learning algorithms, we utilized evaluation metrics available in the scikit-learn library, specifically employing MAE as a primary parameter (1) and Val_loss as a secondary metric (2). These metrics play a crucial role in quantifying the performance of the models, with MAE providing a measure of the average absolute errors between predicted and actual values, and Val_loss offering insights into the model's performance during the validation phase. Utilizing such established evaluation metrics allows for a comprehensive understanding of the algorithms' effectiveness in the context of the study [31].

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

$$\mathrm{Val\_loss} = \frac{1}{n}\sum_{i=0}^{n-1}(y_i - \hat{y}_i)^2 \tag{2}$$

Where:
n : Number of samples
y : Observed traffic flow
$\hat{y}$: Predicted traffic flow
$\bar{y}$: Mean

3. RESULTS AND DISCUSSION

Following multiple iterations aimed at refining our models using a dataset partitioned into 70% for training, 20% for testing, and 10% for validation, these adjustments, coupled with meticulous alterations of model parameters, yielded significant impacts during the training phase. These adaptations notably enhanced outcomes concerning two pivotal metrics, specifically MAE and val_loss, compared to our previous experimentation endeavors. This underscores the critical role of data preprocessing in augmenting result quality and precision. Figure 5 depicts the fluctuation in validation loss concerning the AverageSpeed variable between two models: one subjected to initial preprocessing attempts and the other refined further for 8-hour predictions. To ascertain and validate our work, a comparative analysis is conducted between the proposed approach and alternate models.

Table 1 illustrates a comparative analysis showcasing two key metrics, MAE, and val_loss. The outcomes from the deep learning algorithms notably exhibit effectiveness and reliability in predicting traffic patterns, demonstrating substantial proximity between them. Yet, the RD-LSTM model emerges as the top performer in this evaluation, showcasing exceptional performance characterized by minimal error rates. This underscores its superiority and positions it as the preferred choice for traffic forecasting and simulation purposes.

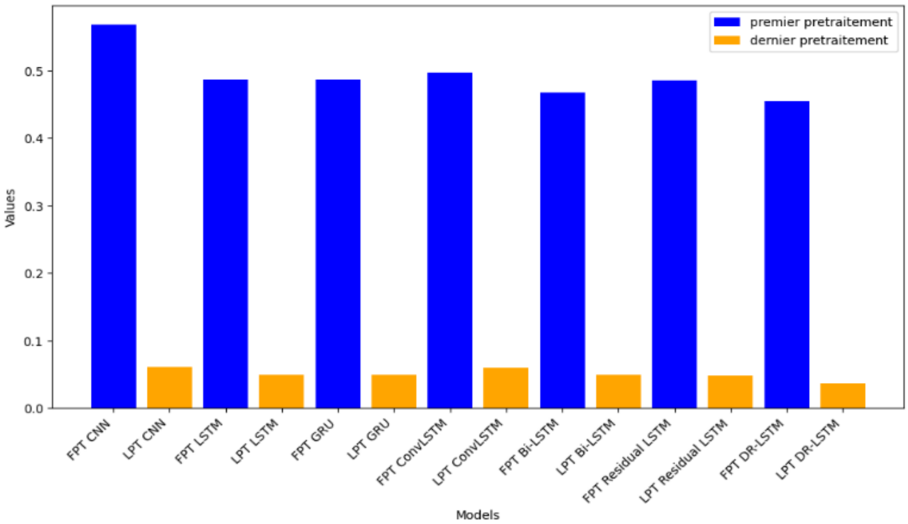


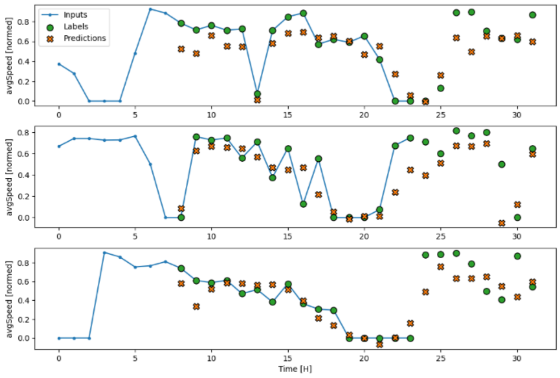
Figure 5. Comparison of validation loss for averagespeed between preprocessed models: initial attempt vs. enhanced prediction for 8-hour intervals

