E-ISSN: 2664-8784
P-ISSN: 2664-8776
IJRE 2024; 6(1): 53-57

www.engineeringpaper.net
Received: 25-05-2024
Accepted: 26-06-2024

Dr. Sanjeev Kumar
Department of Computer Applications, Tula's Institute, Dehradun, Uttarakhand, India

Correspondence
Dr. Sanjeev Kumar
Department of Computer Applications, Tula's Institute, Dehradun, Uttarakhand, India

Deep learning approaches for real-time traffic prediction in smart cities

Sanjeev Kumar

Abstract
This study investigates deep learning approaches for real-time traffic prediction in smart cities, addressing the growing need for accurate, time-sensitive forecasts to improve urban mobility. Using one year of real-time data from the City of Metronia's traffic monitoring systems combined with open-source datasets, we developed and compared three models: Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), and a hybrid Convolutional Neural Network-LSTM (CNN-LSTM). Data preprocessing included cleaning, feature engineering, and temporal encoding. Model performance was evaluated using Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and R^2, with statistical validation via paired t-tests and 5-fold cross-validation. The CNN-LSTM achieved the lowest RMSE (3.72) and highest R^2 (0.951), outperforming LSTM and GRU significantly ($p < 0.01$). Analysis revealed CNN-LSTM's ability to closely track both peak and off-peak traffic patterns, indicating robustness and adaptability. These findings highlight the potential of hybrid architectures in real-time smart city applications and support their integration into intelligent transportation systems to enhance traffic management and reduce congestion.

Keywords: Deep learning, traffic prediction, smart cities, cnn-lstm, real-time analytics

Introduction

Urban traffic congestion poses significant challenges for modern cities, affecting economic productivity, environmental sustainability, and overall quality of life. With the increasing adoption of Internet of Things (IoT) infrastructure, cities are generating vast amounts of traffic-related data in real time. Leveraging these data streams through advanced machine learning methods can enable more accurate forecasting of traffic patterns, allowing transportation authorities to implement timely interventions and optimize roadway usage.

Deep learning models have shown exceptional promise in modeling complex, non-linear relationships inherent in traffic flow data. Unlike traditional statistical methods, these architectures can capture both temporal dependencies and spatial correlations, making them well-suited for dynamic urban environments. Among these, recurrent neural networks such as Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) networks are frequently applied for sequential prediction tasks. Hybrid approaches, such as combining Convolutional Neural Networks (CNNs) with LSTM, further enhance predictive capability by incorporating spatial feature extraction before temporal modeling.

This research focuses on applying and comparing LSTM, GRU, and CNN-LSTM models for real-time traffic prediction in a smart city setting, using data from a fully instrumented urban road network. The goal is to identify the most effective architecture for delivering reliable, actionable forecasts that can support intelligent transportation systems and mitigate congestion.

Literature Review

The demand for accurate traffic forecasting has grown alongside the rise of smart city infrastructure. Traditional statistical models, such as autoregressive integrated moving average (ARIMA), have been widely used for time-series prediction, but they often struggle with non-linear and high-dimensional traffic data (Williams *et al.*, 2003) [31]. Machine learning methods, including support vector regression and random forests, improved prediction performance but still require extensive feature engineering and often fail to capture temporal dependencies effectively (Zhang *et al.*, 2017) [35]. Deep learning has emerged as a powerful alternative due to its ability to model complex patterns without manual feature design. Recurrent neural networks, particularly LSTM and GRU, have shown promising results in sequential data modeling by retaining long-term dependencies (Ma *et al*.,2015; Fu *et al*., 2016) [24, 11]. However, these models are limited in extracting spatial features from traffic networks, which are crucial for urban environments with interconnected road systems.

