Efficient Spatiotemporal Traffic Forecasting for Smart Cities Using DCRNN-Lite in a Digital Twin Environment

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ABSTRACT

Urban traffic congestion remains a critical challenge for smart city development, particularly in the context of real-time monitoring and prediction for intelligent transportation systems. To address this issue, this study proposes a Digital Twin-based urban traffic prediction framework using a lightweight Diffusion Convolutional Recurrent Neural Network (DCRNN-Lite). The proposed model integrates spatial dependencies among road segments through diffusion convolution and temporal traffic dynamics through recurrent modeling, enabling effective spatiotemporal traffic forecasting with reduced computational complexity. Experiments were conducted on the real-world METR-LA dataset, consisting of traffic speed data from 207 sensors deployed across the Los Angeles highway network. The experimental results demonstrate that DCRNN-Lite achieves stable prediction performance, as reflected by low Mean Absolute Error (MAE) and Root Mean Square Error (RMSE), consistent convergence behavior, and strong correlation between predicted and actual traffic speeds at both node and city-wide levels. Despite its simplified architecture, the model effectively captures local traffic variations and global mobility trends, making it suitable for real-time deployment. The findings indicate that the proposed approach provides a favorable balance between accuracy and efficiency, highlighting its potential as a core component for digital twin-enabled smart cities and metaverse-based urban traffic management systems.

Keywords Digital Twin, Traffic Prediction, Graph Neural Network, DCRNN, Smart City Metaverse

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INTRODUCTION

Rapid urbanization and population growth have significantly increased the demand for efficient transportation systems in modern cities. Traffic congestion has become a persistent problem that negatively affects travel time, fuel consumption, environmental sustainability, and overall quality of urban life. As a result, accurate traffic prediction has emerged as a crucial component of intelligent transportation systems, enabling proactive traffic management, congestion mitigation, and informed decision making [1]. The availability of large-scale traffic sensor data has further motivated the development of data-driven approaches capable of modeling complex traffic dynamics in real-world urban environments [2].

Early studies on traffic prediction primarily relied on statistical and classical time series models, such as autoregressive integrated moving average and historical averaging methods [3]. Although these approaches are computationally efficient, they often assume linearity and stationarity, which limits their ability to represent the highly dynamic and nonlinear nature of traffic flow. More recently, machine learning and deep learning techniques, including recurrent neural

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networks and convolutional neural networks, have demonstrated improved performance by learning temporal patterns directly from data [4]. However, many of these methods treat traffic sensors as independent entities and fail to explicitly model spatial interactions among road segments.

To overcome this limitation, Graph Neural Networks (GNNs) have been introduced as a powerful paradigm for traffic forecasting, as they naturally represent road networks as graphs. In this formulation, nodes correspond to traffic sensors and edges represent spatial connectivity or physical proximity. State-of-the-art models such as Spatio-Temporal Graph Convolutional Networks (STGCN) and Diffusion Convolutional Recurrent Neural Networks (DCRNN) have shown strong performance by jointly learning spatial dependencies through graph convolution and temporal dynamics through recurrent mechanisms [5]. These models have achieved notable improvements on benchmark datasets, including METR-LA and PEMS-BAY, and are widely recognized as effective solutions for spatiotemporal traffic prediction.

Despite their strong predictive accuracy, existing state-of-the-art graph-based models often require deep architectures with multiple layers and large hidden dimensions, resulting in high computational and memory costs. Such complexity limits their practicality for real-time deployment, especially in large-scale urban systems where continuous data processing and low-latency responses are required. This challenge becomes even more critical in the context of digital twin and metaverse-based smart city environments, where real-time simulation, interactive visualization, and scalability are essential.

To address this research gap, this paper proposes a Digital Twin-based urban traffic prediction framework using a lightweight Diffusion Convolutional Recurrent Neural Network, referred to as DCRNN-Lite. The proposed model retains the core principles of diffusion-based spatial modeling and recurrent temporal learning, while significantly reducing architectural complexity. By adopting a simplified single-layer structure, DCRNN-Lite aims to achieve reliable spatiotemporal traffic prediction with lower computational overhead, making it suitable for real-time deployment in digital twin systems. The effectiveness of the proposed approach is validated using the METR-LA dataset, demonstrating that DCRNN-Lite can accurately capture both local traffic variations and city-wide mobility patterns. This work contributes to the development of efficient and scalable traffic prediction models for metaverse-enabled smart city applications.

