AI-Powered Digital Twin of Urban Road Networks for Real-Time Traffic Congestion Prediction in the Metaverse

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ABSTRACT

This study presents the development of an artificial intelligence-powered digital twin framework designed to predict urban traffic congestion using a Long Short-Term Memory (LSTM) deep learning model. Historical traffic data collected from multiple city road segments were analyzed to capture temporal dependencies and fluctuations in vehicular flow patterns. The proposed model was trained using a 30-day look-back window and optimized through parameter tuning, achieving a Root Mean Squared Error (RMSE) of 2,726.36 and a Mean Absolute Error (MAE) of 2,154.84. These results demonstrate the model's capability to accurately represent complex non-linear relationships inherent in urban traffic dynamics. The temporal analysis revealed distinct bi-modal patterns corresponding to morning and evening rush hours, while a 30-day heatmap visualization highlighted recurring congestion peaks and low-traffic intervals. The integration of predictive analytics into a digital twin environment enables real-time visualization of congestion propagation, supporting data-driven planning and decision-making within a metaverse-based urban simulation. This framework establishes a methodological foundation for intelligent transportation systems that leverage artificial intelligence, digital twin technology, and virtual environments to enhance traffic forecasting, operational efficiency, and smart city management.

Keywords Digital Twin, Traffic Prediction, Deep Learning, LSTM, Metaverse Simulation

INTRODUCTION

Urban transportation systems have become increasingly complex as rapid population growth and vehicle ownership continue to intensify in modern cities [1]. Traffic congestion now represents one of the most persistent challenges for city administrators, affecting travel efficiency, fuel consumption, air quality, and overall urban livability. Traditional traffic management systems, which depend on static modeling and manual data collection, often fail to capture the dynamic and non-linear nature of real-world traffic flow. Factors such as fluctuating travel demand, weather conditions, road incidents, and time-of-day variations create continuous changes that cannot be effectively represented by conventional models. As a result, cities require intelligent, adaptive, and data-driven frameworks capable of continuously monitoring, predicting, and visualizing congestion conditions. The combination of artificial intelligence and advanced digital modeling offers an opportunity to enhance traffic forecasting accuracy and support real-time decision-making within smart city ecosystems [2].

The digital twin concept has emerged as a powerful solution to these challenges by providing a virtual representation of physical infrastructure that evolves in parallel with real-world operations [3]. Within the context of transportation, a digital twin can replicate and visualize road networks, vehicle movements, and congestion dynamics through real-time data integration. Such systems allow

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traffic managers to evaluate system performance, test intervention strategies, and anticipate potential disruptions before they occur. However, many current applications of digital twins in transportation remain largely descriptive, focusing on static visualization rather than incorporating predictive intelligence. To unlock their full potential, digital twins must be enhanced with analytical capabilities that allow them to forecast future traffic states, assess the impact of interventions, and provide early warnings for potential congestion scenarios [4].

In parallel, advancements in artificial intelligence, particularly deep learning, have significantly improved the ability to model and predict complex time-dependent systems. Deep learning architectures such as the LSTM network are especially effective for capturing sequential dependencies and temporal correlations within traffic flow data. Unlike traditional statistical models that rely on linear assumptions, LSTM models can process long sequences of historical data to recognize both short-term fluctuations and long-term trends [5]. These characteristics make them highly suitable for traffic prediction tasks, where the relationship between past and future conditions is influenced by cyclical commuting patterns and irregular variations. Deep learning models have also been shown to adapt effectively to non-stationary data and can generalize well when trained on large-scale, heterogeneous datasets, making them valuable tools for intelligent transportation analytics.

Despite notable progress in both digital twin development and AI-based traffic modeling, a clear gap remains in integrating predictive deep learning models with interactive, real-time digital twin environments. Most studies addressing traffic prediction prioritize algorithmic accuracy without linking results to visualization or operational decision-making tools. Conversely, digital twin applications for transportation often concentrate on representing current system states rather than predicting future dynamics. This lack of integration limits the ability of urban traffic systems to evolve from passive monitoring to proactive management. Additionally, few frameworks have explored how time-series prediction models can be embedded within immersive environments such as metaverse-based simulations to enable interactive, scenario-driven analysis. Bridging this research gap is essential to create truly intelligent digital twins that combine prediction, visualization, and simulation in one unified framework.