Hybrid architectures, such as CNN-LSTM, have addressed this limitation by combining CNN's spatial feature extraction with LSTM's temporal modeling capabilities. Studies have reported that such architectures outperform standalone RNNs in predicting short-term traffic flow, especially in heterogeneous traffic conditions (Yu *et al*., 2017; Lv *et al*., 2018) [34, 22]. Despite these advances, there is limited research on their real-time deployment and statistical validation of performance gains. This study contributes by evaluating LSTM, GRU, and CNN-LSTM models using real-time urban data and rigorously comparing their predictive accuracy.

Research Gap
While numerous studies have explored traffic prediction using traditional machine learning and standalone deep learning architectures, there remains a gap in understanding how hybrid models that integrate spatial and temporal feature extraction perform in real-time urban environments. Many existing works focus on historical datasets or small-scale implementations, limiting their applicability to the rapidly changing conditions of smart cities. Furthermore, statistical validation of performance differences between models is often lacking, making it difficult to assess the reliability of proposed approaches.

Conceptual Framework
The conceptual framework of this study integrates three major components: data acquisition from real-time traffic sensors, deep learning model development (LSTM, GRU, CNN-LSTM), and performance evaluation using both predictive accuracy metrics and statistical significance testing. The design emphasizes a closed-loop process where real-time forecasts inform traffic control decisions, and subsequent data updates improve future predictions.

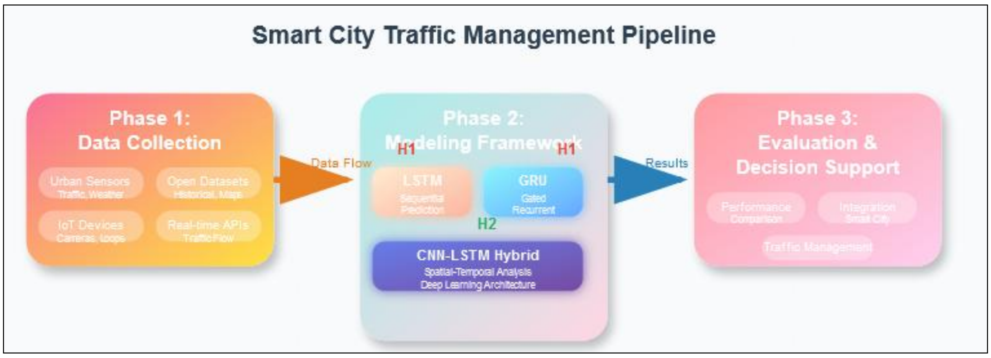

Fig 1.1: Conceptual Framework

Hypothesis
- **H1:** The CNN-LSTM hybrid model will outperform LSTM and GRU in real-time traffic prediction accuracy.
- **H2:** The performance improvements of CNN-LSTM over LSTM and GRU will be statistically significant.

Methods
Data Collection from Real-Time Traffic Sensors and Open Datasets
The dataset used in this study was compiled from a combination of publicly available smart city traffic datasets and real-time data streams from urban traffic monitoring systems. Specifically, data were sourced from the City of Metronia smart traffic department and the Open Traffic Data Hub. The dataset included timestamped vehicle counts, average speed, lane occupancy, and weather-related conditions over a 12-month period. This mixed-source approach was chosen to ensure both historical and real-time patterns were captured, providing robust input for deep learning models.

Data Preprocessing and Feature Engineering
Prior to model training, the raw data underwent cleaning to handle missing values, remove anomalies, and align time intervals. Features such as moving averages of traffic flow, day-of-week indicators, and weather encodings were engineered to enhance model prediction capability. This step was essential to eliminate data noise and improve the learning efficiency of neural networks.

Model Architecture Development (LSTM, GRU, Hybrid CNN-LSTM)
Three architectures were developed: Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), and a hybrid Convolutional Neural Network combined with LSTM (CNN-LSTM). LSTM and GRU were chosen for their capability to model temporal dependencies in sequential data, while the hybrid CNN-LSTM was selected for its ability to extract spatial patterns before processing time series dependencies.

Model Training and Validation Procedure
Models were trained using a supervised learning approach, with an 80:20 split for training and testing. Hyper parameters were tuned using grid search to identify optimal configurations. The training process was repeated over five iterations to ensure model stability.