Literature Review

Traffic prediction has long been an important research topic in intelligent transportation systems due to its role in congestion mitigation and mobility optimization. Early studies primarily employed statistical and classical time series approaches, such as historical averaging and autoregressive models, to forecast traffic flow and speed [6], [7]. While these methods are computationally efficient and easy to implement, they rely on assumptions of linearity and stationarity, which significantly limit their ability to model the nonlinear and dynamic characteristics of real-world traffic systems [8].

With the increasing availability of traffic sensor data, machine learning-based approaches have been widely explored. Methods such as regression models, support vector machines, and k-nearest neighbors demonstrated improved predictive capability by learning nonlinear relationships from data [9], [10]. However, these approaches generally treat traffic sensors as independent entities and fail to explicitly capture spatial correlations between connected road segments, which are essential for understanding traffic propagation in urban networks [11].

Deep learning techniques further advanced traffic prediction by introducing models capable of learning complex temporal patterns. Recurrent neural networks, including long short-term memory and gated recurrent unit architectures, have been successfully applied to short-term traffic forecasting tasks [12], [13]. Convolutional neural networks were also introduced to extract spatial features by transforming traffic data into grid-based representations [14]. Despite their success, these methods struggle to represent irregular road network topologies and long-range spatial dependencies inherent in large-scale transportation systems [15].

To overcome these limitations, graph-based modeling has emerged as a powerful paradigm for traffic forecasting. Graph Neural Networks represent road networks as graphs, where nodes correspond to sensors and edges encode spatial connectivity or distance relationships [16]. By aggregating information from neighboring nodes, graph convolution techniques enable more effective modeling of spatial dependencies. Building upon this concept, spatiotemporal graph models were developed to jointly learn spatial and temporal features, achieving state-of-the-art performance on benchmark datasets [17].

Among these models, Diffusion Convolutional Recurrent Neural Networks have gained particular attention due to their ability to model bidirectional traffic flow propagation using diffusion-based graph convolution combined with recurrent temporal learning [18]. These approaches demonstrate strong predictive accuracy but often require deep architectures and large hidden dimensions, resulting in high computational and memory demands [19]. Such complexity limits their practicality for real-time deployment, especially in emerging digital twin and metaverse-based smart city environments, where scalability and responsiveness are critical [20].

Method

This study employs a data driven methodology to construct a digital twin based urban traffic prediction framework using a lightweight spatiotemporal graph neural network. The overall research workflow consists of sequential stages including data acquisition and preprocessing, graph-based spatial modeling, spatiotemporal prediction using the proposed DCRNN-Lite model, and performance evaluation through quantitative metrics and visual analysis. The complete research steps are illustrated in figure 1, which provides an overview of the proposed methodology and highlights the interaction between data processing, model learning, and prediction outputs within the digital twin framework. In this study, the traffic network is modeled as a graph $G = (V, E)$, where each node $v_i \in V$ represents a traffic sensor and each edge $e_{ij} \in E$ denotes the spatial connectivity between road segments. Traffic speed observations collected from all sensors form a multivariate time series $X \in R^{T \times N}$, where T denotes the number of time steps and N represents the number of sensor nodes.