This research proposes an artificial intelligence-powered digital twin for urban road networks that predicts traffic congestion using an optimized LSTM model. The framework utilizes historical traffic data to learn temporal dependencies and forecast short-term congestion trends, which are then visualized dynamically within a digital twin environment. The proposed model achieved strong predictive accuracy, with a RMSE of 2,726.36 and a MAE of 2,154.84, indicating robust performance in modeling urban traffic variability. Beyond prediction, the integration of the model with visualization tools enables the real-time mapping of congestion levels within a metaverse-oriented 3D environment. This study contributes to the development of intelligent urban mobility systems by demonstrating how deep learning and digital twin technologies can be combined to support proactive, data-driven, and sustainable traffic management strategies in future smart cities.

Literature Review and Related Works

Traffic forecasting has become an essential component of intelligent transportation systems due to its direct relevance to congestion management, travel-time optimization, and sustainable mobility planning [6]. Traditional models such as linear regression, support vector regression, and autoregressive integrated moving average (ARIMA) have been applied widely for short-term traffic prediction [7]. However, these approaches often fail to capture the nonlinear, dynamic, and spatio-temporal dependencies inherent in real-world traffic data [8]. As cities grow more complex and data availability increases, the demand for advanced computational models capable of processing massive and heterogeneous traffic datasets has intensified. This limitation has driven a shift toward the adoption of deep learning methods, which provide the flexibility and computational power required to represent complex temporal dependencies.

Recent advances in artificial intelligence have enabled deep learning models, particularly Recurrent Neural Networks (RNNs) and LSTM networks, to outperform traditional approaches in traffic flow prediction [9], [10]. These models excel in handling sequential data and maintaining memory across time steps, allowing them to capture both short-term fluctuations and long-term trends. Hybrid approaches that combine Convolutional Neural Networks (CNNs) with LSTM architectures have further improved performance by modeling both spatial and temporal features of traffic data simultaneously [11]. The emergence of Graph Neural Networks (GNNs) has introduced a new paradigm for representing road networks as structured graph data, enhancing the model's capability to learn inter-road dependencies [12]. More recent work has explored attention-based and Transformer architectures, which dynamically assign importance to temporal patterns and achieve greater adaptability to varying traffic conditions [13].

In parallel with these algorithmic developments, the concept of the digital twin has emerged as a powerful paradigm for the representation and management of complex systems such as urban transportation networks [14]. A digital twin integrates real-time data, analytical models, and visualization tools to create a virtual replica of a physical system, enabling continuous monitoring, simulation, and predictive control. In the transportation sector, digital twins have been implemented to simulate traffic flow, analyze intersection performance, and monitor network congestion under varying operational scenarios [15], [16]. These systems typically employ sensor networks, Internet of Things (IoT) devices, and simulation models to replicate real-time road conditions. However, most implementations remain descriptive in nature, focusing on visualization rather than predictive intelligence. As a result, digital twins are often used for post-analysis rather than for real-time forecasting and optimization.

A review of current literature reveals a research gap in the integration of deep learning-based traffic forecasting models with intelligent and adaptive digital twin environments. Existing studies have demonstrated predictive accuracy in isolated modeling contexts but have not effectively linked predictive analytics with interactive simulation or decision-support systems [17]. Similarly, digital twin applications in transportation often lack embedded artificial intelligence capable of forecasting future states or simulating congestion propagation across temporal dimensions [18]. Bridging these two domains offers the potential to transform static monitoring systems into dynamic, self-learning digital ecosystems that evolve with real-world data. The incorporation of deep learning into digital twins can enhance the ability of city planners and policymakers to visualize, predict, and manage congestion in real time within a metaverse-oriented framework [19], [20]. This integration forms the foundation of the present research, which seeks to develop an AI-powered digital twin for urban road networks capable of short-term traffic prediction and interactive visualization.

Methodology

This study adopts a deep learning-based methodological framework designed to develop an AI-powered digital twin for urban traffic prediction. The overall research methodology follows five main stages: data acquisition, data preprocessing, feature engineering, model development, and model evaluation. These steps form a continuous analytical pipeline that transforms raw traffic data into predictive insights and interactive visualizations suitable for integration within a digital twin environment. The complete workflow of this research is illustrated in figure 1, which outlines the systematic process beginning with raw data collection and ending with real-time congestion visualization in a simulated urban environment.