Table 1. Performance metrics comparison of deep learning models for traffic prediction

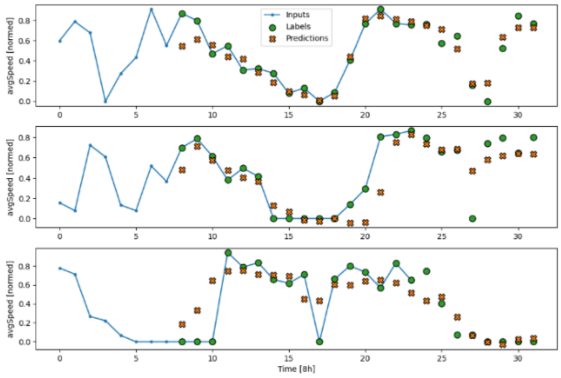
Model	MAE	Val_loss	Execution time (s)
CNN	0.1856	0.0609	34
LSTM	0.1696	0.0496	180
GRU	0.1696	0.0496	300
CONV-LSTM	0.1870	0.0602	120
Residual-LSTM	0.1679	0.0498	240
Bi-LSTM	0.1647	0.0481	360
RD-LSTM	0.1635	0.0476	300

The presented models, evaluated based on MAE, Val_loss, and execution time, showcase diverse performance characteristics. CNN offers moderate metrics with a shorter execution time, while LSTM and GRU exhibit competitive prediction accuracy with longer execution times. CONV-LSTM demonstrates slightly higher errors but shorter execution durations. Residual-LSTM and Bi-LSTM showcase improved prediction accuracy with longer processing times, especially Bi-LSTM requiring the lengthiest computation. Notably, the RD-LSTM model emerges as a standout performer, delivering superior prediction accuracy with the lowest MAE and Val_loss metrics among the listed models, maintaining a reasonable execution time. RD-LSTM's balance between accuracy and computational efficiency positions it favorably for scenarios where precise predictions are crucial within a manageable timeframe, highlighting its potential for various practical applications.

Through an examination and comparison of the numerical and graphical results presented in Figure 6, which illustrates a comparative analysis of various model predictions in test and validation phases spanning 30 hours-highlighting the Figure 6(a) CNN model, Figure 6(b) LSTM model, Figure 6(c) GRU model, Figure 6(d) Conv-LSTM model, Figure 6(e) residual-LSTM model, Figure 6(f) Bi-LSTM model, and Figure 6(g) RD-LSTM model, particularly focusing on metrics like MAE and val_loss-it is discernible that the RD-LSTM model emerges as the optimal choice for long-term predictions. This preference for the RD-LSTM model is rooted in a thorough evaluation of performance metrics, revealing that this model exhibits a more robust and precise capability in anticipating trends over extended periods. The results highlight the trade-off between computational resources and prediction accuracy. Bi-LSTM and RD-LSTM showcase superior accuracy but demand more computational time. LSTM, GRU, and Residual-LSTM offer a balance between accuracy and computational efficiency. The choice of model should consider the specific application's requirements, weighing the need for accuracy against computational resources available for deployment.



(a)



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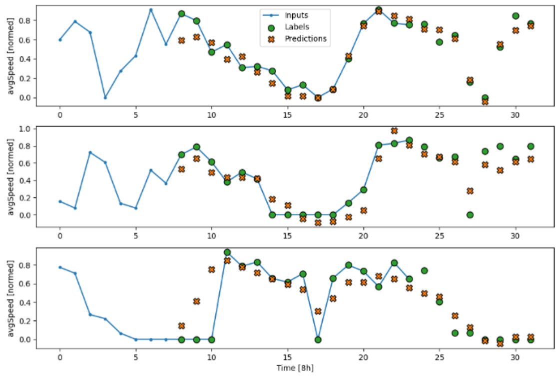