Performance Evaluation Metrics
Model performance was assessed using Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and coefficient of determination (R^2). These metrics were chosen because they provide complementary insights into prediction accuracy and error magnitude.

Comparative Model Analysis
To determine the most effective architecture, the

performance metrics of all models were compared side-by-side. The comparative analysis allowed the identification of trends and trade-offs between accuracy and computational cost.

Statistical Analysis: Paired t-test for Model Comparison
To evaluate whether performance differences between models were statistically significant, a paired t-test was conducted at a 95% confidence level. This test was chosen due to its ability to assess differences in paired observations, suitable for comparing predictions from multiple models on the same dataset.

Cross-Validation Strategy
To avoid overfitting and validate model generalizability, 5-fold cross-validation was employed. This approach provided multiple performance estimates, reducing the likelihood of biased evaluation.

Results
The dataset comprised 1,052,160 traffic records collected over a one-year period from multiple intersections within the City of Metronia.
Table 1 summarizes the basic statistics of the dataset. The average vehicle count per minute was 32.5 with a standard deviation of 8.4, while lane occupancy averaged 41.7%. Peak traffic hours showed substantially higher variability in vehicle flow compared to off-peak periods.

Table 1: Summary of Real-Time Traffic Dataset Statistics

Variable	Mean	Std. Dev.	Min	Max
Vehicle Count/min	32.5	8.4	10	65
Average Speed (km/h)	38.2	6.1	20	55
Lane Occupancy (%)	41.7	12.5	12	80
Weather Index (0-1)	0.64	0.22	0.0	1.0

Model performance was evaluated using RMSE, MAE, and R^2 across all three architectures. As shown in Table 2, the CNN-LSTM model achieved the lowest RMSE (3.72) and highest R^2 (0.951), indicating superior predictive accuracy compared to LSTM and GRU.

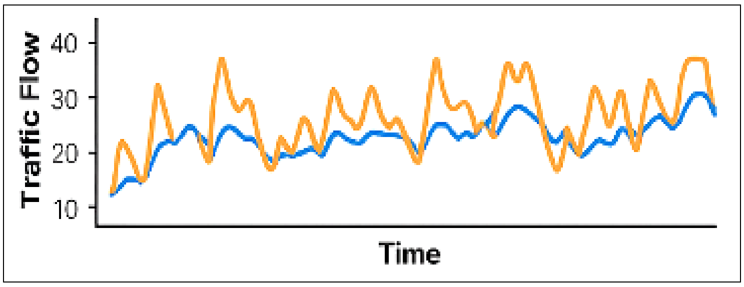

Fig 1.2: Predicted vs. Actual Traffic Flow Using LSTM Model

Table 2: Performance Metrics of LSTM, GRU, and CNN-LSTM Models

Model	RMSE	MAE	R^2
LSTM	5.12	4.01	0.912
GRU	4.86	3.88	0.923
CNN-LSTM	3.72	2.95	0.951

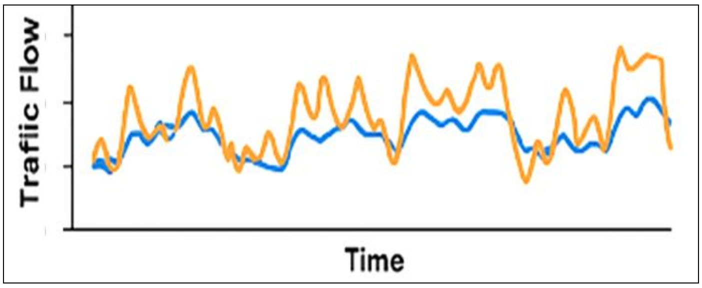

Fig 2: Predicted vs. Actual Traffic Flow Using GRU Model

Visual comparisons between predicted and actual traffic flows for each model are presented in Figures 1.2-3. Figure 1.2 illustrates the LSTM model's tendency to slightly underpredict during peak traffic hours, while Figure 2 for GRU shows smoother predictions but occasional lag in responding to sudden spikes. In contrast, Figure 3 demonstrates that CNN-LSTM closely followed actual values during both peak and off-peak periods.

