University of Tehran

*Earth Observation and Geomatics Engineering*

Online ISSN: 2588-4360

Homepage: https://eoge.ut.ac.ir/

# Evaluation of a Hybrid CNN-TCN-LSTM Model for Traffic Flow Prediction

**Farhad Hosseinali** [1]✉, **Zahra Shirmohammadi** [2], **Mohammad Ahangar kiasari** [3], **Abolfazl Yousefi** [1], and **Mojtaba Farmani**[2]

1. Department of Surveying Engineering, Faculty of Civil Engineering, Shahid Rajaee Teacher Training University, Tehran, Iran. E-mail: f.hosseinali@sru.ac.ir (Corresponding Author), yousefiabolfazl2012@yahoo.com
2. Department of Computer Architecture, Faculty of Computer Engineering, Shahid Rajaee Teacher Training University, Tehran, Iran. E-mail: shirmohammadi@sru.ac.ir, mojtabafarmani@sru.ac.ir
3. Department of Control Engineering, Faculty of Electrical Engineering, K.N.Toosi University of Technology, Tehran, Iran. E-mail: ahangar100@gmail.com

## Article Info

**Article type:**
Research Article

**Article history:**
Received 2024-06-06
Received in revised form 2024-11-08
Accepted 2024-11-17
Available online 2025-01-01

***Keywords***:
Traffic Speed Prediction,
Machine Learning,
Inductive Loop Detector,
Combined Model
Convolutional Neural Network

## ABSTRACT

Accurate prediction of road traffic speed has a crucial impact in estimating traffic conditions and plays a role in optimizing transportation and traffic system's function. However, the nonlinear nature of traffic systems and the complexity of uncertainty introduce challenges for speed variables. Therefore, finding hidden patterns in traffic is the most critical issue in predicting traffic speed. This paper uses a new hybrid model to predict the traffic flow in the street highways. Previous methods proposed to address these challenges are fundamentally limited in providing optimal solutions due to their inability to capture local and global nonlinear patterns accurately. To overcome these limitations, this paper proposes a method that combines Convolutional Neural Networks (CNNs), Temporal Convolutional Networks (TCNs), and Long Short-Term Memory (LSTM) networks, denoted as CNN-TCN-LSTM. The incorporation of CNNs aims to effectively extract localized features within the data. Concurrently, Recurrent Convolutional Networks (RCNs) and Long Short-Term Memory (LSTM) networks are employed to model both local and global temporal dynamic dependencies. The dataset comprises information obtained from loop inductive detectors deployed along the freeways within the Seattle metropolitan region during the year 2015. Data was gathered from a total of 323 sensor stations positioned along the designated route. The evaluation of the proposed model shows a performance and accuracy improvement of 1% and 9% compared to LSTM and RNN-based prediction methods, respectively.

**Cite this article:** Hosseinali, F., Shirmohammadi, Z., Ahangar kiasari, M., Yousefi, A. & Farmani, M. (2023). Evaluation of a Hybrid CNN-TCN-LSTM Model for Traffic Flow Prediction. *Earth Observation and Geomatics Engineering*, Volume 7, Issue 2, Pages 56-65. http//doi.org/ 10.22059/eoge.2024.377633.1152



Publisher: University of Tehran.

DOI: http//doi.org/ 10.22059/eoge.2024.377633.1152

## 1. Introduction

As urban areas expand, they encounter a rise in various challenges, one of which is the escalation of traffic issues. We tend to model various phenomena even city expansion for better management (Hosseinali et al., 2014). Traffic management also needs modeling and forecasting. The intelligent transportation and traffic system represents a basic component within a smart city infrastructure. This system can play a main role in enhancing vehicular flow efficiency, reducing waiting times at intersections, and mitigating queue lengths and traffic congestion. For instance, based on 2014 data Moskvitch (2014), drivers in the ten most congested cities in the USA spent an average of 42 hours in traffic jams, leading to approximately $121 billion in wasted fuel. Therefore, intelligent transportation systems can empower local residents and travelers to avoid road traffic congestion, facilitate route planning, identify points of interest, reduce traffic accidents, and effectively manage travel itineraries and eventually reduce the fuel consumed (Ni et al., 2016; Zeynali et al., 2015). Therefore, accurate anticipation of traffic dynamics through Internet of Things (IoT) technology stands as a crucial milestone in optimizing the efficacy of intelligent transportation and traffic systems (Dohler et al., 2011; Jin et al., 2014; Sethi & Sarangi, 2017). By predicting parameters like traffic volume, travel time, and real-time traffic status, commuters can plan routes to save time and reduce costs. Consequently, the precise prediction of traffic speed emerges as a pivotal metric for gauging the prevailing traffic conditions within road networks (Kazemi & Hosseinali, 2022; Tang et al., 2017).

In recent years, a multitude of methodologies has been introduced to forecast traffic variables including volume, speed, density, and travel time. These methods can be categorized into Machine Learning (ML) (Ahmad Rahi, 2019; Kamble & Kounte, 2020; Mohammed & Kianfar, 2018) and Deep Learning (DL) based approaches (Cui et al., 2020; Wang et al., 2016). However, DL-based approaches mostly outperform previous ML-based ones due to their capability to address more dynamic and complex data. For example, Wang et al. (2016) proposed a deep learning method with a structure of error feedback recurrent convolutional neural network (eRCNN) for continuous traffic speed prediction. In Cui et al. (2020), a stacked bidirectional and unidirectional LSTM neural network (SBU LSTM) architecture is proposed for predicting forward and backward dependencies in traffic speed time series data at the network level.

