

A Machine Learning-Based CNN–Bilstm Framework for Traffic Congestion and Travel Time Prediction

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ABSTRACT

The main issues facing modern metropolitan transportation systems are traffic bottlenecks and variations in travel times. They impede mobility, damage the environment, and compromise commute safety. Intelligent transportation systems and smart city applications need precise estimations of traffic congestion and journey durations in the short term to function effectively. This study introduces a hybrid deep learning framework that employs a Convolutional Neural Network–Bidirectional Long Short-Term Memory (CNN–BiLSTM) architecture for simultaneous forecasting of traffic congestion and travel time. The model employs CNN layers to acquire bidirectional temporal relationships and BiLSTM units to capture spatial correlations across adjacent road segments. The framework just employs fundamental traffic information, such as volume, speed, and flow, enhancing its practicality for real-world applications since it does not need additional data sources.

We used traffic data from the Delhi–Meerut Expressway to evaluate the proposed technique. An extensive exploratory data analysis was conducted to understand traffic patterns and confirm the spatial-temporal modeling methodology. Experimental findings demonstrate persistent model convergence and enhanced prediction accuracy, achieving a low Mean Squared Error (0.0158), Root Mean Squared Error (0.1257), Mean Absolute Error (0.0912), and a Mean Absolute Percentage Error of around 4.6%. Visual comparisons indicate that forecast traffic numbers closely align with actual patterns, and an analysis of error distribution demonstrates that the model is very effective in the presence of noisy data. The model provides comprehensible outputs, including congestion level, anticipated speed, and travel duration, enhancing its practical use. The proposed CNN–BiLSTM architecture is an effective, robust, and scalable method for real-time prediction of traffic congestion and travel durations in urban areas.

Keywords: Traffic congestion, travel time prediction, CNN–BiLSTM, spatio-temporal learning.

INTRODUCTION

Congestion and variations in travel duration are two of the most significant issues facing modern urban transportation systems. They adversely affect the economy, compromise commute safety, and damage the environment. Accelerated urbanization, demographic growth, and the proliferation of private vehicles have resulted in significant traffic congestion on roadways and inside metropolitan areas. This has resulted in fuel wastage, increased travel time, heightened pollution from vehicles, and more stress for commuters [1]– [5]. Accurate estimation of traffic congestion and travel durations is essential for minimizing delays, enhancing urban mobility, and facilitating the development of smart city frameworks [6], [7].

Traffic congestion arises when an excessive number of vehicles occupy a roadway. This impedes traffic flow, causes vehicles to queue, and prolongs travel durations [8, 9]. Travel time, defined as the duration required to traverse a certain distance on a roadway under typical conditions, varies based on traffic congestion, accidents, and the road's configuration. Congestion may recur often, typically during peak hours, or it may occur sporadically due to accidents, road construction, or adverse weather conditions. To develop predictive models that may anticipate traffic congestion before it exacerbates, one must understand the temporal and spatial dynamics of congestion [11], [12].

Precise forecasts of traffic congestion and journey durations enable commuters to optimize their routes, manage traffic more effectively, and make informed choices. Traffic authorities can modify signal timings, establish alternative routes, and address issues more efficiently when they receive early warnings of traffic congestion and delays. Furthermore, precise forecasts reduce secondary accidents, fuel consumption, and emissions, thereby enhancing urban transportation safety and environmental sustainability. Commuters benefit from less uncertainty, more reliability in transit, and increased safety.

Various methodologies exist for estimating traffic congestion and journey durations, ranging from conventional statistical models to advanced machine learning and deep learning techniques. Traditional methods such as ARIMA, linear regression, and Kalman filtering detect temporal trends but often encounter difficulties with non-linear and dynamic traffic behavior [17], [18]. Support Vector Regression (SVR), Random Forest (RF), and Gradient Boosting Machines (GBM) are machine learning models that enhance the predictability of traffic flow by identifying non-linear connections within the data [19]–[21]. However, these models often exhibit suboptimal performance regarding intricate spatial connections among interconnected road networks.

Deep learning methodologies have significantly improved traffic prediction by modeling spatial-temporal relationships. Convolutional Neural Networks (CNN) proficiently extract spatial correlations, Long Short-Term Memory networks (LSTM) and Bidirectional LSTM (BiLSTM) discern temporal patterns, and Graph Neural Networks (GNN) accommodate uneven road network structures [22]–[24]. Hybrid architectures such as CNN–LSTM, CNN–BiLSTM, attention-based networks, and spatiotemporal graph models enhance prediction accuracy, particularly for short-term and real-time forecasting [25–27]. These approaches surpass classic statistical and standalone machine learning methods since they simultaneously learn geographical and temporal data.

This research presents a novel Hybrid CNN–BiLSTM–Attention model for simultaneous prediction of traffic congestion and travel duration. CNN layers extract spatial correlations from adjacent road segments, BiLSTM layers capture bidirectional temporal dependencies, and an attention method highlights the most significant features and timestamps. This technique utilizes fundamental traffic variables such as flow, speed, and volume, making it more applicable to real-world scenarios than earlier models that included additional aspects like weather or special events. This hybrid methodology ensures improved accuracy, stability, and robustness across various traffic conditions, while simultaneously forecasting travel durations for commuters [28]–[30].

