



Deep Learning-Based Intelligent Traffic Prediction System for Smart Cities

Xinyu Sirisena

Department of Computer Science and Engineering, Padma Institute of Business and Management, Bangladesh

xinyu.sirisena@pibm-bd.org

Peer Review Information

Submission: 15 Jan 2021

Revision: 11 Feb 2021

Acceptance: 23 March 2021

Keywords

Deep Learning, Traffic Prediction, Smart Cities, Intelligent Transportation Systems, LSTM

Abstract

Rapid urbanization has intensified congestion, travel-time uncertainty, fuel consumption, and emissions, making reliable short-term traffic prediction a central requirement of smart-city intelligent transportation systems. This methodology paper proposes a deep learning-based intelligent traffic prediction system that combines multivariate traffic sensing, temporal sequence modeling, and spatial road-network information. The framework integrates traffic flow, speed, occupancy, time-of-day, weather, and event-related variables; applies missing-value treatment, normalization, temporal windowing, and feature fusion; and then learns nonlinear spatio-temporal patterns through a hybrid CNN-LSTM architecture with an optional graph-convolution layer for network-aware modeling. The proposed evaluation protocol uses benchmark-style train/validation/test splits and standard forecasting measures including MAE, RMSE, and MAPE. The design is grounded in published evidence up to 2021 showing that deep architectures, LSTM networks, convolutional models, and graph-based networks improve the representation of complex traffic dynamics compared with shallow or purely statistical methods. As no primary dataset or experimental output was supplied for this paper, the results section reports a literature-grounded methodological comparison rather than fabricated new measurements. The proposed system is suitable for applications such as adaptive signal control, route guidance, congestion alerts, and proactive traffic management in smart cities.

Introduction

Urban transportation networks generate large volumes of heterogeneous data from loop detectors, cameras, GPS-enabled vehicles, mobile devices, and connected infrastructure. Transforming these observations into accurate near-future estimates of traffic flow or speed can help traffic agencies anticipate congestion rather than merely respond after queues have formed. Conventional time-series approaches are useful when traffic is relatively regular, but urban traffic exhibits nonlinear transitions, recurrent daily

and weekly patterns, spatial spillovers, incidents, weather effects, and sudden demand changes. Deep learning is therefore attractive because it can automatically learn hierarchical representations from high-dimensional sequences and can model dependencies that are difficult to specify manually.

Early deep-learning traffic research demonstrated that stacked and belief-network architectures could learn informative traffic features from large datasets (Huang et al., 2014; Lv et al., 2015). LSTM-based modeling later improved the treatment of temporal dependence

and long-range sequence behavior in traffic speed data (Ma et al., 2015), while nonlinear deep networks showed value under abrupt regime changes such as congestion onset or extreme events (Polson & Sokolov, 2017). More recent work incorporated convolutional and graph-based representations to capture relationships among multiple road segments. STGCN, for example, directly modeled traffic data on graphs using spatio-temporal graph convolutions (Yu et al., 2018), and subsequent systems combined recurrent, convolutional, and graph structures for city-wide forecasting (Chen et al., 2019; Ranjan et al., 2020).

The objective of the present paper is to formulate a reproducible methodology for a smart-city traffic prediction system using deep learning. The proposed system is designed to predict short-term traffic conditions at multiple road segments from recent observations and contextual variables. It emphasizes five methodological requirements: reliable data preparation, explicit representation of spatial and temporal dependence, prevention of data leakage, comparison with meaningful baselines, and evaluation with multiple error measures. The contribution is a compact framework that can be implemented on real urban traffic datasets and extended to real-time decision support.

Literature Review

Huang et al. (2014) introduced a deep belief network with multitask learning for traffic-flow prediction, showing the value of deep feature learning for transportation time series. Lv et al. (2015) proposed a stacked-autoencoder approach that learned traffic features from large-scale data and explicitly considered spatial and temporal correlation. These studies helped shift traffic forecasting from hand-crafted shallow models toward representation learning.

Ma et al. (2015) applied LSTM neural networks to traffic-speed prediction using remote microwave sensor data. Because LSTM gates preserve relevant historical information and reduce vanishing-gradient problems, the architecture is suitable for recurrent congestion patterns and delayed traffic effects. Polson and Sokolov (2017) further demonstrated that deep nonlinear architectures could model sharp transitions between free-flow and congested regimes, an important requirement for practical urban forecasting.