In Zhongjian et al. (2018), the LC-RNN model is introduced as a novel approach aimed at enhancing the accuracy of traffic speed prediction in contrast to prevailing solutions. Rahman and Hasan (2018) introduces a deep learning model tailored specifically for forecasting traffic speed on freeways. In another research, Fu et al. (2016) explores the utilization of Short-Term Memory (LSTM) and Gated Recurrent Unit Neural Networks (GRU) for short-term traffic flow prediction. Further contributing to this field, BaloujiJonas et al. (2023) proposes an innovative deep-learning framework designed for predicting both the distance and travel time of vehicles. Despite the extensive research conducted, this domain exhibits the characteristic of persistent traffic issues that are amenable to enhancement while the issue of traffic congestion remains unsolvable. Consequently, continual opportunities for refinement and further exploration within this domain persist.

Given that traffic data contains both spatial and temporal features, we aim to develop a model that efficiently captures both types of features to enhance prediction performance. To this end, we propose a hybrid model incorporating Convolutional Neural Networks (CNNs), Temporal Convolutional Networks (TCNs), and Long Short-Term Memory networks (LSTMs). CNNs (Convolutional Neural Networks) are designed to automatically learn spatial hierarchies of features from input data, making them effective for image and grid-like data analysis (Li et al., 2022). TCNs (Temporal Convolutional Networks) handle temporal data, capturing short to medium-range dependencies with stability using causal convolutions (Bai et al., 2018; Lea et al., 2017; Lea et al., 2016). LSTMs (Long Short-Term Memory networks) capture long-term dependencies in sequence data by retaining information over extended periods with gated mechanisms (Graves, 2012). In this paper, the aim of using CNN layers is to capture local correlations between traffic sensors. To capture dynamic temporal dependencies, a combination of TCNs and LSTMs is proposed, where TCNs effectively capture short- to medium-range temporal dependencies and LSTMs handle long-term dependencies. Spatiotemporal data collected from inductive loop detectors is utilized to predict traffic speed at the network level. The continuation of the article is as follows:

In Section 2, we review previous works in the field of traffic speed prediction methods. In Section 3, the proposed method is presented. In Section 4, an analysis of the results of the proposed method is discussed. Section 5 concludes the article.

## 2. Related works

Intelligent transportation and traffic management applications heavily rely on the quality of traffic information. Recently, with a significant increase in the overall volume of traffic and the generated data, notable opportunities and challenges have emerged in the field of transportation and traffic management research. This includes how to effectively and accurately understand and leverage the received data. Short-term traffic prediction based on data-driven models utilizing machine learning for Intelligent Transportation Systems (ITS) applications is one of the rapidly developing areas of research, making extensive use of vast traffic data and influencing the overall performance of various transportation and traffic systems. In the literature, various methods have been proposed for traffic prediction in terms of speed, volume, density, and travel time.

In Wang et al. (2016), a deep learning method with a recurrent convolutional neural network with error feedback (eRCNN) structure was proposed for continuous traffic speed prediction. In this approach, the spatiotemporal traffic speed of continuous road sections is received as an input matrix, and eRCNN utilizes contextual correlations between adjacent sections to improve prediction accuracy. In Cui et al. (2020), a bidirectional and unidirectional stacked LSTM network architecture (SBU LSTM) is suggested, considering forward and backward dependencies in time series data to predict network-level traffic speed. Zhongjian et al. (2018) proposed a new model called LC-RNN for achieving more accurate traffic speed prediction. This model combines two RNN and CNN models logically to learn meaningful temporal patterns that can adapt to the dynamic traffic conditions in surrounding areas. Additionally, since traffic evolution is constrained by the underlying road network, an embedded convolution structure is suggested to capture topology-aware features. Integration with other information, including periodicity and environmental factors, is also considered for further improving prediction accuracy.

In the study of Han et al. (2019), a new approach for predicting vehicle speed is presented by combining a one-dimensional convolutional neural network with a bidirectional short-term memory network (CB-LSTM). This approach utilizes information provided by V2V (vehicle-to-vehicle) and V2I (vehicle-to-infrastructure) communications. Basak et al. (2019) focus on analyzing the cascading effects of traffic congestion using LSTM networks. This data-driven approach proposes a function of congestion in adjacent sections to predict traffic density propagation in road sections. Moreover, an extensive urban set of connected LSTM models for intersection levels and mechanisms to identify congestion events using network predictions is suggested.

In Rahman and Hasan (2018), a deep learning model for predicting traffic speed on highways under severe traffic demand, such as during evacuation scenarios, is introduced. This model, using a Short-Term Memory Neural Network (LSTM-NN), aims to predict speed. Modi et al. (2022) extended deep learning-based methods to provide accurate multi-step traffic speed predictions, considering spatiotemporal traffic dependencies. The proposed method was tested with real-world traffic speed data collected from various sensors in Los Angeles and the Bay Area (United Staes).

Fu et al. (2016) employed short-term memory methods (LSTM) and gated recurrent unit neural networks (GRU) for short-term traffic flow prediction. Experiments demonstrated that recurrent neural networks (RNN) based on deep learning methods like LSTM and GRU outperform the Autoregressive Integrated Moving Average (ARIMA) model. Zheng et al. (2022) introduced a new deep learning model named SAGCN-SST to address the problem of multi-step traffic speed prediction in large-scale road networks. This model considers the impact of different road sections on future traffic conditions, using graph convolutional networks for spatiotemporal dynamics.

Chen et al. (2021) proposed a novel hierarchical learning framework called Adaptive Hierarchical Spatial-Temporal Network (AHSTN) for traffic forecasting. This approach uses adaptive spatiotemporal sampling for learning spatial patterns and obtaining spatial multi-scale correlations. The results of testing the approach with real data showed its advantages of it over the traditional previous models. Moreover, the learning rate of AHSTN is significantly improved.