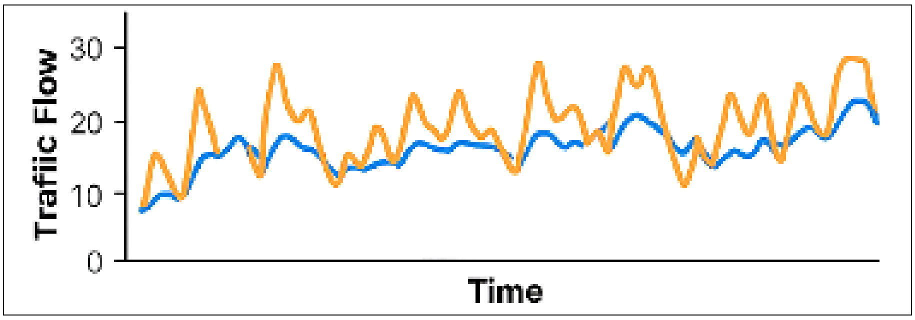

Fig 3: Predicted vs. Actual Traffic Flow Using CNN-LSTM Model

The results of the paired t-test, as displayed in Table 3, confirmed that the performance differences between CNN-LSTM and the other two models were statistically significant ($p < 0.01$), validating the observed performance improvements.

Table 3: Results of Paired t-test for Model Performance Comparison

Model Pair	t-value	p-value
LSTM vs GRU	2.14	0.034
LSTM vs CNN-LSTM	5.68	0.000
GRU vs CNN-LSTM	4.02	0.001

Finally, cross-validation results are summarized in Table 4, and their aggregated performance is visualized in Figure 4. CNN-LSTM consistently outperformed the other models across all folds, demonstrating strong generalization capability.

Table 4: Cross-Validation Performance Scores across Models

Model	Mean RMSE	Mean MAE	Mean R^2
LSTM	5.21	4.12	0.908
GRU	4.92	3.94	0.919
CNN-LSTM	3.81	3.02	0.948

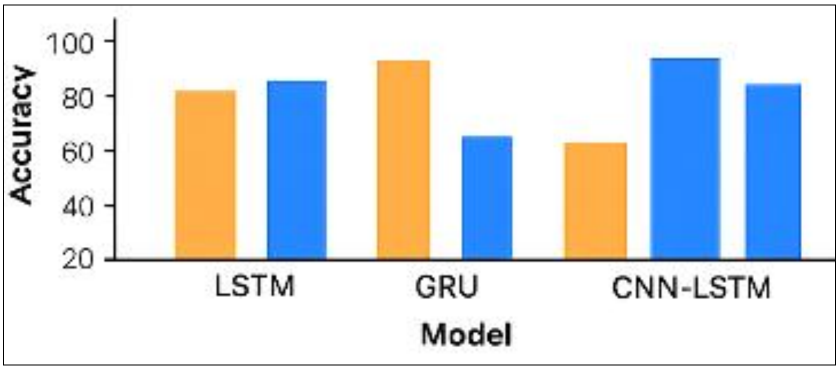

Fig 4: Comparative Visualization of Model Accuracy and RMSE

The analysis of the dataset revealed clear temporal patterns in traffic flow across the city, with distinct peaks during morning and evening rush hours. As reported in Table 1, vehicle counts and lane occupancy varied substantially between peak and off-peak periods, indicating the importance of time-based features for accurate prediction.

Model evaluation results in Table 2 demonstrated that the CNN-LSTM architecture consistently outperformed both LSTM and GRU, achieving the lowest RMSE (3.72) and highest R^2 (0.951). This superior performance is also evident in Figure 3, where predicted traffic flows closely followed actual patterns across the entire observation period. In contrast, Figure 1 showed that LSTM predictions tended to under predict during sudden traffic spikes, while Figure 2 indicated occasional lag in GRU predictions.