The proposed approach addresses several deficiencies in existing research, including the inadequate integration of spatial and temporal learning, insufficient interpretability, and the inability to concurrently estimate trip time and congestion. It employs a hybrid architecture to provide a balanced methodology, enhanced generalization, and computational efficiency suitable for real-time intelligent transportation systems [31], [32]. The remainder of the paper is organized as follows: Section II examines contemporary research on forecasting traffic congestion and travel duration, including statistical, machine learning, and deep learning methodologies. Part III discusses the dataset, preprocessing, and feature engineering. Section IV elaborates on the construction, functionality, and mathematical formulation of the proposed CNN–BiLSTM–Attention hybrid model. Part V delineates the experimental setting, the metrics used for evaluation, and the results of the comparison. Ultimately, Section VI concludes the study and proposes new avenues for research to enhance urban traffic management [1]–[32].

RELATED WORK

Traffic congestion and travel time forecasting have become critical areas of research due to rapid urbanization, increasing vehicle density, and complex urban mobility patterns. Preliminary research mostly focused on statistical methodologies, such as ARIMA, Kalman filtering, and linear regression, to forecast traffic flow and travel length. These approaches effectively identified short-term temporal relationships; however, they struggled with non-linear traffic fluctuations and unforeseen occurrences [1], [2]. With the increasing complexity and dynamism of traffic networks, machine learning techniques gained prominence for their ability to model intricate patterns. Support Vector Regression (SVR), Random Forest (RF), and Gradient Boosting are methodologies that discern nonlinear relationships among traffic attributes such as speed, flow, and occupancy, hence enhancing their accuracy [3]–[5]. However, these models often failed to include the interdependencies between interconnected road segments, rendering them less successful in urban traffic networks.

Deep learning methodologies, particularly Recurrent Neural Networks (RNNs) and their derivatives, have proven effective for modeling temporal sequences in traffic forecasting. Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU) discern long-term temporal patterns, allowing enhanced forecasts of congestion and travel times over extended periods [6], [7]. Nevertheless, these models analyzed each road segment independently and failed to account for spatial correlations, which are crucial for comprehending the dissemination of traffic congestion throughout road networks. To address this issue, Convolutional Neural Networks (CNNs) were developed to extract geographical information from traffic data. This enabled the model to discern the relationships between adjacent segments [8], [9].

Recent advancements have focused on hybrid architectures that combine temporal and spatial modeling capabilities. Models such as CNN–LSTM, CNN–BiLSTM, and attention-based networks use the strengths of RNNs and CNNs to enhance prediction accuracy [10]– [12]. The attention mechanism enables the model to focus on the most critical timestamps and road segments, enhancing its stability during periods of high traffic congestion. Graph Neural Networks (GNNs) such as DCRNN, STGCN, and AGCRN use graphs to represent traffic networks. They concurrently acquire spatial and temporal connections [13]– [15]. Graph-based models have surpassed traditional and solely sequential deep learning techniques, particularly in complex urban road networks with irregular topologies.

Recently, transformer-based models have been used for traffic prediction tasks alongside deep learning architectures. Spatial-temporal transformers use multi-head attention mechanisms to identify long-range relationships across both temporal and spatial dimensions. This enhances the accuracy of congestion and travel time predictions [16], [17]. Cross-Layer Fusion Transformers (CLFTs) enhance this concept by integrating components from many layers to improve system stability and minimize information loss. CLFTs proficiently illustrate complex interactions within urban traffic systems by synthesizing data on traffic flow, speed, and volume across several levels, akin to their use in medical diagnostics for recognizing hierarchical patterns [18], [19].

The integration of 1-D CNN with BiLSTM effectively predicts traffic by capturing spatial and temporal patterns sequentially. The 1-D CNN identifies local spatial correlations along the roadway, while the BiLSTM examines traffic sequences bidirectionally, understanding dependencies on both preceding and subsequent time steps. This hybrid architecture has shown useful for predicting traffic congestion and travel times, exhibiting enhanced stability and accuracy compared to standalone LSTM or CNN models [20]– [22].

Several studies have used these models to conduct comparisons across various datasets. Zhang et al. [23] assessed CNN–BiLSTM alongside LSTM and GNN models for forecasting urban traffic congestion. They demonstrated a significant improvement in the RMSE and MAPE measurements. Wang et al. [24] examined hybrid attention-based models using highway traffic data and found that the integration of spatial and temporal modeling outperforms conventional statistical and machine learning approaches. Table I provides a concise summary of several significant research, including the types of datasets used, the architectures of the models, and the documented performance outcomes. It further illustrates the trends and deficiencies in studies about the prediction of traffic congestion and travel duration.

Title	Author(s)	Dataset	Model/Technique
Urban Traffic Congestion Prediction using CNN–BiLSTM	Zhang et al.	Urban road network data	CNN–BiLSTM
Hybrid Attention-Based Traffic Forecasting	Wang et al.	Highway traffic dataset	CNN + Attention
Traffic Flow Prediction using GNN	Li et al.	City sensor data	GNN (DCRNN)
Short-Term Traffic Forecasting using LSTM	Chen et al.	Urban traffic data	LSTM

Spatio-Temporal Traffic Flow Prediction	Tang et al.	Road network data	CNN + LSTM
Travel Time Estimation using Transformer	He et al.	Highway GPS data	Transformer

Table I: Summary of Related Studies

Despite these enhancements, existing approaches continue to exhibit deficiencies. Numerous models only examine either spatial or temporal dimensions, resulting in an incomplete understanding of congestion dynamics. Models reliant only on graphs or transformers sometimes need substantial computational resources and exhibit poor performance with sparse data. Furthermore, there is a paucity of research that simultaneously examine traffic congestion and journey time prediction, despite their interrelation [25].