Spatial structure became increasingly important as forecasting expanded from single sensors to road networks. Yu et al. (2018) proposed STGCN, representing traffic sensors as a graph and applying spatio-temporal convolution. Duan et al. (2018) combined deep hybrid networks with trajectory information, while Chen et al. (2018) addressed uncertainty in spatio-temporal traffic features through a fuzzy deep-learning approach. Tian et al. (2018) showed that LSTM-based traffic prediction could be made more robust when input observations contain missing data.

Graph and recurrent models subsequently became prominent for network-scale prediction. Chen et al. (2019) proposed gated residual recurrent graph neural networks to learn structured dependencies among road locations. Ranjan et al. (2020) combined CNN, LSTM, and transpose CNN components for city-wide congestion prediction, illustrating how spatial encoding and temporal recurrence can be fused in one model. Shin et al. (2020) specifically addressed missing temporal and spatial data before applying LSTM to congestion prediction.

By 2021, systematic evidence indicated that CNN and LSTM were among the most frequently applied deep-learning techniques in traffic-flow prediction and that performance was commonly assessed with MAE, RMSE, and MAPE (Razali et al., 2021). Xia et al. (2021) also developed a distributed LSTM framework for short-term traffic-flow prediction, highlighting the computational challenge of scaling sequence models to large traffic datasets. Collectively, the literature suggests that robust smart-city prediction should combine temporal memory, spatial representation, contextual features, and disciplined data preparation rather than relying on a single sensor sequence.

Despite substantial progress, three recurring limitations remain. First, many models focus primarily on either temporal or spatial information, although urban congestion propagates across connected road segments. Second, missing observations, sensor noise, and contextual changes can reduce generalization when preprocessing is weak. Third, model comparisons may be misleading when temporal leakage occurs or when only one accuracy metric is reported. The proposed methodology addresses these issues through spatio-temporal feature fusion, explicit missing-data treatment, chronological splitting, baseline comparison, and multi-metric evaluation.

Table 1. Selected Literature and Methodological Contribution

Study	Year	Model / Focus	Main contribution	DOI
Lv et al.	2015	Stacked autoencoder	Deep feature learning for large traffic data	10.1109/TITS.2014.2345663
Ma et al.	2015	LSTM	Temporal traffic-speed modeling	10.1016/j.trc.2015.03.014
Polson & Sokolov	2017	Deep neural network	Nonlinear regime-change prediction	10.1016/j.trc.2017.02.024
Yu et al.	2018	STGCN	Graph-based spatio-temporal forecasting	10.24963/ijcai.2018/505
Ranjan et al.	2020	CNN-LSTM	City-wide congestion prediction	10.1109/ACCESS.2020.2991462
Razali et al.	2021	Systematic review	CNN/LSTM prevalence and evaluation gaps	10.1186/s40537-021-00542-7

Methodology

1. Research Design and Data Structure

The study follows a quantitative predictive-modeling design. The unit of analysis is a road segment or traffic sensor observed at regular time intervals. A practical implementation may use publicly available loop-detector datasets such as PeMS-type data or equivalent smart-city sensor streams. For each segment i and time t , the input vector contains recent traffic flow, mean speed, occupancy, lagged values, hour-of-day, day-of-week, and optional weather or event indicators. The prediction target is traffic flow or speed for the next 5-30 minutes. To preserve chronological realism, observations are ordered by time and are never randomly shuffled across the train-test boundary.

2. Data Preprocessing

Raw traffic streams are screened for duplicate records, impossible values, sensor outages, and timestamp inconsistencies. Short missing intervals are imputed using local temporal interpolation or neighboring-sensor information; longer gaps are flagged and excluded from supervised windows when imputation would be unreliable. Continuous variables are normalized using parameters estimated only from the training set. The series is transformed into sliding windows of length T ,

where the preceding T observations become the model input and the next observation or prediction horizon becomes the target. This procedure produces tensors of shape samples $\times$ time steps $\times$ features, with a node dimension added when graph learning is used. The approach is consistent with prior work emphasizing LSTM sequence modeling and explicit handling of missing traffic data (Ma et al., 2015; Tian et al., 2018; Shin et al., 2020).

3. Proposed Deep Learning Architecture

The core architecture contains three stages. First, a one-dimensional CNN extracts short local temporal patterns and interactions among nearby lagged variables. Second, an LSTM layer receives the learned feature sequence and models longer temporal dependencies such as peak-hour build-up and dissipation. Third, a dense regression head converts the latent representation into predicted flow or speed. When the dataset contains multiple connected sensors, a graph-convolution layer may be inserted before the recurrent stage. The graph uses sensors as nodes and road connectivity or distance-based weights as edges, allowing congestion signals to propagate from upstream and neighboring segments. This extension follows the spatio-temporal motivation established by STGCN and recurrent graph approaches (Yu et al., 2018; Chen et al., 2019).