In Luo et al. (2022), a novel spatiotemporal transformer-based framework named STGIN is proposed to tackle the challenge of long-term traffic prediction. Gated Attention Layers (GAT) and Informer layers are integrated to capture spatial and temporal relationships in traffic data.

Thachayani and Rubavani (2023) proposed a framework based on RCNN for predicting the number of vehicles using records of traffic cameras. The system developed by Python, achieved an accuracy of 99.3%. By automatically counting the vehicles, the system is able to provide intelligent traffic light control. This was a basis for implementing an intelligent traffic management system.

Jia et al. (2023) tried to combine Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEDMDAN) algorithm and LSTM neural network to build a predictor model and test it with real data. The proposed combined model revealed a high accuracy in predicting the travel time in various time laps. The accuracy of the proposed model was somewhat better than LSTM, Attention-Based LSTM, and Convolutional LSTM. The model is especially effective for short-time forecasting. However, the training time was a bit more than other previous models.

Wang et al. (2024) introduced a model called Spatial-Temporal Similarity Fusion Graphs Adversarial Convolutional Networks (STSF-GACN) for traffic flow forecasting which utilizes preprocessing techniques. The model Uses a directed graph in an integrated Generative Adversarial Network (GAN) architecture. They argued that their model is not only accurate but also robust against varying traffic conditions.

Shi et al. (2024) addressed spatiotemporal graph learning for geographical traffic forecasting. For this purpose they developed a deep transformer-based heterogeneous spatiotemporal graph learning model which can be categorized as a geospatial artificial intelligence model. The model was implemented on data achieved from

California's Highways (USA) and revealed desirable results. The model also achieved state-of-the-art results compared with other methods.

Reviewing previous works, it is evident that deep learning methods in traffic prediction have not been fully exploited in terms of model architecture depth, spatial prediction area scale, and the ability to predict spatiotemporal data comprehensively. The proposed methods have often focused on either spatial or temporal information, neglecting the influence of other methods. Therefore, this article suggests a hybrid approach based on deep learning that incorporates both spatial and temporal dependencies for more comprehensive predictions.

## 3. Proposed Method

The general steps of the study are illustrated in Figure 1. The following explains the methodology and its related details.

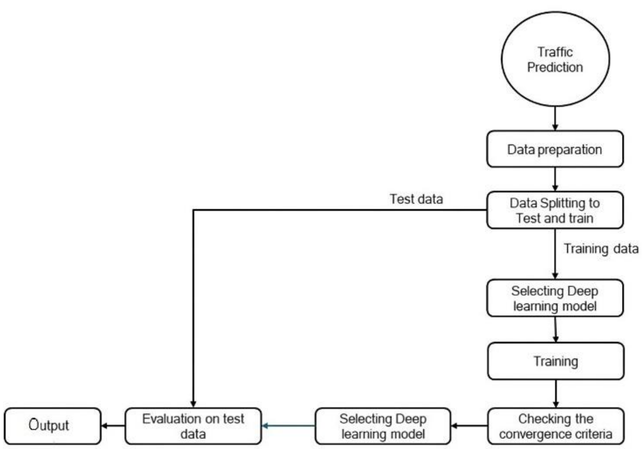



Figure 1. The flowchart of the study

### 3.1. Convolutional Neural Networks

Convolutional Neural Networks (CNN) utilize convolutional computations to extract features from data, making it suitable for scenarios where spatial features are crucial, such as images. The structure of this network typically includes a convolutional layer, a pooling layer, and a fully connected layer. The convolutional layer plays the role of feature extraction, the pooling layer performs subsampling of features, and finally, the fully connected layer is responsible for connecting the extracted features and obtaining classification results (Alferaidi et al., 2022).

### 3.2. Temporal Convolutional Networks

Temporal convolutional network (TCN) has emerged to hierarchically capture both temporal and spatial information (Hu et al., 2022). TCN is composed of one-dimensional convolution, causal convolution sequence model, expansion convolutions and residual connections. The performance of the activation function TCN in relation to equations (1) and (2) is specified. An overall structure of TCN with d layers is illustrated in Figure 2.

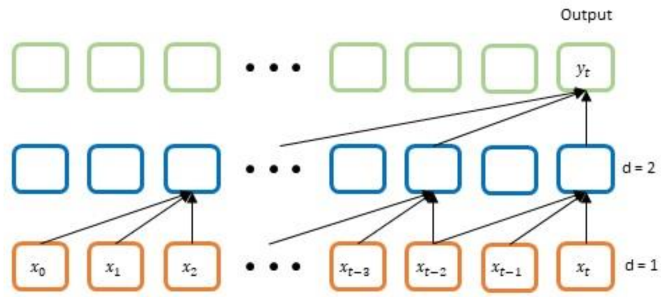



Figure 2: The overall structure of a TCN model with dilation factors 1 and 2 in first and second layers, respectively.

$$\hat{R}_t^{(i,l)} = F\left(W^{(1)} R_{t-s}^{(i,l-1)} + W^{(2)} S_t^{(i,l-1)} + b\right) \quad (1)$$

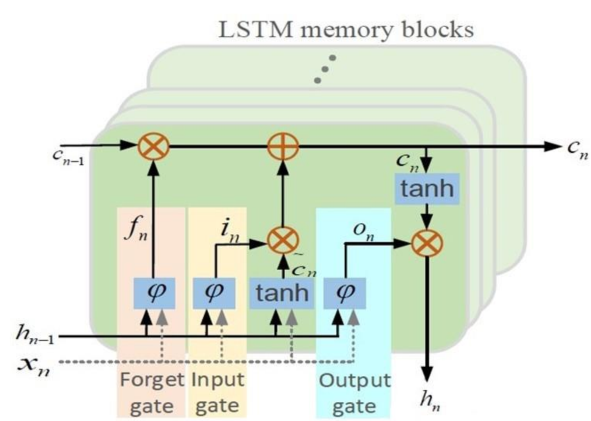
$$R_t^{(i,l)} = \left(R_t^{(i,l-1)} + V \hat{R}_t^{(i,l)} + e\right) \quad (2)$$

where $W$ indicates the trainable weight matrix, $b$ represents the trainable bias, $i$ and $l$ represent unit and layer number, respectively. $S^{(i,l)}$ indicate training function. $\hat{R}_t^{(i,l)}$ indicates expansion convolution at t. $R_t^{(i,l)}$ is the result of expansion convolution after adding residual value t.