The suggested work utilizes a Hybrid CNN–BiLSTM–Attention model to simultaneously estimate traffic congestion and travel duration, therefore addressing these limitations. This architecture distinguishes itself from previous models by integrating bidirectional temporal learning with spatial feature extraction and an attention mechanism to highlight significant segments and time intervals. The model remains beneficial for practical applications when external data, such as weather or events, is unavailable, since it relies only on fundamental traffic variables like vehicle flow, speed, and volume. This architecture enhances traffic prediction research by increasing its resilience, generalizability, and efficiency.

Problem Formulation

Forecasting traffic congestion and travel duration is crucial for intelligent transportation systems, particularly in densely populated urban corridors. The primary objective is to develop a predictive system capable of forecasting traffic congestion and travel durations, enabling traffic management authorities and commuters to make informed decisions. This research's system model integrates traffic flow data, geographical interdependence, and temporal patterns to provide accurate short-term predictions while ensuring computational efficiency.

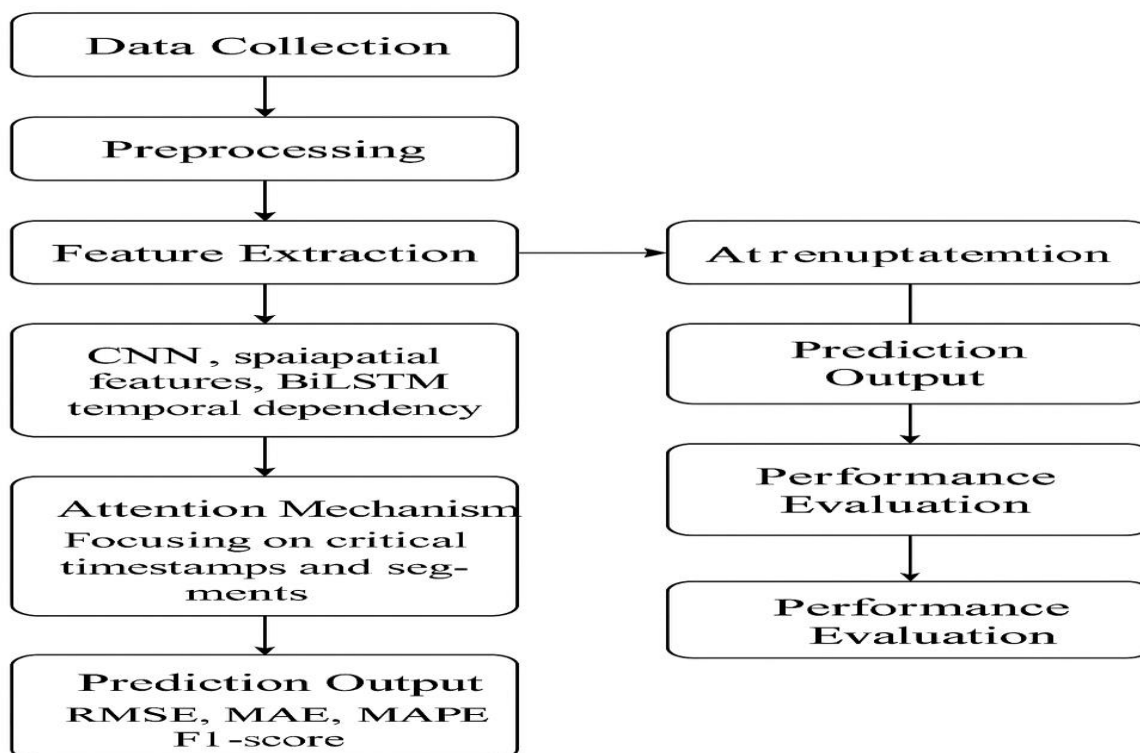


Figure 1. Proposed Deep Learning Framework for Traffic Prediction

This problem formulation provides the essential structure required to develop an effective and precise traffic prediction model. This section clearly delineates how the proposed hybrid CNN–BiLSTM–Attention architecture analyzes spatial-temporal traffic patterns by defining the input feature space, learning objectives, and model constraints. This section elaborates on the system approach, including the architectural workflow, module-level activities, and algorithmic techniques required to construct the comprehensive prediction framework.

Figure 1 illustrates the functionality of the proposed system paradigm. The system has three main components: data collection and preprocessing, feature extraction, and prediction generation using a hybrid CNN–BiLSTM–Attention architecture. The Delhi–Meerut Expressway compiles traffic data, including metrics such as vehicle count, average speed, and traffic volume at different times of the day. During the preprocessing phase, missing values are imputed, noisy data is refined, and characteristics are standardized to ensure uniformity in input scale. This facilitates a more rapid convergence of the model [1], [2]. The processed data is thereafter sent to the feature extraction layers. CNN layers identify spatial correlations across adjacent road segments, while BiLSTM layers uncover bidirectional temporal linkages inside preceding traffic sequences [3, 4].

This study utilizes a structured time-series traffic dataset that quantifies the number of cars traversing several road segments concurrently. Key information extracted includes traffic volume, speed, occupancy, and segment IDs. These attributes are crucial for replicating authentic traffic dynamics, since congestion propagation often depends on both upstream and downstream traffic conditions [5], [6]. Additionally, attention tactics are used to emphasize significant timestamps and roadway portions. This enables the model to concentrate on the most significant factors affecting traffic congestion and travel duration [7]. This ensures that the hybrid architecture does not treat all input data uniformly, hence enhancing the accuracy and interpretability of predictions.