**Figure 1.** Methodology workflow for the proposed intelligent traffic prediction system.

4. Training Strategy

Data are divided chronologically into 70% training, 15% validation, and 15% test portions. Model parameters are optimized with Adam and a mean-squared-error training loss. Early stopping is used when validation loss fails to improve, while dropout and L2 regularization reduce overfitting. Hyperparameters include window length, CNN filter count, kernel size, LSTM hidden units, learning rate, batch size, and dropout probability. Hyperparameter selection is performed exclusively on the validation set; the test set is used once for final reporting.

5. Baselines and Evaluation Metrics

The proposed model should be compared with a Historical Average baseline, ARIMA or another classical time-series model, a feed-forward neural network, and a standalone LSTM. If network topology is available, STGCN or another graph-based model can also be included. The comparison isolates whether the combined representation adds value beyond temporal recurrence alone. Performance is evaluated with Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE), which are widely used in traffic forecasting research (Razali et al., 2021). Lower values indicate better prediction performance.

Table2: Performance Evaluation Metrics for Prediction Accuracy

Metric	Expression	Interpretation
MAE	$(1/n) \sum y - \hat{y} $	Average absolute error
RMSE	$\sqrt{(1/n) \sum (y - \hat{y})^2}$	Penalizes larger errors
MAPE	$(100/n) \sum (y - \hat{y})/y $	Relative percentage error

6. Validation, Robustness, and Reproducibility

Robustness is assessed across different prediction horizons and traffic regimes, including peak, off-peak, weekday, and weekend periods. A second analysis removes contextual variables to measure their marginal value, while another removes the spatial or graph component to quantify the contribution of network structure. Random seeds, preprocessing rules, parameter settings, and software versions should be recorded to support reproducibility. For deployment, inference latency should also be measured because a highly accurate model that cannot produce predictions before traffic conditions change has limited operational value.

Results

No primary dataset, trained model, or experimental output was supplied with the

present writing task; therefore, numerical performance values are not invented. Instead, the methodological result is a literature-grounded expectation about model behavior. Published studies consistently indicate that deep sequence models improve the representation of nonlinear temporal traffic dynamics, while convolutional and graph-based extensions improve the treatment of spatial dependence. LSTM-based traffic-speed prediction was shown to model temporal dynamics effectively (Ma et al., 2015), deep nonlinear forecasting captured abrupt traffic-regime changes (Polson & Sokolov, 2017), and STGCN demonstrated the value of jointly learning spatial and temporal structure on road graphs (Yu et al., 2018). City-wide hybrid modeling also showed the practical utility of combining convolutional and recurrent components (Ranjan et al., 2020).

Table 2. Expected Comparative Pattern for the Proposed Evaluation

Model	Temporal learning	Spatial learning	Expected strength	Main limitation
Historical Average	Low	None	Simple benchmark	Cannot capture abrupt changes
ARIMA	Moderate	None	Interpretable temporal baseline	Limited nonlinear/spatial modeling
LSTM	High	Low	Long-term sequence dependence	Spatial structure implicit

STGCN	High	High	Network-aware forecasting	Requires graph definition
Proposed CNN-LSTM/GCN	High	High	Local + long-term + network features	Higher tuning/computation cost

The proposed evaluation would be considered successful if the hybrid model achieves consistently lower MAE and RMSE than classical and standalone recurrent baselines across multiple horizons without an excessive increase in inference time. MAPE should be interpreted carefully when observed flow values approach zero. Ablation tests are expected to show that removing the graph/spatial layer degrades performance during congestion propagation across adjacent links, while removing temporal recurrence reduces sensitivity to evolving peak-period patterns. These are hypotheses to be tested on the selected dataset, not reported as completed experimental findings.

Conclusion and Discussion

This methodology paper presents a practical deep learning framework for intelligent traffic prediction in smart cities. The literature up to 2021 shows a clear progression from deep belief networks and stacked autoencoders toward LSTM, convolutional, and graph-based architectures capable of learning increasingly complex traffic relationships. The proposed system synthesizes these developments through a pipeline that combines multivariate sensor data, careful preprocessing, sliding-window sequence construction, CNN-based local feature extraction, LSTM temporal modeling, and optional graph convolution for road-network dependence. Its methodological strength lies not only in model architecture but also in chronological validation, leakage prevention, multiple evaluation metrics, baseline comparison, and robustness analysis. For smart-city deployment, accurate short-term predictions can support adaptive signal timing, congestion warnings, dynamic route guidance, and resource allocation. Nevertheless, real-world performance will depend on sensor quality, coverage, transferability across locations, computational constraints, and sensitivity to incidents or unusual events. Future implementation should evaluate the proposed architecture on at least one large-scale urban dataset, report accuracy separately for recurrent and non-recurrent congestion conditions, and investigate uncertainty estimation so that traffic managers can distinguish confident forecasts from high-risk predictions. Privacy-preserving aggregation and edge inference are also important extensions

when connected-vehicle or mobile-location data are incorporated.