### 3.3. LSTM

The purpose of designing short-term memory networks is to address the issue of long-term dependencies, which is resolved by using a continuous memory denoted as $C_n$ (Hochreiter & Schmidhuber, 1997). The architecture of the short-term memory structure is illustrated in Figure 3.

Figure 3: The overall structure of a LSTM model.




In the first step, information needs to be erased from the cell state, a process performed by a sigmoid layer called the forget gate. This gate outputs a value of zero or one to the cell state $C_{n-1}$ based on the values of $h_{n-1}$and $x_n$ for each element. If the value is one, all values of the cell state $C_{n-1}$ are passed to $C_t$, and if the value is zero, it erases the information from the cell state $C_{t-1}$, and no values are entered into $C_n$, as indicated in equation (3) (Hochreiter & Schmidhuber, 1997):

$$f_n = \sigma\left(W_f * [h_{n-1}, x_n] + b_f\right) \tag{3}$$

In the second step, decisions need to be made to determine which new information should be stored in the cell state. This is accomplished by a sigmoid layer called the input gate. Next, a hyperbolic tangent layer produces values denoted as $C_n$, which are added to the cell state. Finally, these two steps are combined with each other to update the value of the cell state, as depicted in equations (4) and (5):

$$i_n = \sigma(W_i * [h_{n-1}, x_n] + b_i) \tag{4}$$

$$\tilde{C}_n = tanh(W_c * [h_{n-1}, x_n] + b_c) \tag{5}$$

Now, to update the cell state from $C_{n-1}$ to $C_n$, it is necessary to multiply the previous cell state value by $f_n$. Then, $i_n * \tilde{C}_n$ is added, resulting in the new values for the cell state, as indicated in equation (6):

$$C_n = f_n * C_{n-1} + i_n * \tilde{C}_n \tag{6}$$

A sigmoid layer decides which part of the cell state should be sent to the output. Then, the value of the cell state is passed through a hyperbolic tangent layer, and its value is multiplied by the output of the previous sigmoid layer to determine the relevant portions to be sent to the output, as shown in equations (7) and (8) (Hochreiter & Schmidhuber, 1997):

$$i_n = \sigma(W_i * [h_{n-1}, x_n] + b_i) \tag{7}$$

$$\tilde{C}_n = tanh(W_c * [h_{n-1}, x_n] + b_c) \tag{8}$$

The proposed combined LSTM and TCN model's overall structure is depicted in Figure 4. The model comprises two parallel branches, consisting of LSTM and TCN models. Within each branch, a 1D convolution layer is employed for initial feature extraction. The outputs of these branches are aggregated and then passed through a sigmoid activation function to transfer feature values between 0 and 1. LSTMs are known for their ability to capture long-term dependencies due to their gating mechanisms, which help retain relevant past information over long sequences. This makes LSTMs particularly effective for tasks where patterns may recur over extended periods. On the other hand, TCNs, which utilize dilated causal convolutions, are adept at capturing local temporal patterns with a fixed receptive field that can also expand to cover a wide range of time steps due to the dilation. This structure allows TCNs to process sequences more efficiently and in parallel, potentially providing faster convergence and a more robust temporal representation. By combining LSTM and TCN, a model can benefit from both global and local temporal dependencies, which can reduce overfitting to specific temporal patterns and improve the overall robustness and accuracy in regression tasks. Subsequent sections elaborate on the implementation details, data preparation process, and results.

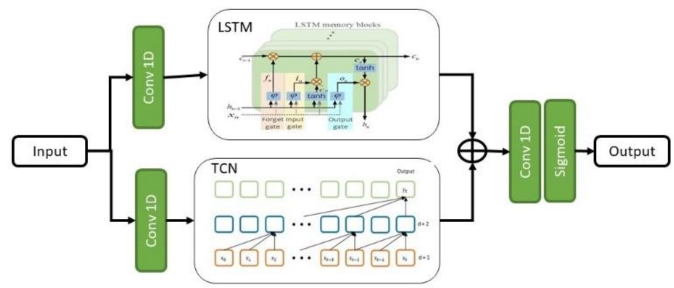



Figure 4: The overall structure of the combined LSTM and TCN model.

## 4. Implementation and Results

This section presents details regarding the hardware and software settings, followed by an elaboration on the dataset employed for training, evaluation, and testing purposes. Furthermore, a quantitative comparison is also provided in Table 1.

In this stage, the proposed method is implemented in the Python environment using PyTorch 2.0 for neural network models, and its performance is evaluated. All processes were performed on a computer with an Intel Core i7 – 8750H CPU @ 2.2 GHz and 32GB of memory. Additionally, all neural network models were trained and evaluated on an NVIDIA GeForce GTX 1080 with 12GB of memory.

In this implementation, loop inductive detectors were used as traffic sensors to collect traffic data. The advantages of this technology include being unaffected by weather conditions such as rain, fog, and snow, as well as the ability to measure basic parameters such as volume, occupancy, speed, flow ratio, and distance between two vehicles. To obtain appropriate data, Seattle city in the state of Washington, USA was selected. Fig. 5 (a) shows the location of the city on the map of the United States. This research leverages two comprehensive datasets capturing real-world traffic speeds across a network. The first dataset comprises data from inductive loop detectors located on four major highways (I-5, I-405, I-90, and SR-520) in the Greater Seattle Area, as illustrated in Fig. 5 (b). Available publicly, this dataset includes traffic metrics from 323 sensor sites, recorded every 5 minutes throughout 2015.