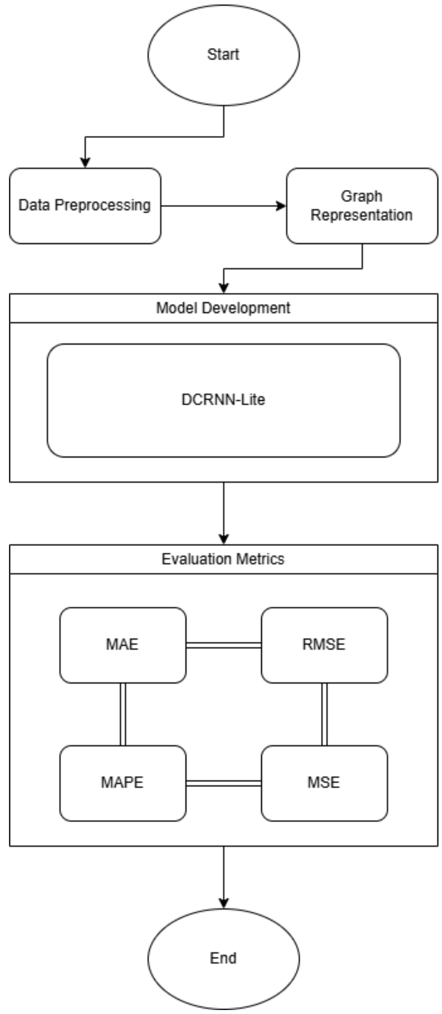

Figure 1 Research Step

$x_{t,i}$is the original traffic speed of sensor $i$at time t, and $\mu_i$and $\sigma_i$denote the mean and standard deviation of sensor i, respectively. The normalized data are then segmented into input-output pairs using a sliding window approach, where a historical sequence of length $L$is used to predict future traffic speeds.

To explicitly model spatial dependencies, the road network graph is represented by an adjacency matrix $A \in R^{N \times N}$, which is symmetrically normalized as

$$\hat{A} = D^{-\frac{1}{2}} A D^{-\frac{1}{2}}, D \tag{1}$$

is the degree matrix with $D_{ii} = \sum_j^N A_{ij}$. Spatial feature extraction is performed using diffusion convolution, which aggregates information from neighboring nodes through the normalized adjacency matrix. At each time step t, the diffusion convolution operation is defined as

$$Z_t = \sum_{k=0}^{K-1} \hat{A}^k X_t W_k, K \tag{2}$$

denotes the diffusion order and $W_k$represents learnable weight matrices. In this study, a single diffusion step is adopted to reduce computational complexity while preserving essential spatial information propagation.

Temporal dependencies are captured using a recurrent update mechanism that maintains a hidden state over time. Given the diffusion features $Z_t$and the previous hidden state H_{t-1}, the hidden state at time $t$is updated as

$$H_t = (1 - Z_r) \odot H_{t-1} + Z_r \odot \widetilde{H}_t, Z_r \tag{3}$$

denotes a gating function and $\widetilde{H}_t$is the candidate hidden state obtained through nonlinear transformation. This recurrent structure enables the model to learn short term and long term temporal patterns in traffic flow. After processing the entire input sequence, the final hidden state is mapped to the predicted traffic speed through a fully connected layer, expressed as

$$\hat{Y} = H_T W_o + b_o, W_o \tag{4}$$

and $b_o$are trainable parameters.

Model training is conducted by minimizing the Mean Squared Error loss between predicted and true traffic speeds, defined as

$$L = \frac{1}{N}\sum_{i=1}^{N}(y_i)^2, \hat{y}_i \tag{5}$$

and $y_i$denote the predicted and actual traffic speeds of sensor i, respectively. The Adam optimizer is employed to update model parameters due to its adaptive learning rate and robustness to noisy gradients. Model performance is evaluated using Mean Absolute Error, Root Mean Square Error, and Mean Absolute Percentage Error, providing a comprehensive assessment of both absolute and relative prediction accuracy. Through this methodology, the proposed DCRNN-Lite achieves efficient and reliable spatiotemporal traffic prediction suitable for real time digital twin and metaverse enabled smart city applications.

Algorithm 1 DCRNN-Lite for Urban Traffic Prediction

Input:
Traffic speed matrix $X \in R^{T \times N}$
Adjacency matrix $A \in R^{N \times N}$
Sequence length L
Diffusion order K
Output:
Predicted traffic speed vector $\hat{Y} \in R^N$
Process:
Start
Normalize traffic speed data