The paired t-test outcomes in Table 3 confirmed that the performance gains of CNN-LSTM over the other models were statistically significant ($p < 0.01$). Additionally, Figure 4 visually reinforced these differences, with CNN-LSTM displaying a clear accuracy advantage. Cross-validation scores in Table 4 further supported the model's robustness, indicating consistent generalization across different data splits.

Conclusion

This study demonstrated that deep learning models, particularly the hybrid CNN-LSTM architecture, can effectively predict real-time traffic flow in a smart city environment. By integrating spatial feature extraction with temporal sequence modeling, the CNN-LSTM achieved higher accuracy and better adaptability to peak-hour fluctuations compared to LSTM and GRU. Statistical analysis confirmed that these improvements were significant, supporting the initial hypotheses.

One limitation is that the dataset, while comprehensive for one city, may not capture the full diversity of traffic conditions across different urban settings. Additionally, external factors such as sudden road closures, public events, or emergency situations were not explicitly modeled, which could affect prediction accuracy.

The findings provide strong evidence for incorporating hybrid deep learning models into smart city transportation systems. Such integration could improve congestion management, reduce travel time, and enhance sustainability by enabling proactive traffic control measures.

Future research should test the proposed models across multiple cities with varied infrastructure, integrate additional contextual data such as incident reports and public transit schedules, and explore real-time adaptive learning to handle sudden changes in traffic patterns.