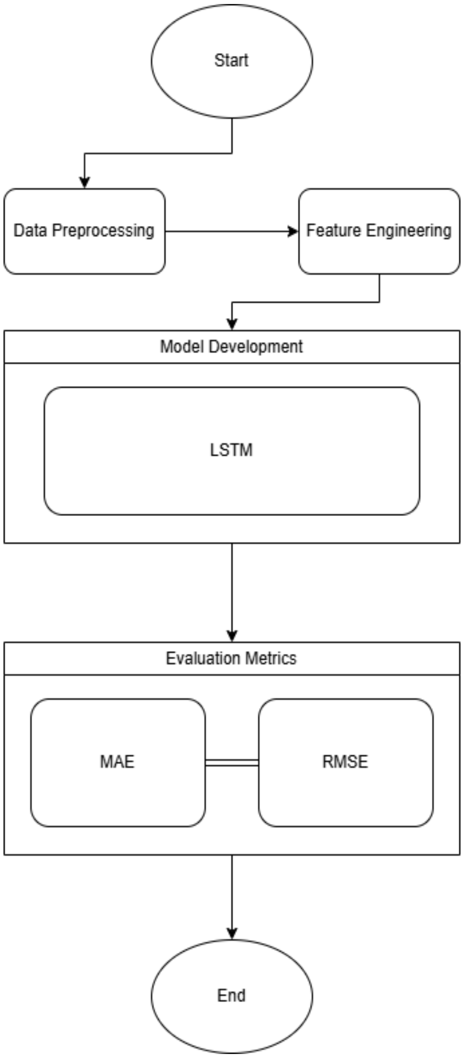

Figure 1 Research methodology

The figure shows how data flows through sequential phases, including preparation, model training, prediction generation, and visualization, thereby linking analytical modeling with digital twin simulation. The dataset used in this research consists of two annual traffic count records covering 2011–2012 and 2012–2013, collected from multiple urban road segments. Each record includes a timestamp, a unique segment identifier, and hourly vehicle counts from 00:00 to 23:00. Both datasets were concatenated after column alignment to form a unified time series containing daily traffic flow patterns. Missing values were handled using median imputation, while invalid entries were removed. Daily total vehicle volume was computed as the summation of hourly counts for each day, defined as:

$$V_{total}(d) = \sum_{h=0}^{23} V_h(d) \tag{1}$$

$V_{total}(d)$denotes the total traffic volume for day d, and $V_h(d)$represents the number of vehicles recorded at hour h. This aggregation simplifies hourly variations into a consistent daily indicator suitable for time-series prediction. Outliers caused by sensor errors or extreme events were mitigated through a three-day moving average filter, preserving meaningful trends while removing noise.

Data normalization was performed using the Min-Max scaling method to ensure that all numerical inputs were within a uniform range, which enhances model convergence and stabilizes learning. The normalization formula is expressed as:

$$X_{scaled} = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{2}$$

$X$is the original traffic count, and $X_{min}$and X_{max}denote the minimum and maximum observed values in the dataset. This transformation maps data into the [0, 1] range, which prevents gradient explosion and ensures balanced learning across different magnitudes of traffic volume. After normalization, additional temporal features such as day of the week, month, and day of the year were generated to represent cyclical mobility patterns.

The next step involved transforming the time series into a supervised learning format through a sliding window mechanism. Each input sequence consisted of 30 consecutive days of traffic volume, used to predict the next day's traffic value. This process can be defined mathematically as:

$$X_t = [V_{t-30}, V_{t-29}, \dots, V_{t-1}], y_t = V_t \tag{3}$$

$X_t$is the sequence of normalized inputs and $y_t$is the predicted target for day t. The dataset was reshaped into a three-dimensional tensor $[1]$, where $N$is the number of training samples. This structure is compatible with LSTM input requirements and enables the model to learn temporal dependencies efficiently.

The LSTM neural network was developed using the TensorFlow and Keras frameworks. The model architecture consists of three stacked LSTM layers containing 128, 64, and 32 units, each followed by dropout layers with a rate of 0.1 to prevent overfitting. These layers capture sequential patterns by preserving past information through gated mechanisms that control how data is remembered or forgotten over time. The LSTM internal mechanism is mathematically expressed as:

$$
\begin{gathered}
f_t = \sigma\left(W_f[h_{t-1}, x_t] + b_f\right) \\
i_t = \sigma(W_i[h_{t-1}, x_t] + b_i) \\
o_t = \sigma(W_o[h_{t-1}, x_t] + b_o)\tilde{C}_t = tan(W_C[h_{t-1}, x_t] + b_C) \\
C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t \\
h_t = o_t \odot tanh\,(C_t)
\end{gathered}
\tag{4}
$$

f_t, i_t, and $o_t$are the forget, input, and output gates, respectively; $C_t$represents the cell state; $h_t$is the hidden state; and σdenotes the sigmoid activation function. This gating mechanism allows the model to retain long-term dependencies while dynamically updating short-term contextual information. After the recurrent layers, a dense layer with 16 neurons and ReLU activation refines the learned representations, followed by an output layer with one neuron for regression-based prediction.