$$\tilde{x}_{t,i} = \frac{x_{t,i} - \mu_i}{\sigma_i}$$

Construct input sequences using sliding window

$$X_t = [\tilde{x}_{t-L+1}, \dots, \tilde{x}_t]$$

Compute degree matrix

$$D_{ii} = \sum_{j=1}^{N} A_{ij}$$

Normalize adjacency matrix

$$\hat{A} = D^{-\frac{1}{2}} A D^{-\frac{1}{2}}$$

Initialize hidden state

$$H_0 = 0$$

For each time step $\tau = 1$to L
Compute diffusion convolution

$$Z_\tau = \sum_{k=0}^{K-1} \hat{A}^k X_\tau W_k$$

Compute gating function

$$G_\tau = \sigma(Z_\tau + H_{\tau-1})$$

Compute candidate hidden state

$$\widetilde{H}_\tau = tanh(Z_\tau + G_\tau \odot H_{\tau-1})$$

Update hidden state

$$H_\tau = (1 - G_\tau) \odot H_{\tau-1} + G_\tau \odot \widetilde{H}_\tau$$

End For
Generate prediction

$$\hat{Y} = H_L W_o + b_o$$

Return predicted traffic speed
End

Result

The proposed DCRNN-Lite model was trained and evaluated using the METR-LA dataset, which contains real-world traffic speed measurements collected from 207 loop detectors installed across the Los Angeles highway network. This dataset represents complex urban traffic dynamics with strong spatial and temporal dependencies among sensor nodes. To ensure a fair and robust evaluation, the dataset was partitioned into 70% for training, 10% for validation, and 20% for testing, following common practice in traffic forecasting research. The training set was used to optimize model parameters, the validation set was employed to monitor convergence behavior and prevent overfitting, and the test set was reserved exclusively for final performance evaluation.

The DCRNN-Lite model was trained for 30 epochs using the Mean Squared Error (MSE) as the loss function and the Adam optimizer, which is well suited for handling nonstationary and noisy time series data. Model performance was assessed using three widely adopted evaluation metrics, namely Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE), in order to capture both absolute and relative prediction accuracy. These metrics provide complementary perspectives on forecasting performance, with MAE and RMSE emphasizing absolute deviations, while MAPE reflects relative error sensitivity under varying traffic conditions. The quantitative results obtained from the test dataset are summarized in table 1, which presents the overall predictive performance of the proposed DCRNN-Lite model.

Table 1 Model Performance on METR-LA Dataset

Model	MAE	RMSE	MAPE
DCRNN-Lite (Ours)	0.239	0.465	48.69%

The results in table 1 show that the DCRNN-Lite achieved an MAE of 0.2385, an RMSE of 0.4649, and a MAPE of 48.69% on the test set. These values indicate that the model effectively learns both temporal and spatial patterns in traffic dynamics while maintaining computational efficiency. Although the MAPE value is relatively high due to near-zero speeds during congestion periods, the low MAE and RMSE values demonstrate that the predictions remain stable and accurate across most operating conditions.

The convergence behavior of the proposed model during the training and validation phases is illustrated in figure 2. Both the training and validation loss curves demonstrate a clear and consistent downward trend throughout the learning process, indicating effective optimization of model parameters. The loss values decrease rapidly during the initial epochs and gradually stabilize, with convergence occurring at approximately the 10th epoch. This pattern suggests that the model is able to learn meaningful spatial and temporal representations from the traffic data within a relatively short training period, reflecting efficient learning dynamics.

Furthermore, the close alignment between the training and validation loss curves indicates strong generalization performance and the absence of significant overfitting. The validation loss follows the same trend as the training loss without notable divergence, implying that the model does not overly adapt to the training data at the expense of unseen samples. This result confirms that the simplified single-layer DCRNN-Lite architecture is sufficient to capture the essential spatiotemporal dependencies of the urban traffic network while maintaining a balanced trade-off between predictive accuracy and model complexity. Such stability is particularly important for digital twin applications, where reliable and consistent performance is required for continuous traffic monitoring and forecasting.