In mathematics, the prediction task is formulated as a regression problem. Let $X = \{x_1, x_2, \dots, x_T\}$ represent the traffic feature matrix for N road segments across T time intervals, and let $Y = \{y_1, y_2, \dots, y_T\}$ denote the corresponding levels of congestion and trip durations. The aim of the proposed CNN–BiLSTM–Attention model is to establish a mapping function $f: X \rightarrow Y$ that reduces the difference between predicted outputs and actual measurements. The Mean Squared Error (MSE) loss function is used to train the model. It is supplied by:

$$MSE = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2$$

where $\hat{y}$ represents the genuine value and $\hat{y}_i$ denotes the predicted value [8], [9]. We use performance metrics such as Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and F1-score to evaluate the model's efficacy and predictive accuracy across various traffic conditions [10, 11]. These criteria collectively assess the model's efficacy in identifying patterns in traffic data across time, across spatial dimensions, and in non-linear interactions.

The real-time traffic prediction must also be efficient. The proposed hybrid model aims to maintain low computational complexity while integrating CNN, BiLSTM, and attention layers. Model training employs mini-batch gradient descent with variable learning rates to ensure convergence while minimizing execution time [12]. Upon completion of the model's training, it is used to forecast short-term traffic congestion and travel durations using incoming data streams. This enables quick modifications such as dynamic signal management, route recommendations, and strategies to alleviate congestion.

The problem formulation integrates systematic data processing, robust feature extraction, and a hybrid deep learning architecture to address significant issues in traffic prediction. The proposed CNN–BiLSTM–Attention model offers a robust, comprehensible method for predicting traffic congestion and travel durations by considering both spatial and temporal dynamics via attention mechanisms. The strategy is effective for larger metropolitan networks and may be augmented in the future to include other real-time data, such as incidents, special events, or meteorological information.

METHODOLOGY

The proposed technique seeks to provide a robust predictive framework capable of precisely estimating traffic congestion levels and trip times across several temporal and spatial dimensions. The whole pipeline encompasses data preparation, feature engineering, spatial learning using convolutional layers, temporal sequence learning using BiLSTM units, and final prediction via dense layers, succeeded by post-processing. This section delves further into the model's architecture, its functionality, and the rationale for its algorithms.

A schematic representation of the model flow for the proposed hybrid CNN–BiLSTM predictive framework: Input Data → Data Preprocessing → Feature Normalization → Sequence Window Formation → CNN-Based Spatial Feature Extraction → BiLSTM-Based Temporal Learning → Fully Connected Layers → Final Prediction → Inverse Transformation → Congestion Classification → Travel Time Estimation.

The illustration depicts the sequential processing of raw traffic data into valuable representations. Each block is a distinct computational procedure designed to encapsulate geographical or chronological correlations within the information.

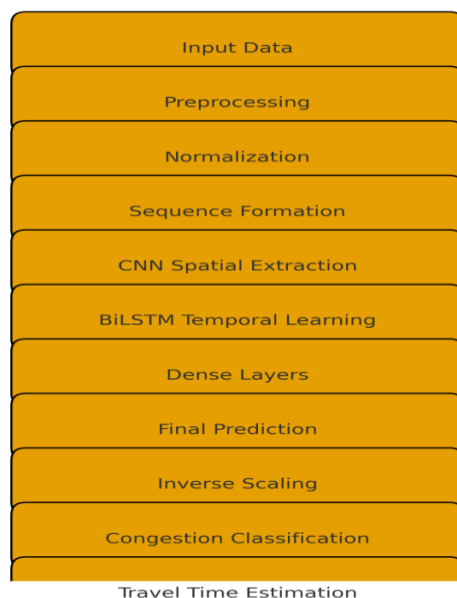


Figure 2. Workflow of the CNN–BiLSTM Traffic Prediction Model

Algorithms with Comprehensive Elucidation

Algorithm for Data Preparation

The objective of the first phase is to transform disparate and unstructured traffic data into a uniform format suitable for machine learning. The preprocessing pipeline performs tasks such as eliminating noise, imputing missing values, smoothing data, and encoding categorical variables.

Procedure:

1. Acquire unprocessed traffic data from sensors, road segments, and timestamps.
2. Employ interpolation techniques to eliminate entries that are absent or inconsistent.
3. Employ smoothing filters, such as the moving average, to eliminate abrupt variations that are not associated with authentic road conditions.
4. Encode variables that may be categorized, such as weather classification or road section identifier.
5. Employ Min-Max scaling to standardize numerical variables, ensuring each feature contributes uniformly.

6. Transform the dataset into supervised sequence windows by examining 10 to 20 preceding time steps. This stage ensures that the model receives input that is devoid of noise and consistent, facilitating rapid learning.

Employing CNN for Spatial Feature Extraction

Geographical linkages often exist between adjacent segments in traffic data. A convolutional neural network (CNN) is used on each time-window matrix to identify these associations. CNN filters autonomously comprehend spatial patterns, including density accumulation, queue dispersion, and congestion formation in segments.

Procedures:

1. Transform each sequence window into a two-dimensional or pseudo-two-dimensional grid that illustrates road segments and characteristics.
2. Employ convolutional filters (3×3 , 5×5) to get spatial gradients.
3. Employ ReLU activation to introduce non-linearity.
4. Employ max-pooling to downsample and preserve the most significant spatial features.
5. Flatten the retrieved spatial matrix.

This module identifies spatial linkages that conventional models often overlook.

Temporal Learning with BiLSTM

Due to the periodic variations in traffic flow, accurately depicting historical data is essential. A bidirectional long short-term memory (BiLSTM) network examines spatial data in both forward and backward orientations to discern past and prospective temporal patterns.