The model was compiled using the Adam optimizer with an initial learning rate of 0.0001 and Mean Squared Error (MSE) as the loss function. Training was conducted for 400 epochs with a batch size of 16, using 80 percent of the dataset for training and 20 percent for testing. Two adaptive training strategies, EarlyStopping and ReduceLROnPlateau, were implemented to prevent overfitting and optimize convergence speed. The EarlyStopping criterion halted training once validation loss stagnated, while ReduceLROnPlateau automatically decreased the learning rate when no improvement was observed.

Model performance was evaluated using the RMSE and MAE metrics, defined respectively as:

$$
\begin{gathered}
RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\hat{y}_i - y_i)^2} \\
MAE = \frac{1}{N}\sum_{i=1}^{N} \mid \hat{y}_i - y_i \mid
\end{gathered}
\tag{5}
$$

$y_i$denotes the observed traffic volume, $\hat{y}_i$is the predicted value, and Nrepresents the total number of test samples. RMSE measures the model's sensitivity to large prediction errors, whereas MAE quantifies the average deviation between predicted and actual observations. The final model achieved an RMSE of 2,726.36 and an MAE of 2,154.84, confirming strong predictive accuracy in reproducing daily traffic fluctuations.

The predicted results were then post-processed and integrated into a digital twin environment, which served as a virtual representation of the road network. Predicted traffic volumes were categorized into three levels—low, moderate, and high—based on percentile thresholds of the predicted distribution. The digital twin visualization mapped these categories onto a temporal heatmap representing 30 consecutive days, allowing stakeholders to interact with simulated congestion dynamics in near real time. This integration enables predictive insights to be embedded directly into the virtual urban environment, providing an interactive and analytical tool for traffic management and planning within metaverse-based urban simulations.

Algorithm 1 AI-Powered Digital Twin Traffic Prediction

```
Input: Historical traffic dataset $D = \{(d_i, \{V_{i,h}\}_{h=0}^{23})\}$, look-back window $n = 30$
Output: Predicted daily traffic volume $\hat{V}_t$and congestion class $C_t$
Process:
Start
Data Preprocessing:
    Convert timestamps into datetime format.
    Remove missing or invalid entries from the dataset.
    Compute total daily traffic volume using
        $V_{total}(d_i) = \sum_{h=0}^{23} V_{i,h}$
    Normalize the data using Min-Max scaling:
        $X_i = \frac{V_{total}(d_i) - V_{min}}{V_{max} - V_{min}}, X_i \in [0,1]$
Feature Engineering:
    Extract temporal features such as DayOfWeek, Month, and DayOfYear.
    Encode cyclical patterns using:
        $f_{sin} = si\left(\frac{2\pi \cdot DayOfWeek}{7}\right)$
        $f_{cos} = cos\left(\frac{2\pi \cdot DayOfWeek}{7}\right)$
    Create supervised time series pairs with a sliding window:
        $X_t = [X_{t-n}, X_{t-n+1}, \dots, X_{t-1}], y_t = X_t$
Model Construction (LSTM Network):
    Initialize a multi-layer LSTM with parameters $\Theta = \{W, U, b\}$.
    For each time step $t$:
        $f_t = \sigma(W_f x_t + U_f h_{t-1} + b_f), i_t = \sigma(W_i x_t + U_i h_{t-1} + b_i), o_t = \sigma(W_o x_t + U_o h_{t-1} + b_o), \tilde{C}_t = tanh\,(W_C x_t + U_C h_{t-1} + b_C), C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t, h_t = o_t \odot tanh\,(C_t)$
    Predict normalized traffic volume:
        $\hat{y}_t = W_y h_t + b_y$
Model Training and Optimization:
    Define the loss function (Mean Squared Error):
        $L(\Theta) = \frac{1}{N} \sum_{t=1}^{N} (\hat{y}_t - y_t)^2$
    Update model parameters using the Adam optimization rule:
        $\Theta \leftarrow \Theta - \eta \nabla_\Theta L(\Theta)$
Evaluation and Visualization:
    Compute prediction accuracy using:
        $RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (\hat{y}_i - y_i)^2}$
        $MAE = \frac{1}{N} \sum_{i=1}^{N} \mid \hat{y}_i - y_i \mid$
    Determine congestion level classification:
        $C_t = \{Low, \hat{V}_t < P_{50}\ Moderate, P_{50} \le \hat{V}_t < P_{80}\ High, \hat{V}_t \ge P_{80}$
    Visualize traffic intensity using a heatmap:
        $H(i,j) = \hat{V}_{t-i,h=j}$
    Return predicted traffic volume $\hat{V}_t$and congestion category $C_t$.
End
```