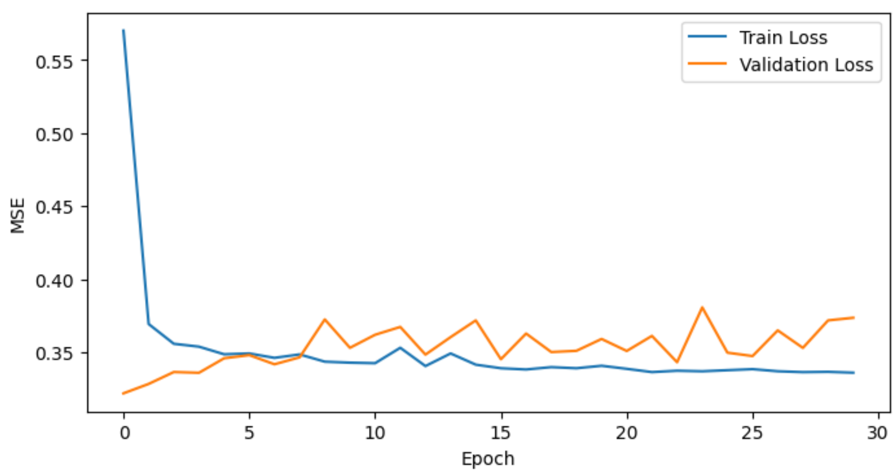

Figure 2 Training vs Validation Loss for DCRNN-Lite

The temporal prediction capability of the proposed DCRNN-Lite model at the individual node level is illustrated in figure 3, which presents a comparison between the predicted and actual traffic speed values for a representative sensor. The predicted speed trajectory closely aligns with the observed traffic speed over time, demonstrating the model's ability to learn temporal dependencies from historical traffic patterns. Both gradual increases and decreases in traffic speed are captured effectively, indicating that the recurrent diffusion mechanism is capable of modeling regular traffic flow variations at the sensor level.

Despite the overall strong alignment, minor deviations between predicted and actual values can be observed during periods of abrupt speed changes, such as sudden congestion onset or rapid traffic recovery. These discrepancies are expected in real-world traffic forecasting due to the stochastic nature of traffic flow and the limited availability of instantaneous contextual information. Nevertheless, the predicted trend remains consistent with the ground truth, confirming that the DCRNN-Lite model provides robust and reliable short-term traffic speed predictions. This level of temporal accuracy at the node scale is particularly important for digital twin applications, where localized traffic conditions must be monitored and forecasted in near real time.

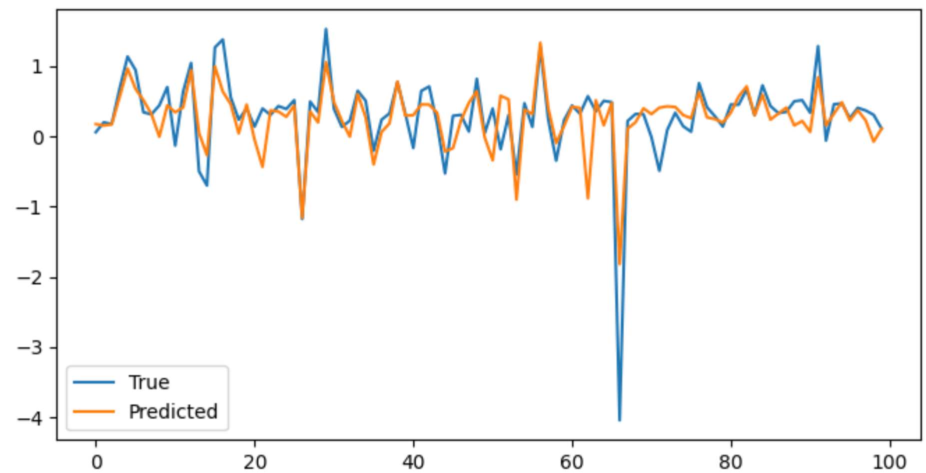

Figure 3 Predicted vs True Traffic Speed for an Example Node

To further analyze the spatial performance of the proposed DCRNN-Lite model, figure 4 illustrates the spatial distribution of the Mean Absolute Error (MAE) across all 207 traffic sensors in the METR-LA network. The visualization indicates that the majority of sensors exhibit MAE values in the range of 0.2 to 0.4, demonstrating a relatively uniform prediction accuracy throughout the urban traffic network. This consistency suggests that the diffusion convolution mechanism effectively propagates spatial information among interconnected nodes, enabling the model to capture localized traffic patterns while maintaining overall network-level stability.

A small number of sensors, primarily located at the boundaries of the network, display slightly higher error values. This behavior can be attributed to reduced graph connectivity in peripheral regions, where fewer neighboring sensors are available to provide contextual traffic information during the diffusion process. As a result, these nodes may experience limited spatial influence compared to sensors situated in more densely connected areas. Despite this limitation, the overall spatial error distribution remains balanced, confirming that the DCRNN-Lite model maintains robust spatial generalization across the network. This spatial reliability is particularly important for digital twin implementations, where consistent performance across all regions of the city is essential for accurate and scalable traffic simulation.