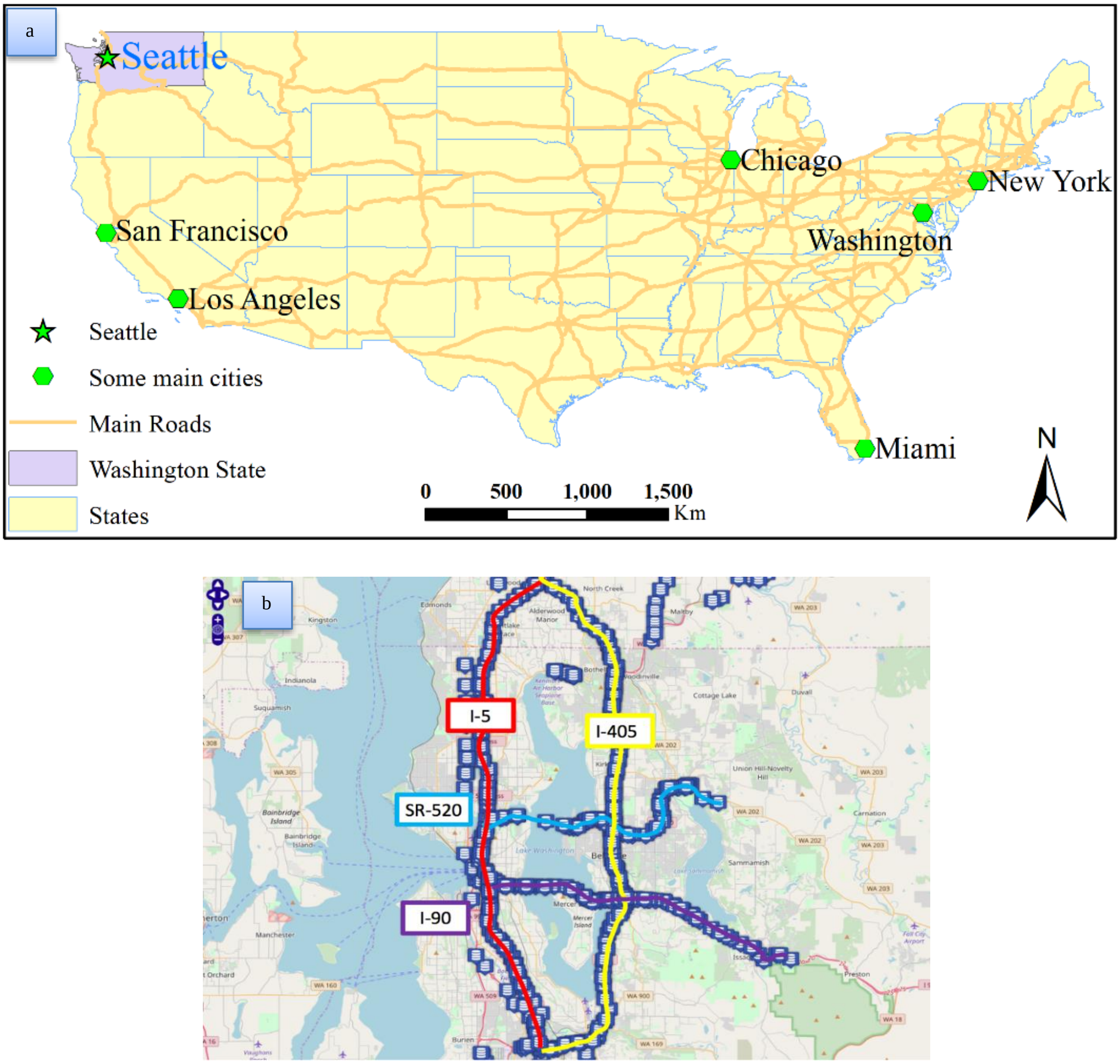



Figure 5: (a) Seattle city in the United States, (b) Freeways of Seattle city

To process the received dataset from roadside sensors, it is divided into two categories of train and test. In fact, 80% of data was used for training and the remained 20% was considered as the test dataset. Cross-validation technique was also utilized to prepare better usage of data. In the Train phase, which consists of two stages, input and output, the inputs include data received from roadside sensors up to the time t, and the output is the target for predicting traffic speed at the next time step. Once the model is trained using inputs and outputs, and the Train phase is completed, the next step is the Test phase. In this phase, the input data related to the Test phase is given to the model, and the received output is compared with the actual value. It is worth mentioning that in the model implementation, Back Training is used, meaning that in one training step, a random subset of the data is selected and fed into the network, and the model parameters are updated. Then, another subset of data is randomly selected.

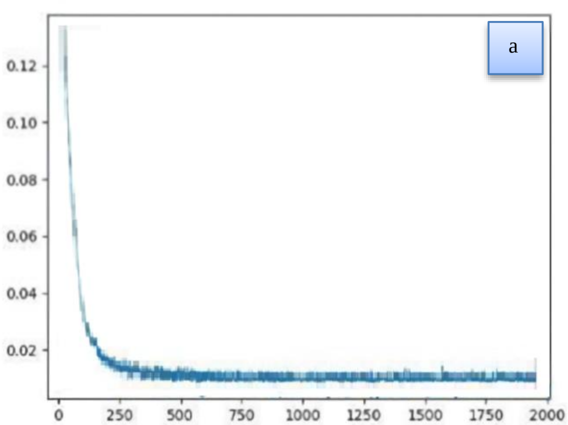
To evaluate the proposed method, its results are compared with the results of RNN and LSTM methods, as shown in Table 1. L1 (Norm1) and MSE are used to evaluate the accuracy of the proposed method. According to Table 1, the accuracy and performance of the proposed method are better compared to RNN and somewhat better compared to LSTM methods.