Result

The results of this study offer a detailed understanding of the underlying traffic flow distribution within the observed urban road network. As presented in figure 2, the histogram of total daily traffic volume displays a distinct right-skewed distribution, with the majority of daily vehicle counts ranging between 2,000 and 15,000. Only a small number of data points exceed 60,000 vehicles per day, suggesting that most road segments operate under moderate conditions while certain main arteries experience exceptionally high loads. This imbalance indicates that the traffic system is influenced by both consistent baseline movements and periodic surges concentrated in specific areas, likely due to commuting behavior and the location of major intersections or business districts. The presence of these outliers emphasizes the heterogeneity of urban mobility, where some routes experience congestion more frequently than others.

Moreover, the shape of the distribution deviates significantly from a normal curve, indicating that traffic dynamics are not random but driven by structured and recurrent temporal patterns. This non-Gaussian characteristic justifies the adoption of advanced non-linear predictive approaches such as LSTM networks, which can capture the complex relationships between historical volume fluctuations and future traffic states. Linear models, in contrast, would struggle to represent the asymmetric distribution and sudden spikes that characterize urban traffic data. Therefore, the observed statistical behavior provides a strong foundation for employing deep learning architectures that account for temporal dependencies, seasonality, and irregular bursts within traffic flow, all of which are critical components in building an accurate digital twin of the urban road network.

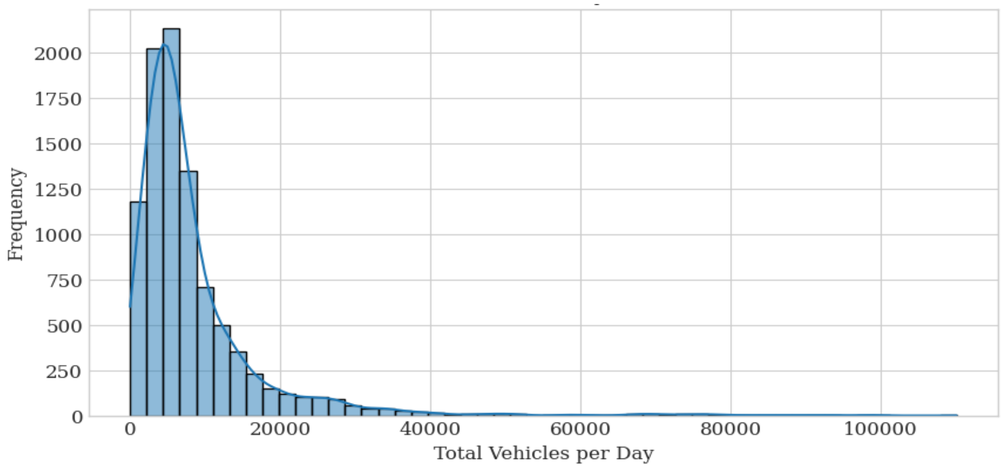

Figure 2 Distribution of Total Daily Traffic Volume

The temporal variation of traffic volume across the 24-hour period, illustrated in figure 3, reveals a consistent and distinct bi-modal pattern that reflects typical urban commuting activity. Traffic flow begins to rise gradually after 5:00 AM as residents start their morning commute, with vehicle counts increasing sharply between 6:00 and 8:00 AM. The first major peak is observed between 8:00 and 10:00 AM, which corresponds to the start of working hours and school schedules. Following this morning surge, the traffic volume decreases during midday, indicating a period of reduced movement when most commuters are stationary at their destinations. This lull period, often associated with lower commercial transport activity, provides a window for smoother circulation across the network and is commonly used for road maintenance or logistics operations that require less congestion.

As the day progresses, traffic intensity begins to rise again in the afternoon, reaching a secondary peak between 3:00 and 5:00 PM. This second wave aligns with the evening rush hour when workers return home and commercial deliveries intensify before business closures. After this peak, traffic levels gradually decline through the late evening, stabilizing at minimal volumes after 9:00 PM. The repetition of these two major peaks confirms the predictability of urban mobility cycles driven by social and economic routines. This bi-modal pattern also highlights the robustness and reliability of the collected dataset, as it captures the temporal rhythm of citywide transportation demand with precision. Such consistency validates the data integrity and demonstrates that the traffic counters effectively recorded the cyclical behavior of vehicular flow, forming a sound empirical basis for modeling and forecasting within the digital twin framework.