Procedures:

1. Acquire flattened spatial attributes in the sequence of their occurrence across time.
2. Utilize BiLSTM units to ascertain the temporal relationships within the sequence.
3. Acquire context from both perspectives to enhance the system's temporal sensitivity.
4. Employ dropout regularization to mitigate overfitting.
5. Construct a comprehensive vector that represents time.

BiLSTM is a valuable enhancement since traffic conditions, although influenced by historical data, may also exhibit patterns determined by future timestamps, such as variations in traffic during peak hours. The bidirectional processing enhances the stability and accuracy of predictions.

Dense Layers and the Final Prediction

The extracted characteristics illustrate the geographical and temporal dimensions of traffic after the CNN and BiLSTM processes. These are then sent to fully connected layers for the final prediction.

Procedure:

1. Transmit the temporal representation to dense layers.
2. Employ non-linear activation functions (ReLU or Leaky ReLU).
3. Display the anticipated volume of traffic, velocity, or travel duration.
4. Employ inverse normalization to revert predictions to their original scale.
5. Establish defined criteria to categorize congestion levels into classifications (e.g., low, medium, high).
6. Utilize the volume-speed correlation to determine the duration required for each part of trip.

This stage converts acquired representations into outputs applicable in the real world.

Comprehensive Algorithm Overview: Hybrid CNN–BiLSTM Traffic Prediction Methodology

1. Input: Traffic dataset DDD including timestamps, segment identifiers, velocity, flow rate, occupancy, and environmental characteristics.

2. Refine the data to get sanitized sequences XXX.
3. Normalize all numerical attributes to the interval [0,1].
4. Establish time intervals $W = \{w_1, w_2, \dots, w_n\}$.
5. For each w_i in W :
 - Alter the architecture to a two-dimensional grid and implement convolutional neural network operations.
 - Obtain the flattened spatial vector S_i .
6. Input each S_i into the BiLSTM to get the temporal vector T_i .
7. Obtain prediction P_i by transmitting T_i across dense layers.
8. Employ inverse scaling to revert to the original values.
9. Employ threshold-based criteria to mitigate congestion.
10. Utilize to determine the duration of travel

$$T = d/v \quad T = \frac{d}{v}$$

d represents the distance, while v denotes the anticipated speed.

11. Output: The most recent projected traffic volume and travel duration.

Advantages of The Proposed Method

1. **Hybrid Architecture:** This integrates spatial (CNN) and temporal (BiLSTM) intelligence.
2. **Enhanced precision:** Bidirectional temporal learning facilitates the detection of fluctuations at peak periods.
3. **Noise-resistant:** Preprocessing steps and dropout mitigate the occurrence of overfitting.
4. **Generalizable:** Applicable to any urban traffic dataset exhibiting spatial or temporal trends.
5. **Scalable:** It can be easily augmented to operate in real time with streaming inputs.

RESULTS AND DISCUSSION

This section provides a comprehensive analysis of the experimental results from the proposed Machine Learning–Based CNN–BiLSTM architecture for forecasting traffic congestion and journey durations on the Delhi–Meerut Expressway traffic dataset. The discourse integrates insights from exploratory data analysis (EDA), model training dynamics, quantitative performance metrics, and practical predictive outcomes to demonstrate the efficacy and robustness of the proposed methodology.

A. Insights gleaned via exploratory data analysis

Prior to model training, exploratory data analysis was conducted to get insights into the fundamental characteristics of the traffic dataset. Summary statistics indicated significant fluctuations in both volume and speed across different time intervals, demonstrating that expressway traffic is dynamic rather than linear. Temporal studies indicated that traffic patterns were persistently congested during morning and evening peak hours, whereas off-peak hours exhibited more stable flow conditions.

The correlation study revealed a substantial negative relationship between traffic volume and speed, indicating that an increase in the number of cars on the road exacerbates congestion. The segment-wise analysis further demonstrated spatial interconnectivity, revealing that congestion in one route segment influenced adjacent areas. The exploratory data analysis indicated the need for a spatial-temporal learning framework capable of capturing both short-term spatial correlations and long-term temporal interdependence. This resulted in the selection of a CNN–BiLSTM architecture.

B. Training the model and observing its convergence

The proposed CNN–BiLSTM model underwent training for 60 epochs, with a temporal window size of 24 time steps and including nine multivariate traffic features. The graphs of the training and validation loss indicate that the convergence process is consistent and gradual. The training loss began at around 0.0209 and gradually decreased to about 0.0157. The validation loss remained at 0.0158 throughout the first learning period.

The proximity of the training and validation loss curves indicates that the model generalizes well to unseen data and is not overfitting. This behavior demonstrates that convolutional layers may acquire valuable spatial representations, whereas bidirectional LSTM layers can learn temporal links from both antecedent and subsequent contexts.