**Table 1. Evaluation Results of the Proposed Method compared to LSTM and RNN Algorithms**

| | MSE train | MSE validation | MSE test | Test L1 mean | MSE test- std |
|---|---|---|---|---|---|
| **RNN** | 0.006338 | 0.007097 | 0.006745 | 9.0469 | 0.7679 |
| **LSTM** | 0.005854 | 0.006534 | 0.006157 | 8.3325 | 0.73935 |
| **CNN-TCN-LSTM** | 0.005833 | 0.0065345 | 0.006112 | 8.2726 | 0.6140 |

The loss curves of the proposed model are illustrated in Figure 6 (a) and (b). Figure 6 (a) indicates how well the proposed model aligns with the training data, while Figure 6 (b) demonstrates the alignment of the proposed model with new data.

According to the implementation, the proposed model results in an increase in prediction accuracy of about 1% compared to the LSTM method and around 9% compared to the RNN method.



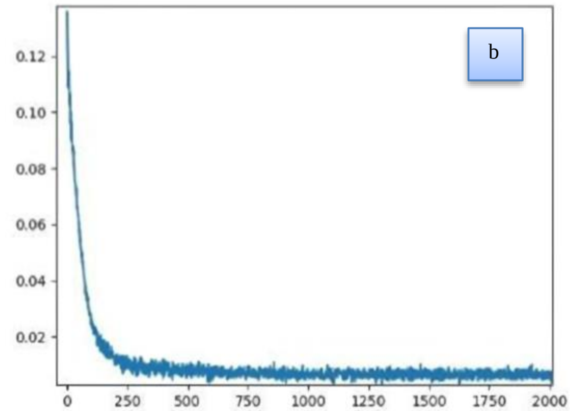




Figure 6: The training loss (a) and the validation error (b)

Table 2 presents the analytical test results across various input sequence lengths, ranging from 5 to 40 minutes, with metrics including mean error and standard deviation error. Regarding the results, the 10-minute sequence shows the lowest mean error at 8.3562, suggesting an optimal sequence length for reducing prediction error. However, increasing in the input sequence length slightly decreases the mean error and showing petter performance. In terms of Standard deviation, lower values suggest more stable predictions, with the 5-minute sequence length achieving the lowest standard deviation error of 0.6616, reflecting high consistency. Conversely, the 10-minute and 25-minute sequence lengths display the highest standard deviation errors, pointing to increased variability. These results underscore the 15-minute sequence length as potentially the most reliable, providing both accurate and stable predictions.

Table 3 presents the analytical test results for various prediction time steps, with metrics including mean error and standard deviation error. The mean error decreases as the prediction time step shortens, with the lowest mean error (8.3512) observed at the 5-minute interval, suggesting that shorter prediction intervals improve accuracy. The highest standard deviation is observed at the 5-minute step (0.7479), compared to the lowest at 40 minutes (0.6313).

**Table 2: Analytical test results for 5, 10, 15, 20, and 25 minutes as different sequence lengths.**

| **Input sequence length** | 5 | 10 | 15 | 20 | 25 | 40 |
|---|---|---|---|---|---|---|
| **Mean error** | 8.5041 | 8.3562 | 8.6805 | 8.3916 | 8.482 | 8.3801 |
| **Standard deviation error** | 0.6796 | 0.7717 | 0.6616 | 0.6988 | 0.6981 | 0.7646 |

**Table 3: Analytical test results for different prediction time steps**

| Prediction time step | 5 | 10 | 20 | 30 | 40 |
|---|---|---|---|---|---|
| Mean error | 8.3512 | 8.4370 | 8.4641 | 8.5299 | 8.6249 |
| Standard deviation error | 0.7479 | 0.7125 | 0.6875 | 0.6789 | 0.6313 |

Figures 7(a) and (b) illustrate the mean error and its associated standard deviation for varying prediction time steps (5, 10, 20, 30, and 40 minutes) and different input sequences (5, 10, 15, 20, and 25 minutes), respectively. The blue line represents the mean values, while the shaded area around it indicates the range of one standard deviation.

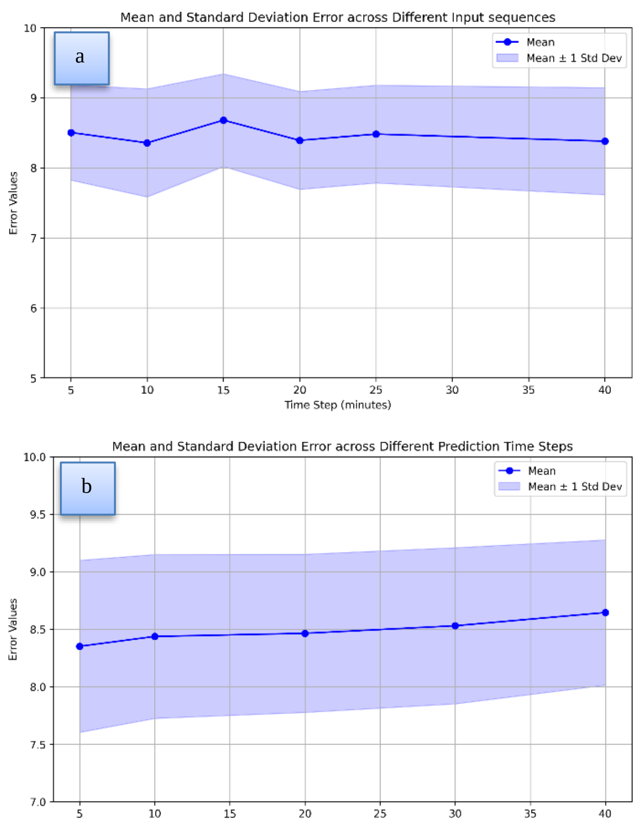



Figure 7: Mean and Standard Deviation on different input sequences and different prediction time steps. (a) Different input sequences and (b) Different prediction time steps