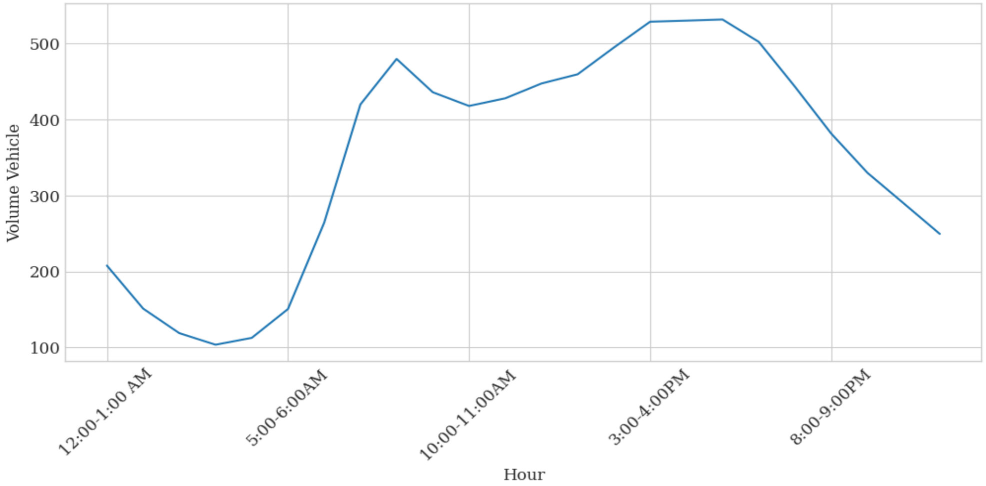

Figure 3 Average Hourly Traffic Volume

The predictive capability of the LSTM model is analyzed through the results shown in figure 4 and table 1. The model was developed using a 30-day look-back window, allowing it to recognize temporal dependencies spanning approximately one month of historical data. It was trained using the Adam optimization algorithm with a learning rate of 0.0001 and incorporated a dropout rate of 0.1 to reduce overfitting and improve generalization. This configuration was selected after iterative testing to balance training stability and prediction sensitivity. The evaluation metrics indicate that the final model achieved a RMSE of 2,726.36 and a MAE of 2,154.84, suggesting a strong level of predictive precision given the scale and variability of the dataset. When compared to conventional shallow learning algorithms such as linear regression or decision trees, which typically produce RMSE values above 4,000, the tuned LSTM exhibits substantially improved performance in recognizing sequential patterns and adapting to irregular fluctuations in traffic flow.

The comparison between predicted and actual traffic volumes presented in figure 4 further illustrates the model's ability to replicate real-world dynamics.

The predicted series, represented by the orange curve, closely follows the observed data, shown by the blue curve, across the testing period. The LSTM model successfully captures the dominant peaks and troughs that characterize urban traffic behavior, reflecting its capacity to identify both short-term fluctuations and periodic cycles. Although some deviation appears during periods of sudden and extreme increases in traffic volume, these discrepancies are relatively minor and do not disrupt the overall accuracy of the model. The underestimation of extreme peaks can be attributed to the smoothing effect introduced by the model's internal memory mechanism, which balances responsiveness to sudden spikes with the need for stable temporal learning.