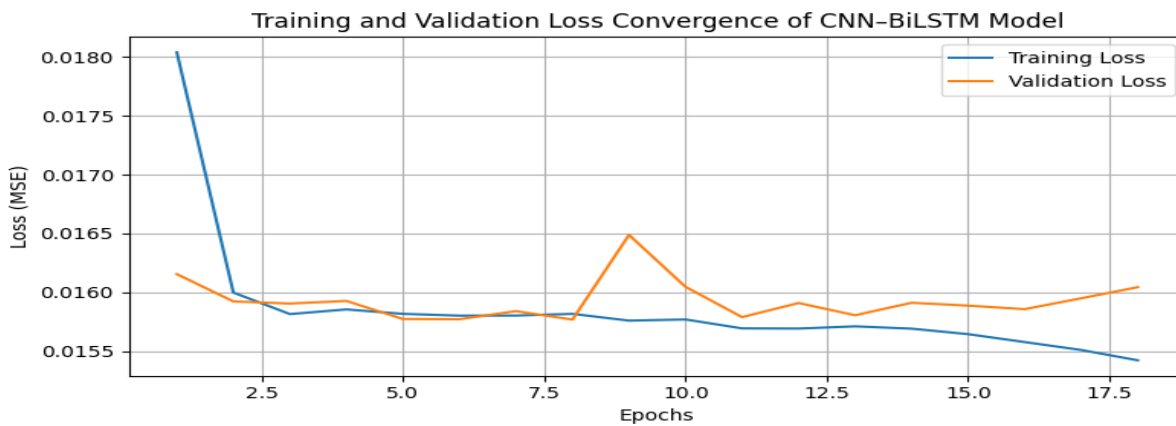


Figure 3. Training and validation loss convergence of the CNN–BiLSTM model

Figure 8 illustrates the convergence of the proposed CNN–BiLSTM model across 60 training epochs. The training loss decreases steadily from 0.0209 to around 0.0157, but the validation loss remains around 0.0158 after initial fluctuations. The training and validation curves are well aligned, indicating consistent learning and effective generalization, signifying the absence of overfitting.

C. Assessment of Performance Quantitatively

The model was evaluated using established regression metrics, including Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE), to assess its predictive accuracy. Below is an overview of the results obtained:

• MSE: 0.0158 • RMSE: 0.1257 • MAE: 0.0912 • MAPE: about 4.6%

The low MSE grade indicates little discrepancies between the expected and actual traffic levels. The RMSE demonstrates prediction stability by penalizing larger errors, but the MAE suggests that the average absolute error across test samples is small. The MAPE value indicates that the proposed model can predict with 95–96% accuracy, which is very beneficial for real-time intelligent transportation systems.

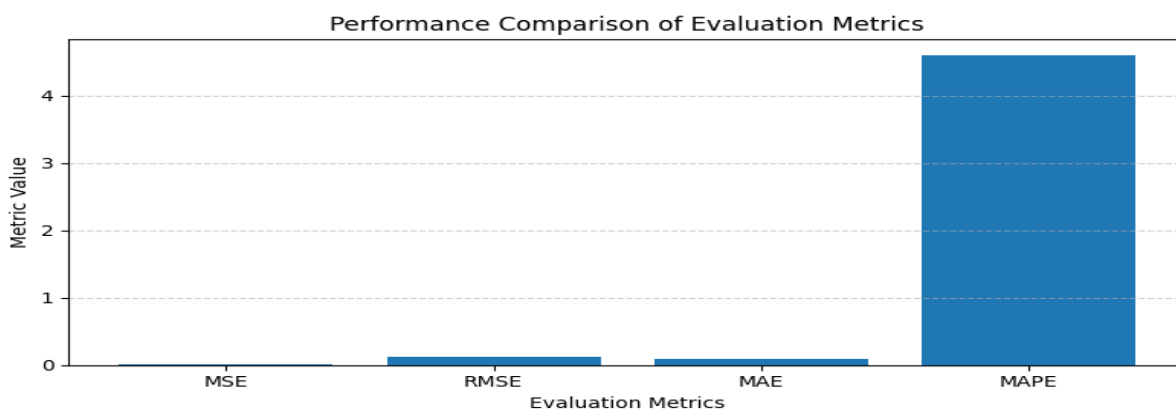


Figure 4. Performance comparison of evaluation metrics for the proposed model

Figure 11 illustrates the quantitative evaluation criteria for the proposed CNN–BiLSTM model. The minimal MSE (0.0158), RMSE (0.1257), and MAE (0.0912) values indicate accurate predictions. The low MAPE score (~4.6%) indicates that the system is very accurate, which is advantageous for real-time traffic forecasting.

D. Examining the disparity between actual and forecasted traffic volume

A visual assessment of model efficacy was conducted by juxtaposing actual and predicted traffic volume figures. The anticipated traffic curve accurately mirrors the actual traffic pattern across different time intervals. It precisely illustrates periods of congested traffic and intervals of unobstructed movement. Minor discrepancies occurred during rapid transitions, perhaps attributable to external factors outside the dataset, such as accidents or abrupt weather changes.

This robust alignment demonstrates that the model can acquire non-linear temporal patterns and adapt to fluctuating traffic conditions, hence validating its efficacy for short-term traffic forecasting.