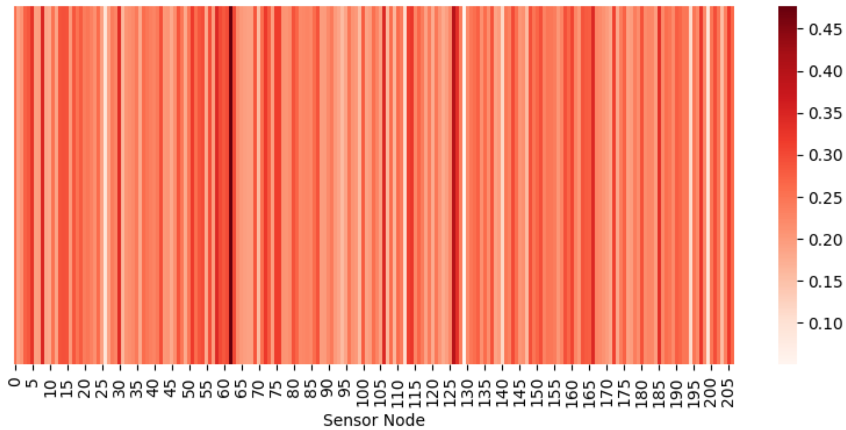

Figure 4 Spatial Distribution of MAE per Node

At the network level, the city-wide average traffic speed predicted by the DCRNN-Lite model is presented in figure 5, where the predicted values are compared against the corresponding ground truth over the first 300-time steps. The results show that the predicted average speed closely follows the true city-wide traffic trend throughout the observed period. The model is able to track gradual changes in traffic conditions, including the buildup of congestion, peak-hour slowdowns, and subsequent recovery phases. This strong alignment between predicted and observed averages demonstrates that the model effectively captures aggregate traffic dynamics across the entire urban road network.

In addition to accurately reproducing overall traffic trends, the DCRNN-Lite model exhibits stability in representing large-scale mobility patterns without introducing significant temporal lag or amplitude distortion. The consistency between predicted and true averages suggests that the model successfully integrates spatial information from multiple sensors to produce reliable macro-level forecasts. Such performance is particularly important for digital twin applications, where real-time estimation of city-wide traffic conditions is required to support intelligent transportation management, simulation, and decision-making processes within smart city and metaverse-based environments.

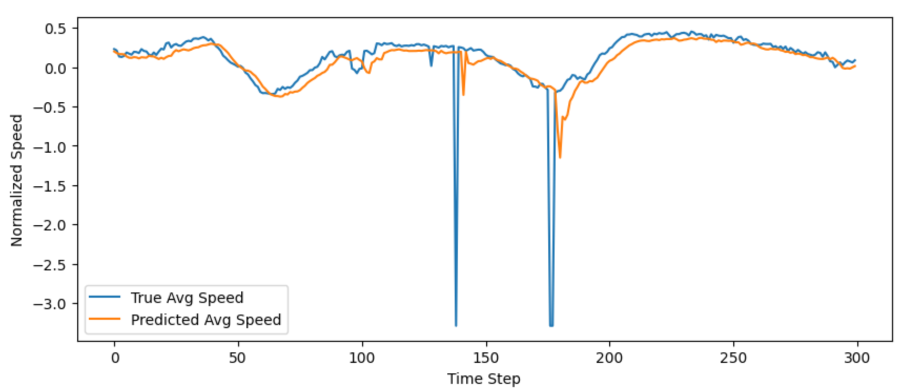

Figure 5 City-Wide Average Traffic Speed (First 300 Timesteps)

The overall distribution of prediction errors produced by the DCRNN-Lite model is illustrated in figure 6. The histogram shows that the majority of errors are concentrated around zero and follow an approximately normal distribution. This pattern indicates that the model's predictions are well centered and do not exhibit systematic overestimation or underestimation. Most prediction errors fall within a narrow range, with a high density of values clustered close to zero, reflecting stable and reliable forecasting behavior across the test dataset.