Overall, based on the results of this research, the main contributions of the article are follows:

- A hybrid model named TCN-CNN-LSTM was proposed for predicting traffic speed, considering both temporal and spatial dependencies.
- Simulation results show that the use of the proposed hybrid model leads to an increase in prediction accuracy of 16.95% compared to LSTM and 20.04% compared to RNN.
- The use of the proposed model has advantages such as travel time management, the possibility of emergency response for emergency vehicles, fuel consumption reduction, and decreased air pollution.

## 3. Conclusion

Predicting traffic speed is a challenging problem in transportation and traffic systems. Traditional methods in the field of transportation and traffic management are not responsive to the essential needs of this area. Furthermore, the performance of transportation and traffic systems depends significantly on the quality of the collected data. Therefore, utilizing Internet of Things (IoT) technology and machine learning for the collection and processing of traffic data, and consequently modeling traffic networks in various dimensions, especially in the field of traffic speed prediction, is a crucial step towards optimizing transportation and traffic systems. In this article, a combined CNN-TCN-LSTM method was proposed for predicting traffic speed. Based on the results obtained from the accuracy evaluation of the combined CNN-TCN-LSTM model compared to LSTM and RNN models, it has shown improvements in accuracy performance by 1% and 9%, respectively. For future work, the impact of environmental conditions, social events, traffic incidents, etc., could be considered in traffic speed prediction modeling to achieve the best available transportation and traffic system.

## Acknowledgement

This work was supported by Shahid Rajaee Teacher Training University under grant number 5973.59

## References

Ahmad Rahi, A. (2019). *Machine Learning Approaches for Traffic Flow Forecasting* University of Hertfordshire.

Alferaidi, A., Yadav, K., Alharbi, Y., Razmjooy, N., Viriyasitavat, W., Gulati, K., Kautish, S., & Dhiman, G. (2022). Distributed Deep CNN-LSTM Model for Intrusion Detection Method in IoT-Based Vehicles. *Mathematical Problems in Engineering*, *2022*, 3424819. https://doi.org/10.1155/2022/3424819

Bai, S., Kolter, J. Z., & Koltun, V. (2018). An Empirical Evaluation of Generic Convolutional and Recurrent Networks for Sequence Modeling. *ArXiv, abs/1803.01271*.

BaloujiJonas, E., Sjöblom, J., Murgovski, N., & Haghir Chehreghani, M. (2023). *Prediction of Time and Distance of Trips Using Explainable Attention-based LSTMs*. https://arXiv.org.

Basak, S., Dubey, A., & Bruno, L. (2019, 9-12 Dec. 2019). Analyzing the Cascading Effect of Traffic

Congestion Using LSTM Networks. 2019 IEEE International Conference on Big Data (Big Data),

Chen, M., Chen, R., Cai, F., Li, W., Guo, N., & Li, G. (2021). Short-Term Traffic Flow Prediction with Recurrent Mixture Density Network. *Mathematical Problems in Engineering*, *2021*, 1-9. https://doi.org/https://doi.org/10.1155/2021/6393951

Cui, Z., Ke, R., Pu, Z., & Wang, Y. (2020). Stacked bidirectional and unidirectional LSTM recurrent neural network for forecasting network-wide traffic state with missing values. *Transportation Research Part C: Emerging Technologies*, *118*, 102674. https://doi.org/https://doi.org/10.1016/j.trc.2020.102674

Dohler, M., Vilajosana, I., Vilajosana, X., & Llosa, J. (2011). Smart cities: An action plan. Barcelona Smart Cities Congress, Barcelona, Spain.

Fu, R., Zhang, Z., & Li, L. (2016, 11-13 Nov. 2016). Using LSTM and GRU neural network methods for traffic flow prediction. 2016 31st Youth Academic Annual Conference of Chinese Association of Automation (YAC),

Graves, A. (2012). *Supervised Sequence Labelling with Recurrent Neural Networks*. Springer Berlin Heidelberg. https://books.google.at/books?id=wpb-CAAAQBAJ

Han, S., Zhang, F., Xi, J., Ren, Y., & Xu, S. (2019, 27-30 Oct. 2019). Short-term Vehicle Speed Prediction Based on Convolutional Bidirectional LSTM Networks. 2019 IEEE Intelligent Transportation Systems Conference (ITSC),

Hochreiter, S., & Schmidhuber, J. (1997). Long Sort-Term Memory. *Neural Computation*, *9*(8), 1735-1780.

Hosseinali, F., Aleseheikh, A. A., & Nourian, F. (2014). Rapid Urban Growth in the Qazvin Region and Its Environmental Hazards: Implementing an Agent-Based Model. *Polish Journal of Environmental Studies*, *23*(3), 727-735.