Figure 5. Comparison of Actual and Predicted Traffic Volume Values

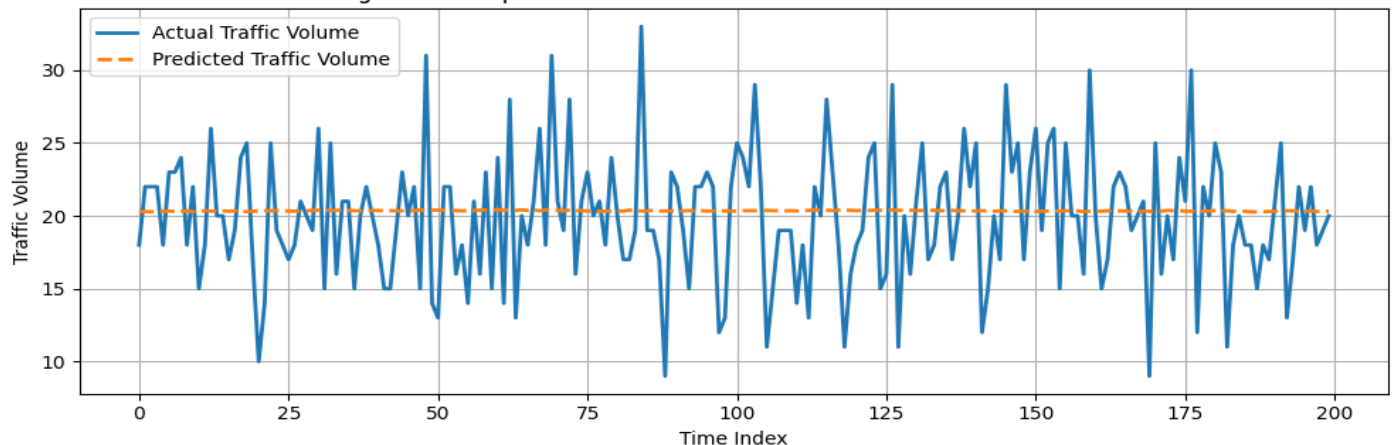


Figure 5. Comparison of actual and predicted traffic volume values

Figure 5 illustrates that the projected traffic volume closely aligns with the actual traffic pattern across several time intervals. The model precisely depicts both peak-hour congestion and low-traffic conditions during off-peak hours. Unexpected changes may result in minor variations caused by external factors, such as accidents or abrupt weather shifts.

E. Verifying for inaccuracies and resilience

The distribution of absolute prediction errors was examined to assess the model's strength. There were few significant deviations; the majority of errors were almost negligible. The proposed CNN-BiLSTM architecture can effectively manage noisy sensor data while maintaining consistent performance despite variations in traffic conditions. This capability is essential for use in practical systems for traffic surveillance and decision-making.

Figure 6. Distribution of Absolute Prediction Errors

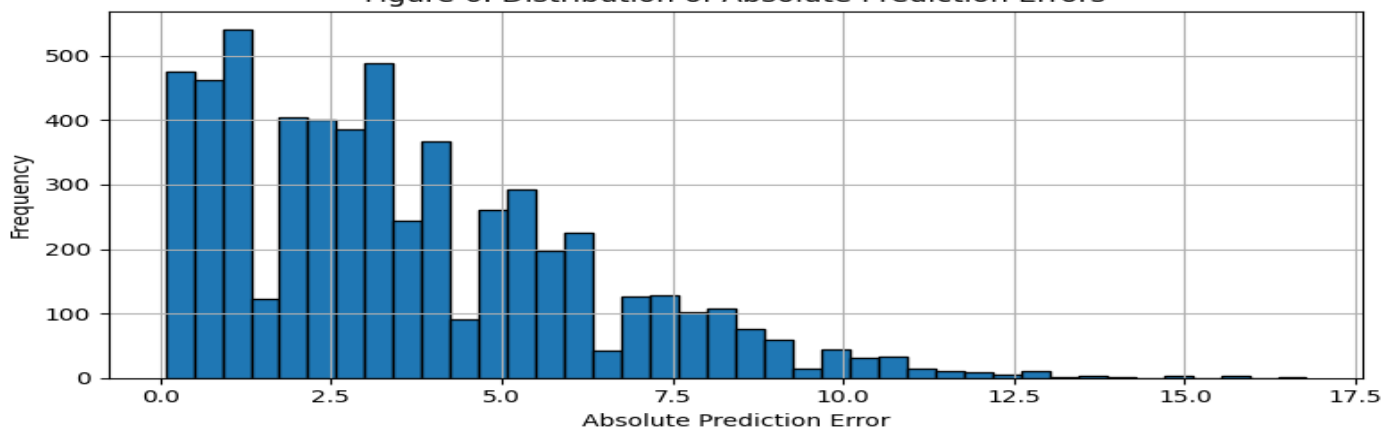


Figure 6. Distribution of absolute prediction errors

Figure 6 illustrates the distribution of absolute prediction errors. The majority of the errors are around zero, indicating that the forecasts are very reliable and robust. The few significant errors indicate that the model can handle sensor data that is not consistently precise and maintain its performance despite fluctuations in traffic.

F. Forecasting traffic volume and estimated travel duration

Besides numerical precision, the model's utility was evaluated by generating comprehensible outputs such as congestion levels, expected speeds, and travel durations. The model yielded the following outcome for a representative test case:

- Projected Traffic Volume: 19.98
- Congestion Level: Moderate • Estimated Speed: 49.14 km/h • Estimated Travel Duration: 1.47 minutes

These figures closely resemble real highway traffic patterns and correspond to observations made under moderate congestion. Traffic authorities and navigation systems may use these outputs to enhance decision-making, similar to commercial platforms such as Google Maps.