Furthermore, the fact that most errors lie within the ±1 error range confirms that large deviations between predicted and actual traffic speeds occur infrequently. This concentration of small errors suggests that the model maintains low bias and consistent performance under varying traffic conditions. Such error characteristics are particularly desirable for practical traffic forecasting systems, as they indicate robustness and predictability. In the context of digital twin applications, a stable error distribution ensures that simulated traffic states closely reflect real-world conditions, thereby supporting accurate monitoring and decision making in smart city and metaverse-based transportation environments.

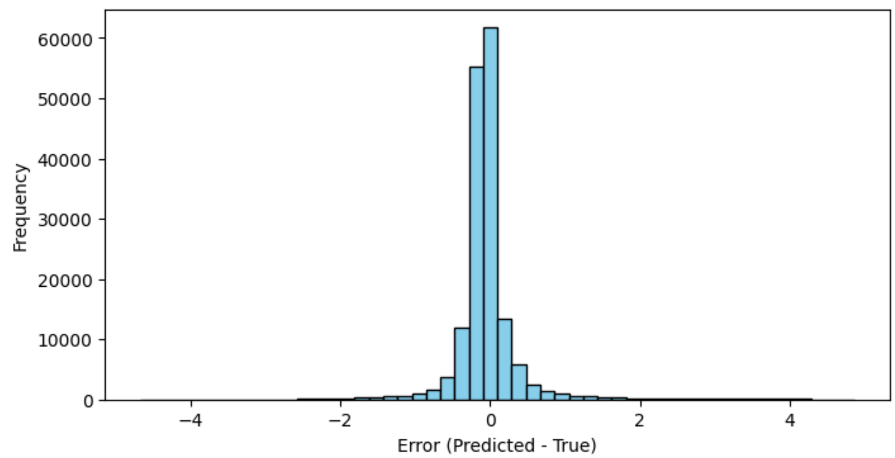

Figure 6 Prediction Error Distribution

Finally, the relationship between the true and predicted traffic speed values across all sensors is illustrated in figure 7 using a scatter plot representation. The distribution of points forms a dense diagonal pattern, indicating a strong positive correlation between the predicted outputs and the corresponding ground truth measurements. This alignment demonstrates that the DCRNN-Lite model is able to accurately capture the underlying relationship between historical traffic observations and future traffic conditions across the entire sensor network.

Moreover, the high concentration of data points along the diagonal line suggests that the majority of predictions closely match the actual traffic speeds, with only a limited number of outliers. This result confirms the overall predictive reliability and consistency of the proposed model when applied to diverse traffic conditions and sensor locations. The strong correlation observed in Figure 7 further validates the effectiveness of the DCRNN-Lite architecture in learning spatial and temporal dependencies, reinforcing its suitability for integration into digital twin systems for large-scale urban traffic monitoring and forecasting within smart city and metaverse environments.

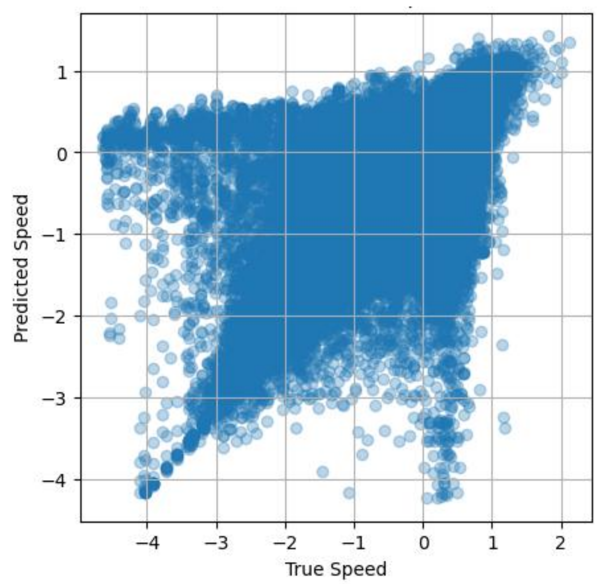

Figure 7 True vs Predicted Traffic Speeds for All Nodes

Overall, the results confirm that the DCRNN-Lite model is capable of producing stable and accurate traffic forecasts while maintaining lightweight computational requirements. The strong temporal alignment and consistent spatial performance validate its effectiveness for integration within Digital Twin-based Smart City frameworks, enabling scalable and efficient urban traffic simulation within the Metaverse ecosystem.