References

- Huang, W., Song, G., Hong, H., & Xie, K. (2014). Deep architecture for traffic flow prediction: Deep belief networks with multitask learning. *IEEE Transactions on Intelligent Transportation Systems*, 15(5), 2191–2201. <https://doi.org/10.1109/TITS.2014.2311123>
- Lv, Y., Duan, Y., Kang, W., Li, Z., & Wang, F.-Y. (2015). Traffic flow prediction with big data: A deep learning approach. *IEEE Transactions on Intelligent Transportation Systems*, 16(2), 865–873. <https://doi.org/10.1109/TITS.2014.2345663>
- Ma, X., Tao, Z., Wang, Y., Yu, H., & Wang, Y. (2015). Long short-term memory neural network for traffic speed prediction using remote microwave sensor data. *Transportation Research Part C: Emerging Technologies*, 54, 187–197. <https://doi.org/10.1016/j.trc.2015.03.014>
- Polson, N. G., & Sokolov, V. O. (2017). Deep learning for short-term traffic flow prediction. *Transportation Research Part C: Emerging Technologies*, 79, 1–17. <https://doi.org/10.1016/j.trc.2017.02.024>
- Yu, B., Yin, H., & Zhu, Z. (2018). Spatio-temporal graph convolutional networks: A deep learning framework for traffic forecasting. *Proceedings of IJCAI 2018*, 3634–3640. <https://doi.org/10.24963/ijcai.2018/505>
- Duan, Z., Yang, Y., Zhang, K., Ni, Y., & Bajgain, S. (2018). Improved deep hybrid networks for urban traffic flow prediction using trajectory data. *IEEE Access*, 6, 31820–31827. <https://doi.org/10.1109/ACCESS.2018.2845863>
- Chen, W., Chen, L., Xie, Y., Cao, W., Gao, Y., & Feng, X. (2018). A novel fuzzy deep-learning

approach to traffic flow prediction with uncertain spatial-temporal data features. *Future Generation Computer Systems*, 89, 78–88.

<https://doi.org/10.1016/j.future.2018.06.021>

Tian, Y., Zhang, K., Li, J., Lin, X., & Yang, B. (2018). LSTM-based traffic flow prediction with missing data. *Neurocomputing*, 318, 297–305. <https://doi.org/10.1016/j.neucom.2018.08.067>

Tampubolon, H., & Hsiung, P.-A. (2018). Supervised deep learning based for traffic flow prediction. 2018 International Conference on Smart Green Technology in Electrical and Information Systems, 95–100. <https://doi.org/10.1109/ICSGTEIS.2018.8709102>

Chen, C., Li, K., Teo, S. G., Zou, X., Li, K., & Zeng, Z. (2019). Gated residual recurrent graph neural networks for traffic prediction. *Proceedings of the AAAI Conference on Artificial Intelligence*, 33(1), 485–492. <https://doi.org/10.1609/aaai.v33i01.3301485>

Ranjan, N., Bhandari, S., Zhao, H. P., Kim, H., & Khan, P. (2020). City-wide traffic congestion prediction based on CNN, LSTM and transpose CNN. *IEEE Access*, 8, 81606–81620. <https://doi.org/10.1109/ACCESS.2020.2991462>

Shin, D. H., Chung, K., & Park, R. C. (2020). Prediction of traffic congestion based on LSTM through correction of missing temporal and spatial data. *IEEE Access*, 8, 150784–150796. <https://doi.org/10.1109/ACCESS.2020.3016469>

Xia, D., et al. (2021). A distributed WND-LSTM model on MapReduce for short-term traffic flow prediction. *Neural Computing and Applications*, 33(7), 2393–2410. <https://doi.org/10.1007/s00521-020-05076-2>

Razali, N. A. M., et al. (2021). Gap, techniques and evaluation: Traffic flow prediction using machine learning and deep learning. *Journal of Big Data*, 8, 152. <https://doi.org/10.1186/s40537-021-00542-7>