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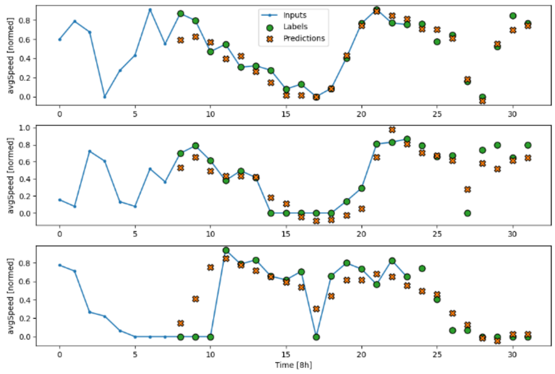
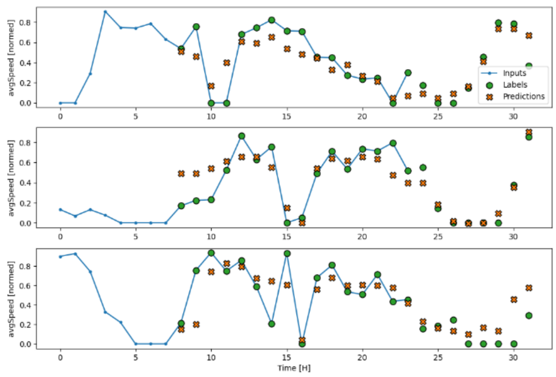


(d)



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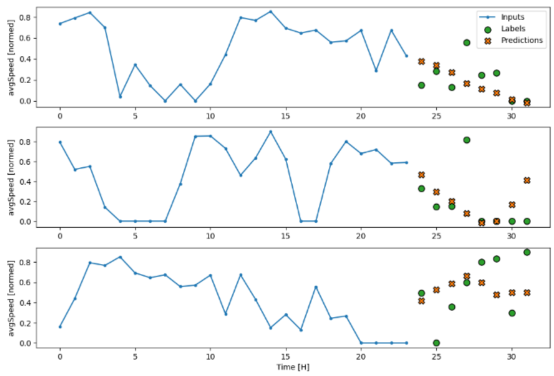
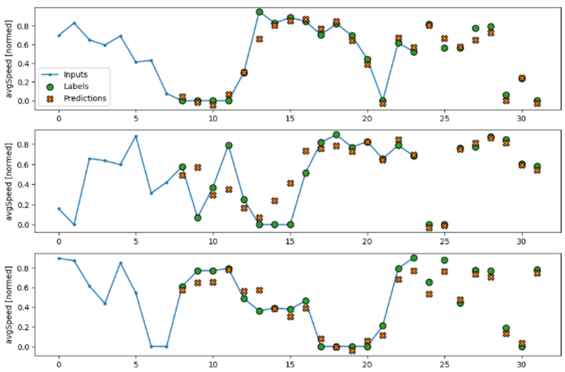


(f)



(g)

Figure 6. Comparative analysis of various model predictions in test and validation phases over 30 hours: (a) CNN model, (b) LSTM model, (c) GRU model, (d) Conv-LSTM model, (e) residual-LSTM model, (f) Bi-LSTM model, and (g) RD-LSTM model

4. CONCLUSION

This study delves into the formidable issue of urban traffic congestion by employing advanced deep learning methodologies. It emphasizes the critical analysis of sequential data to precisely forecast traffic patterns, addressing the imperative requirement for effective urban traffic control. Techniques like LSTM networks, CNNs, and their combinations demonstrate considerable promise in comprehending the complex dynamics of traffic flow. Nonetheless, their effectiveness significantly relies on the caliber of input data, highlighting the vital role of preprocessing methods such as normalization, transformation, outlier detection, and feature engineering. The examination of diverse models such as CNN, RNN, LSTM, Bi-LSTM, Conv-LSTM, and residual-LSTM showcases the adaptability of these techniques across diverse traffic scenarios, encapsulating intricate concepts through stratified models. The introduction of the innovative RD-LSTM method, a fusion of AutoEncoder and LSTM models, signifies a noteworthy advancement. This pioneering approach holds potential in surpassing traditional methodologies, fostering more efficient traffic control and congestion alleviation in urban settings. By systematically delineating the development of an intelligent urban traffic prediction system, this study underscores the pivotal role of time series analysis, highlighting LSTM's impressive aptitude in handling prolonged sequential data. This collective endeavor points towards a promising trajectory for improved urban environments, enriching city life by optimizing traffic management systems.

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