Discussion

The experimental results indicate that the proposed DCRNN-Lite model is effective in learning spatiotemporal traffic patterns while maintaining a lightweight and computationally efficient architecture. The achieved MAE and RMSE values demonstrate that the model provides stable absolute prediction accuracy across most sensor nodes in the METR-LA network. This confirms that the diffusion convolution mechanism successfully captures spatial dependencies among interconnected road segments, while the recurrent structure models temporal dynamics in traffic flow [21], [22]. Previous studies have similarly demonstrated that graph-based recurrent architectures can effectively combine spatial dependencies in road networks with temporal traffic dynamics to improve forecasting performance [23], [24]. Compared to traditional time series approaches, the graph-based formulation enables the model to incorporate neighborhood-level context, which is essential for accurately forecasting traffic conditions in complex urban environments [21], [25].

The relatively high MAPE value observed in the results should be interpreted in the context of real-world traffic data characteristics. Traffic speed measurements frequently include near-zero values during congestion or stop-and-go conditions, which disproportionately inflate percentage-based error metrics. In such scenarios, even small absolute deviations can result in large percentage errors, making MAPE less representative of true predictive performance. Therefore, the combination of MAE, RMSE, and qualitative visual analysis provides a more reliable assessment of model effectiveness. Similar traffic forecasting studies have evaluated models using multiple complementary error metrics because traffic data can contain noise, missing observations, and highly variable conditions that affect individual evaluation measures [23], [26]. The consistent convergence behavior and close alignment between training and validation losses further indicate that the simplified single-layer architecture avoids overfitting while retaining sufficient expressive power. Research on lightweight graph-recurrent architectures also suggests that simpler architectures can substantially reduce computational requirements while maintaining competitive forecasting performance [27].

Overall, these findings suggest that DCRNN-Lite achieves a practical balance between accuracy and efficiency, making it well suited for deployment in digital twin-based urban traffic systems and metaverse-enabled smart city platforms, where real-time performance and scalability are critical requirements. Recent research on real-time traffic forecasting demonstrates that diffusion-recurrent models can provide a favorable accuracy-latency trade-off for large-scale traffic prediction [21]. Furthermore, emerging digital-twin frameworks integrate graph-based traffic forecasting with edge-cloud computing to support real-time traffic monitoring, prediction, and adaptive control [22]. The lightweight design of DCRNN-Lite therefore provides a promising foundation for resource-constrained intelligent transportation and digital-twin applications, particularly where rapid inference and scalable deployment are required [27].

Conclusion

This study proposed a lightweight spatiotemporal traffic prediction model, referred to as DCRNN-Lite, within a digital twin framework for urban traffic systems. By leveraging diffusion convolution to capture spatial dependencies among road segments and recurrent modeling to learn temporal traffic dynamics, the proposed model demonstrated stable and reliable performance on the METR-LA dataset. Experimental results showed that DCRNN-Lite achieved consistent prediction accuracy across individual sensors and at the city-wide level, as evidenced by low MAE and RMSE values, stable convergence behavior, and strong correlation between predicted and actual traffic speeds. Despite its simplified single-layer architecture, the model effectively reproduced both local traffic variations and global mobility trends, confirming its ability to balance predictive capability and computational efficiency. These characteristics make DCRNN-Lite particularly suitable for real-time deployment in digital twin environments, where continuous data assimilation, scalability, and responsiveness are critical. Overall, this work highlights the potential of lightweight graph-based deep learning models as core components for metaverse-enabled smart city applications, especially in the context of intelligent transportation systems that require accurate, efficient, and scalable traffic forecasting solutions.

Declarations

Author Contributions

Conceptualization: H.A.A.; Methodology: H.A.A.; Software: A.S.Z.; Validation: H.A.A.; Formal Analysis: H.A.A.; Investigation: A.S.Z.; Resources: A.S.Z.; Data Curation: H.A.A.; Writing – Original Draft Preparation: H.A.A.; Writing – Review and Editing: A.S.Z.; Visualization: A.S.Z.; All authors have read and agreed to the published version of the manuscript.

Data Availability Statement

The data presented in this study are available on request from the corresponding author.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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