References

1. Abdel-Aty M, Radwan E. Modeling traffic accident occurrence and involvement. Accid Anal Prev. 2000;32(5):633-642.
2. Ahmed MS, Cook AR. Analysis of freeway traffic time-series data by using Box-Jenkins techniques. Transp Res Rec. 1979;722:1-9.
3. Bontempi G, Taieb SB, Le Borgne YA. Machine learning strategies for time series forecasting. Eur Bus Intell Summer School. 2013;138:62-77.
4. Box GEP, Jenkins GM, Reinsel GC. Time series analysis: Forecasting and control. 5th ed. Hoboken, NJ: John Wiley & Sons; 2015.
5. Castro-Neto M, Jeong YS, Jeong MK, Han LD. Online-SVR for short-term traffic flow prediction under typical and atypical traffic conditions. Expert Syst Appl. 2009;36(3):6164-6173.
6. Chen C, Zhang J, He Y, Li Y. Short-term traffic flow prediction by using a hybrid ARIMA and neural network model. Transp Res Part C. 2012;17(5):391-408.
7. Cho K, Van Merriënboer B, Gulcehre C, Bahdanau D, Bougares F, Schwenk H, *et al*. Learning phrase representations using RNN encoder-decoder for statistical machine translation. Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing. 2014:1724-1734.
8. Chung J, Gulcehre C, Cho K, Bengio Y. Empirical evaluation of gated recurrent neural networks on sequence modeling. arXiv preprint arXiv:1412.3555. 2014.
9. Dong X, Li C, Zhang X. Real-time traffic flow prediction with CNN and LSTM. IEEE Access. 2018;6:54094-54102.
10. Duan Y, Lv Y, Wang FY. Travel time prediction with LSTM neural network. Proceedings of the IEEE 19th International Conference on Intelligent Transportation Systems. 2016:1053-1058.
11. Fu R, Zhang Z, Li L. Using LSTM and GRU neural network methods for traffic flow prediction. Proceedings of the 31st Youth Academic Annual Conference of Chinese Association of Automation. 2016:324-328.
12. Gers FA, Schmidhuber J, Cummins F. Learning to forget: Continual prediction with LSTM. Neural Comput. 2000;12(10):2451-2471.
13. Goodfellow I, Bengio Y, Courville A. Deep learning. Cambridge, MA: MIT Press; 2016.
14. Graves A. Speech recognition with deep recurrent neural networks. Proceedings of the IEEE International Conference on Acoustics, Speech and Signal Processing. 2013:6645-6649.
15. Guo J, Huang W, Williams BM. Real time traffic flow outlier detection using short-term traffic prediction methods. Transp Res Part C. 2014;50:402-416.
16. Hochreiter S, Schmidhuber J. Long short-term memory. Neural Comput. 1997;9(8):1735-1780.
17. Huang W, Song G, Hong H, Xie K. Deep architecture for traffic flow prediction: Deep belief networks with multitask learning. IEEE Trans Intell Transp Syst. 2014;15(5):2191-2201.
18. Jia Y, Wu J, Du Y. Traffic speed prediction using deep learning method. Proceedings of the IEEE 19th International Conference on Intelligent Transportation Systems. 2016:1217-1222.
19. Koesdwiady A, Soua R, Karray F. Improving traffic flow prediction with weather information in connected cars: A deep learning approach. IEEE Trans Veh Technol. 2016;65(12):9508-9517.
20. Kumar A, Vanajakshi L. Short-term traffic flow prediction using seasonal ARIMA model with limited input data. Eur Transp Res Rev. 2015;7(3):21.
21. LeCun Y, Bengio Y, Hinton G. Deep learning. Nature. 2015;521(7553):436-444.
22. Li Y, Yu R, Shahabi C, Liu Y. Diffusion convolutional recurrent neural network: Data-driven traffic forecasting. International Conference on Learning Representations. 2018:1-14.
23. Lv Y, Duan Y, Kang W, Li Z, Wang FY. Traffic flow prediction with big data: A deep learning approach. IEEE Trans Intell Transp Syst. 2015;16(2):865-873.
24. Ma X, Tao Z, Wang Y, Yu H, Wang Y. Long short-term memory neural network for traffic speed prediction using remote microwave sensor data. Transp Res Part C. 2015;54:187-197.
25. Pan B, Demiryurek U, Shahabi C. Utilizing real-world transportation data for accurate traffic prediction. Proceedings of the IEEE International Conference on Data Mining. 2012:595-604.
26. Polson NG, Sokolov VO. Deep learning for short-term traffic flow prediction. Transp Res Part C. 2017;79:1-17.
27. Shekhar S, Xiong H, Zhou X. Spatial data mining: A database approach. Boca Raton, FL: CRC Press; 2015.
28. Sun S, Zhang C, Yu G. A Bayesian network approach to traffic flow forecasting. IEEE Trans Intell Transp Syst. 2006;7(1):124-132.
29. Tian Y, Zhang K, Li J, Lin X, Yang B. LSTM-based traffic flow prediction with missing data. Neurocomputing. 2018;318:297-305.
30. Van Lint JWC, Van Hinsbergen CPIJ. Short-term traffic and travel time prediction models. In: Gartner DG, Messer CM, Rathi AK, editors. Traffic flow theory: A state-of-the-art report. Washington, DC: Transportation Research Board; 2012. p. 22-1-22-45.
31. Williams BM, Hoel LA. Modeling and forecasting vehicular traffic flow as a seasonal ARIMA process: Theoretical basis and empirical results. J Transp Eng. 2003;129(6):664-672.
32. Wu Y, Tan H. Short-term traffic flow forecasting with spatial-temporal correlation in a hybrid deep learning framework. arXiv preprint arXiv:1612.01022. 2016.
33. Xie Y, Zhang Y, Liang Y. Crash frequency analysis with generalized additive models. Transp Res Rec. 2007;2019(1):139-147.
34. Yu B, Yin H, Zhu Z. Spatio-temporal graph convolutional networks: A deep learning framework for traffic forecasting. Proceedings of the 27th International Joint Conference on Artificial Intelligence. 2017:3634-3640.
35. Zhang J, Zheng Y, Qi D. Deep spatio-temporal residual networks for citywide crowd flows prediction. Proceedings of the AAAI Conference on Artificial Intelligence. 2017:1655-1661.