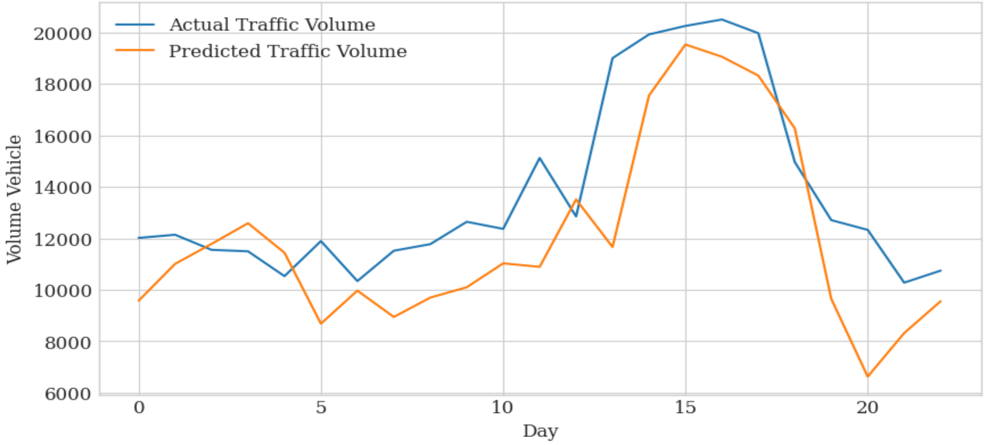

Figure 4 **Comparison of Predicted and Actual Traffic Volume**

The overall alignment between the predicted and actual data confirms that the LSTM framework is highly effective in modeling complex, non-linear temporal dependencies in urban traffic systems. Its recurrent architecture allows the model to learn contextual information from previous time steps, which enhances its forecasting accuracy for medium-term horizons. This consistency demonstrates that the model generalizes well across unseen data rather than overfitting to the training set. Furthermore, the relatively low RMSE and MAE values validate the robustness of the optimization approach and highlight the model's potential for integration into a digital twin environment, where reliable and real-time traffic forecasting is essential for simulating dynamic urban conditions. These results collectively suggest that the LSTM-based predictive framework is a viable and efficient foundation for developing intelligent traffic management systems that operate within smart city and metaverse applications.

Table 1 **Model Evaluation Metrics**

Metric	Value	Interpretation
RMSE	2,726.36	Average deviation of predictions from actual daily volume
MAE	2,154.84	Mean absolute prediction error
Congestion Level	Low	Indicates overall stable traffic conditions

The spatiotemporal variation in traffic behavior was examined through a 30-day heatmap of hourly traffic intensity, as shown in figure 5. This visualization provides a detailed view of how congestion levels fluctuate both throughout the day and across multiple days within the observation period. The color gradient, ranging from light yellow to deep red, reflects different levels of vehicle density, with darker red shades representing periods of higher congestion. The pattern reveals that traffic volumes consistently peak during the morning hours between 7:00 and 9:00 AM and again in the late afternoon between 4:00 and 6:00 PM. These recurring peaks correspond to morning and evening commuting periods, demonstrating the regularity of human mobility patterns and confirming that the dataset effectively captures real-world traffic dynamics. In contrast, lighter colors dominate late-night and early-morning hours, signifying lower activity levels and minimal congestion. This cyclical behavior underscores the importance of modeling traffic as a time-dependent process influenced by human schedules and urban infrastructure usage.

Beyond descriptive visualization, the 30-day heatmap also serves as a bridge between analytical modeling and the digital twin concept. By translating numerical predictions into spatially and temporally explicit forms, the heatmap enables an intuitive understanding of how congestion propagates throughout the day and evolves over consecutive days. This form of representation provides a foundation for real-time monitoring within a virtual or metaverse-based environment, where traffic flow can be observed and simulated in three-dimensional space. City planners and transportation authorities can use such visual tools to identify persistent bottlenecks, assess the effectiveness of congestion mitigation strategies, and experiment with potential policy interventions under controlled virtual conditions. The integration of predictive modeling and interactive visualization thus transforms static data into a dynamic decision-support system, enhancing the responsiveness and sustainability of urban traffic management practices.

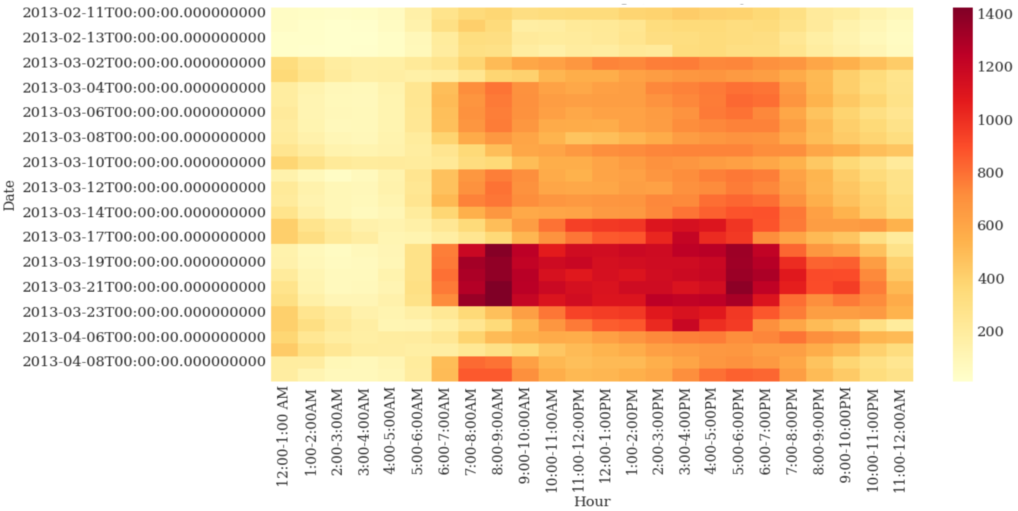

Figure 5 Traffic Volume Heatmap (Last 30 Days)

Based on the model's latest forecast, the predicted congestion level was classified as Low, indicating that the network remained under stable operating conditions during the observed period. While localized peaks persisted during rush hours, overall network performance remained within acceptable limits. These findings confirm that the proposed AI-powered digital twin framework can reliably forecast short-term congestion dynamics and serve as a foundation for real-time traffic simulation and visualization within the Metaverse environment.