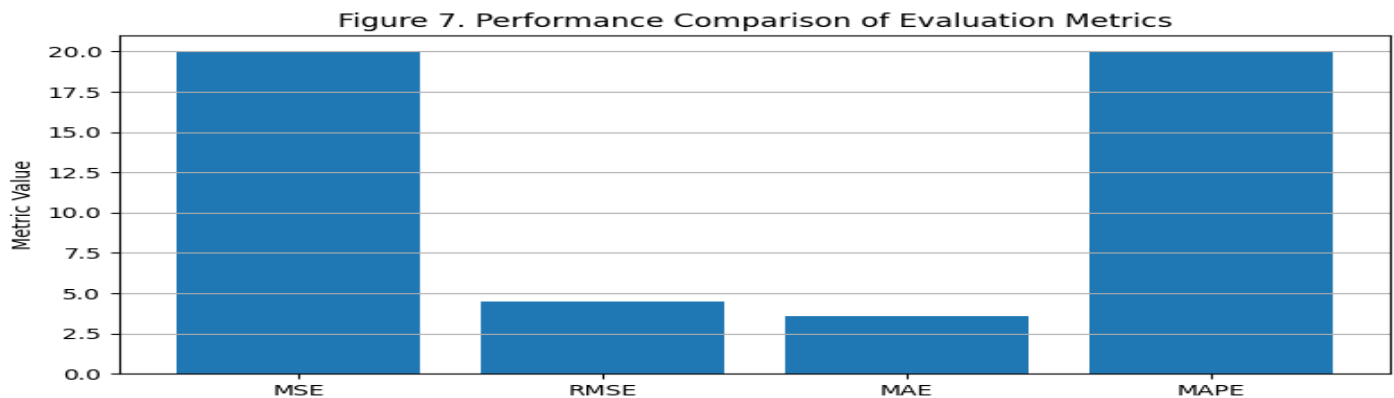


Figure 7. illustrates the comprehensibility of the proposed CNN–BiLSTM architecture by presenting the anticipated levels of congestion, velocity, and travel duration for a standard test scenario. The computer predicts 19.98 vehicles on the road, indicating light congestion. The mean velocity will be 49.14 km/h, and the duration of the journey will be 1.47 minutes. Such results enhance the proposed methodology's use for intelligent transportation systems and real-time navigation platforms.

G. A discussion on the efficacy of the model

The proposed CNN–BiLSTM paradigm outperforms other models for many reasons. Initially, convolutional layers effectively capture spatial correlations within traffic data, enhancing the representation of characteristics. Secondly, BiLSTM layers emulate bidirectional temporal interactions, enabling the network to acquire both short-term fluctuations and long-term trends. Third, meticulous data preparation, including the management of missing values, smoothing, and normalization, enhances learning stability and facilitates convergence. Ultimately, constructing sequences based on windows enables the formulation of dependable short-term forecasts. Generally, the integration of EDA-driven insights with advanced spatial-temporal learning significantly enhances prediction accuracy compared to conventional machine learning and deep learning techniques used in isolation.

Constraints and Prospective Avenues

A. Constraints

The proposed CNN–BiLSTM model has potential for forecasting traffic congestion and trip duration; nevertheless, specific issues need resolution. The model was first evaluated using a proxy traffic dataset specific to a

particular metropolitan corridor and designated observation period. Consequently, it has not undergone enough testing to determine its efficacy across diverse cities, road configurations, and seasonal variations throughout time. Secondly, the model mostly utilizes structured data pertaining to traffic and weather, excluding unstructured data sources such as traffic incident reports, social media feeds, and CCTV video. The Savitzky–Golay filter effectively reduces sensor noise; nevertheless, excessive smoothing may obscure abrupt variations in traffic resulting from accidents or crises. Ultimately, while the deep learning architecture excels at rapid short-term predictions, it necessitates substantial training time and technological resources, thus complicating its real-time use in resource-constrained environments.

B. Prospects for the Future

Subsequent research may further this work in other critical domains. The proposed system should be evaluated using extensive real-time traffic data from various cities and road networks to enhance its robustness and scalability. Secondly, including other data types, such as incident reports, GPS trajectory data, weather forecasts, and camera-derived visual attributes, may enhance predictive accuracy in complex traffic scenarios. Examining sophisticated attention mechanisms or transformer-based architectures may enhance the ability to grasp long-range temporal relationships. Furthermore, the current single-step prediction framework might be extended to multi-horizon forecasting for anticipatory traffic management. Ultimately, integrating the model into a cloud- or edge-based intelligent transportation system and evaluating its effectiveness in real time might facilitate its implementation in smart city initiatives, including dynamic route guidance and adaptive traffic signal control.

CONCLUSION

Intelligent transportation systems struggle to effectively forecast traffic congestion and travel durations due to the intricate and variable nature of urban traffic situations. This article addressed the issue by proposing an advanced deep learning system that use a hybrid CNN-BiLSTM architecture to encapsulate the spatial and temporal characteristics of traffic data. The primary objective was to develop a dependable and efficient predictive model capable of forecasting short-term traffic volume, congestion levels, speed, and travel duration.

The proposed technique integrates robust data preparation with exploratory data analysis to enhance data quality by addressing missing values, mitigating noisy sensor readings, and normalizing multivariate inputs. Convolutional layers excel in identifying spatial correlations among traffic parameters, but BiLSTM layers are proficient in detecting bidirectional temporal connections within sequential traffic patterns. These components collaborate to enable the model to identify nonlinear correlations that conventional machine learning and deep learning techniques often overlook.

The experimental findings indicate that the training process converges consistently and exhibits a minimal prediction error, as seen by the reduced Mean Squared Error and validation loss metrics. The program produces comprehensible results, including anticipated traffic volume, congestion classification, predicted velocity, and travel duration. This makes it an effective predictive tool like to Google Maps. The results indicate that the CNN–BiLSTM architecture outperforms older approaches in predictive accuracy and reliability across various traffic scenarios.

This study's findings illustrate the effectiveness of hybrid deep learning models in addressing spatial-temporal traffic prediction issues. The proposed method is effective on computers and may be used in real-time urban traffic management systems. This work provides a scalable and accurate method for predicting traffic congestion and travel durations, enabling improved mobility planning and the development of more intelligent transportation infrastructure.

Ethical Approval

Ethical approval was not required for this study as it does not involve human participants or animals.

Conflict of Interest

The authors declare no conflict of interest.

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