Hu, C., Zhao, Y., Jiang, H., Jiang, M., You, F., & Liu, Q. (2022). Prediction of ultra-short-term wind power based on CEEMDAN-LSTM-TCN. *Energy Reports*, *8*, 483-492. https://doi.org/https://doi.org/10.1016/j.egyr.2022.09.171

Jia, X., Zhou, W., Yang, H., Li, S., & X, C. (2023). Short-term traffic travel time forecasting using ensemble approach based on long short-term memory networks. *IET Intelligent Transport Systems*, *17*(6), 1-15. https://doi.org/https://doi.org/10.1049/itr2.12331

Jin, J., Gubbi, J., Marusic, S., & Palaniswami, M. (2014). An Information Framework for Creating a Smart City Through Internet of Things. *IEEE Internet of Things Journal*, *1*(2), 112-121. https://doi.org/10.1109/JIOT.2013.2296516

Kamble, S. J., & Kounte, M. R. (2020). Machine Learning Approach on Traffic Congestion Monitoring System in Internet of Vehicles. *Procedia Computer Science*, *171*, 2235-2241. https://doi.org/https://doi.org/10.1016/j.procs.2020.04.241

Kazemi, M., & Hosseinali, F. (2022). Assessing the Use of Public Transportation System in Qazvin City Using a Simulator Model. *Journal of Remote Sensing and Geoinformation Research*, *1*(1), 53-62.

Lea, C., Flynn, M. D., Vidal, R., Reiter, A., & Hager, G. D. (2017, 21-26 July 2017). Temporal Convolutional Networks for Action Segmentation and Detection. 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR),

Lea, C., Vidal, R., Reiter, A., & Hager, G. D. (2016). Temporal convolutional networks: A unified approach to action segmentation. Computer Vision - ECCV 2016 Workshops, Proceedings, Amsterdam, Netherlands.

Li, Z., Liu, F., Yang, W., Peng, S., & Zhou, J. (2022). A Survey of Convolutional Neural Networks: Analysis, Applications, and Prospects. *IEEE Transactions on Neural Networks and Learning Systems*, *33*(12), 6999-7019. https://doi.org/10.1109/TNNLS.2021.3084827

Luo, R., Song, Y., Liping, H., Zhang, Y., & Su, R. (2022). *STGIN: A Spatial Temporal Graph-Informer Network for Long Sequence Traffic Speed Forecasting*. https://arXiv.org.

Modi, S., Bhattacharya, J., & Basak, P. (2022). Multistep traffic speed prediction: A deep learning based approach using latent space mapping considering spatio-temporal dependencies. *Expert Systems with Applications*, *189*, 116140. https://doi.org/https://doi.org/10.1016/j.eswa.2021.116140

Mohammed, O., & Kianfar, J. (2018, 16-19 Sept. 2018). A Machine Learning Approach to Short-Term Traffic Flow Prediction: A Case Study of Interstate 64 in Missouri. 2018 IEEE International Smart Cities Conference (ISC2),

Moskvitch, K. (2014). *Can a city ever be traffic jam-free?* BBC. Retrieved 6/6/2024 from https://www.bbc.com/future/article/20140611-can-we-ever-end-traffic-jams

Ni, J., Lin, X., Zhang, K., & Shen, X. (2016, 18-21 Sept. 2016). Privacy-Preserving Real-Time Navigation System Using Vehicular Crowdsourcing. 2016 IEEE 84th Vehicular Technology Conference

(VTC-Fall),
Rahman, R., & Hasan, S. (2018, 4-7 Nov. 2018). Short-Term Traffic Speed Prediction for Freeways During Hurricane Evacuation: A Deep Learning Approach. 2018 21st International Conference on Intelligent Transportation Systems (ITSC),
Sethi, P., & Sarangi, S. R. (2017). Internet of Things: Architectures, Protocols, and Applications. *Journal of Electrical and Computer Engineering*, *2017*, 9324035. https://doi.org/10.1155/2017/9324035
Shi, G., Luo, L., Song, Y., Li, J., & Pan, S. (2024). Deep transformer-based heterogeneous spatiotemporal graph learning for geographical traffic forecasting. *IScience*, *27*(7), 110175. https://doi.org/https://doi.org/10.1016/j.isci.2024.110175
Tang, J., Liu, F., Zou, Y., Zhang, W., & Wang, Y. (2017). An Improved Fuzzy Neural Network for Traffic Speed Prediction Considering Periodic Characteristic. *IEEE Transactions on Intelligent Transportation Systems*, *18*(9), 2340-2350. https://doi.org/10.1109/TITS.2016.2643005
Thachayani, M., & Rubavani, G. (2023). Recurrent Convolutional Neural Network Based Vehicle Counting Framework for Intelligent Transportation Systems. *International Journal of Engineering Trends and Applications*, *10*(1), 1-3.
Wang, B., Long, Z., Sheng, J., & Zhong, Q. (2024). Spatial–Temporal Similarity Fusion Graph Adversarial Convolutional Networks for traffic flow forecasting. *Journal of the Franklin Institute*, *361*(17), 107299. https://doi.org/https://doi.org/10.1016/j.jfranklin.2024.107299
Wang, J., Gu, Q., Wu, J., Liu, G., & Xiong, Z. (2016, 12-15 Dec. 2016). Traffic Speed Prediction and Congestion Source Exploration: A Deep Learning Method. 2016 IEEE 16th International Conference on Data Mining (ICDM),
Zeynali, S., Hosseinali, F., Sadeghi Niaraki, A., Kazemi Beydokhti, M., & Effati, M. (2015). Spatial analysis of accidents at the suburban intersections using Kernel Density Estimation and Spatial Autocorrelation Methods. *Engineering Journal of Geospatial Information Technology*, *3*(2), 21-42.
Zheng, G., Chai, W. K., & Katos, V. (2022). A dynamic spatial–temporal deep learning framework for traffic speed prediction on large-scale road networks. *Expert Systems with Applications*, *195*, 116585. https://doi.org/https://doi.org/10.1016/j.eswa.2022.116585
Zhongjian, L., Jiajie, X., Kai, Z., Hongzhi, Y., Pengpeng, Z., & Xiaofang, Z. (2018). LC-RNN: A Deep Learning Model for Traffic Speed Prediction. 27th International Joint Conference on Artificial Intelligence Main track, Stockholm, Sweden.