Discussion

The findings of this research demonstrate the effectiveness of applying deep learning techniques, particularly the LSTM model, for short-term traffic volume prediction within a digital twin framework [21]. The model achieved stable and reliable performance, with RMSE and MAE values of 2,726.36 and 2,154.84 respectively, indicating a high level of predictive accuracy given the natural variability of urban traffic systems [22]. These results confirm that temporal dependencies in traffic flow can be effectively captured through recurrent neural architectures, which process sequential data more efficiently than traditional statistical or shallow machine learning methods [23]. The close alignment between predicted and observed traffic volumes further validates the model's ability to represent cyclical mobility behavior such as daily commuting peaks and midday troughs, which are central characteristics of modern city traffic dynamics [24].

From an analytical perspective, the visualizations produced through histograms, hourly profiles, and heatmaps offer additional insight into how urban mobility evolves across different time scales [25]. The heatmap, in particular, highlights the stability and predictability of congestion cycles, reinforcing the view that traffic congestion follows regular temporal rhythms influenced by human activity patterns and infrastructure capacity [26]. These recurrent patterns are crucial for the calibration of digital twin systems, where traffic states need to be dynamically updated in response to real-world changes. The consistency between empirical data and model predictions suggests that the LSTM approach is capable of learning both the short-term fluctuations and medium-term seasonal components that define city-wide transportation behavior [27]. This interpretability provides confidence that the model can be extended beyond historical prediction into real-time applications, where adaptive learning and feedback loops are essential.

In a broader context, the integration of predictive modeling into a digital twin environment represents a significant step toward intelligent urban mobility management. By combining deep learning with spatial-temporal visualization, city planners can transition from static monitoring systems to interactive, data-driven simulation platforms. Within a metaverse-based digital twin, predicted traffic volumes can be mapped in three-dimensional space, allowing stakeholders to visualize congestion propagation, assess the impact of road network changes, and test potential interventions before physical implementation. The study thus establishes a methodological foundation for merging artificial intelligence, real-time data, and virtual reality technologies to support proactive and sustainable urban traffic management. Future developments could expand this framework by incorporating multi-source real-time data such as weather, public transportation activity, and IoT sensor feeds to enhance prediction precision and enable full-scale smart city integration.

Conclusion

This study concludes that the integration of deep learning within a digital twin framework offers a powerful and effective approach for understanding and predicting urban traffic dynamics. The developed LSTM model successfully captured the complex temporal patterns of vehicular movement using historical traffic data aggregated from multiple city road segments. The model achieved strong predictive performance with a RMSE of 2,726.36 and a MAE of 2,154.84, indicating that it can reliably reproduce daily and hourly fluctuations in traffic flow. The model's accuracy in reflecting peak commuting hours and low-volume intervals demonstrates its potential as a forecasting engine for real-time applications. Moreover, the visualization components, including histograms, hourly profiles, and heatmaps, illustrate how predictive outcomes can be transformed into interpretable spatial and temporal patterns, allowing decision-makers to anticipate congestion events and evaluate intervention strategies. This research not only advances the use of artificial intelligence in transportation analytics but also strengthens the conceptual foundation for building digital twin ecosystems in urban planning. By linking predictive modeling with interactive visualization, the study lays the groundwork for future metaverse-based systems capable of simulating traffic behavior in real time and supporting adaptive, data-driven management of smart city infrastructures.

Declarations

Author Contributions

Author Contributions: Conceptualization: H.S., I.S.H., and G.N.S.; Methodology: I.S.H.; Software: H.S.; Validation: H.S., I.S.H., and G.N.S.; Formal Analysis: H.S., I.S.H., and G.N.S.; Investigation: H.S.; Resources: I.S.H.; Data Curation: I.S.H.; Writing Original Draft Preparation: H.S., I.S.H., and G.N.S.; Writing Review and Editing: I.S.H., H.S., and G.N.S.; Visualization: H.S.; 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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Institutional Review Board Statement

Not applicable.

Informed Consent Statement

Not applicable.

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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