A Survey of Traffic Prediction Based on Deep Neural Network: Data, Methods and Challenges

Pengfei Cao, Fei Dai, Guozhi Liu, Jinmei Yang, and Bi Huang(✉)

Big Data and Intelligent Engineering College, Southwest Forestry University, Kunming 650224, China
2955663264@qq.com

Abstract. Traffic prediction plays an important role in the intelligent transportation system (ITS), because it can increase people's travel convenience. Despite the deep neural network has been widely used in the field of traffic prediction, literature surveys of such methods and data categories are rare. In this paper, we have a summary of traffic forecasting from data, methods and challenges. Firstly, we are according to the difference of in spatio-temporal dimensions, divide the data into three types, including the spatio-temporal static data, spatial static time dynamic data, and spatio-temporal dynamic data. Secondly, we explore three significant neural networks of deep learning in traffic prediction, including the convolutional neural network (CNN), the recurrent neural network (RNN), and the hybrid neural networks models. These methods are used in many aspects of traffic prediction, including road traffic accidents forecast, road traffic flow prediction, road traffic speed forecast, and road traffic congestion forecast introduced. Finally, we provide a discussion of some current challenges and development prospects.

Keywords: Deep neural network · Traffic forecasting · Spatio-temporal data

1 Introduction

Since the 21st century, most cities have generally entered a period of rapid urbanization. With the continuous improvement of the urbanization process, the resulting huge traffic demand has caused a lot of pressure on urban traffic. The traffic conditions became very terrible in many big cities, which directly affects the development and environment of a city. In addition, the demand of urban traffic management can no longer be met solely by relying on manpower, so the application and development of traffic prediction are particularly important. In order to solve the problem of people's transportation demand, the intelligent transportation system (ITS) is getting better development gradually, which include electronic sensor technology, data transmission technology, intelligent control technology, and advanced technology into transportation system structures. The purpose of ITS is to provide better service for drivers and passengers, in the context of increasingly serious environmental pollution, more accurate control of traffic conditions can reduce some unnecessary exhaust emissions and provide better channels for energy conservation and environmental protection.

M. R. Khosravi et al. (Eds.): CloudComp 2021, LNICST 430, pp. 17–29, 2022.
https://doi.org/10.1007/978-3-030-99191-3_2

In the process of traffic prediction is used to meet people's needs, researchers use a variety of data, most of which come from road sensors, road reflectors, camera images, aerial photos, remote sensing images, etc. With the development of ITS, more and more data to be used in traffic prediction, the traditional data analysis method is hard to figure out such a huge data in the traffic field, so we need to use deep learning as an important means of the big data analysis methods in traffic prediction, it can be predicted from the following several aspects to traffic development benefits.

1. Vast amounts of diverse and complex data generated in the traffic forecast can be handled by deep learning.
2. Deep learning can improve the validity and accuracy of traffic forecasts. Through fast data collection and analysis of current and historical massive traffic data, the traffic management department can predict traffic conditions in real-time.
3. Deep learning in the data analysis can improve people's travel safety level. Through deep learning analytics, we can effectively predict the occurrence of traffic accidents and congestion.

The overview of traffic prediction in this paper is shown in Fig. 1. The rest of the paper is organized as follows. The architecture of traffic forecasting based on deep learning is discussed in Sect. 2. Section 3 summarizes the data source and collection methods. Deep learning analytics methods are discussed in Sect. 4. Some open challenges of using deep learning in ITS are discussed in Sect. 4. Finally, we conclude the paper in Sect. 5.

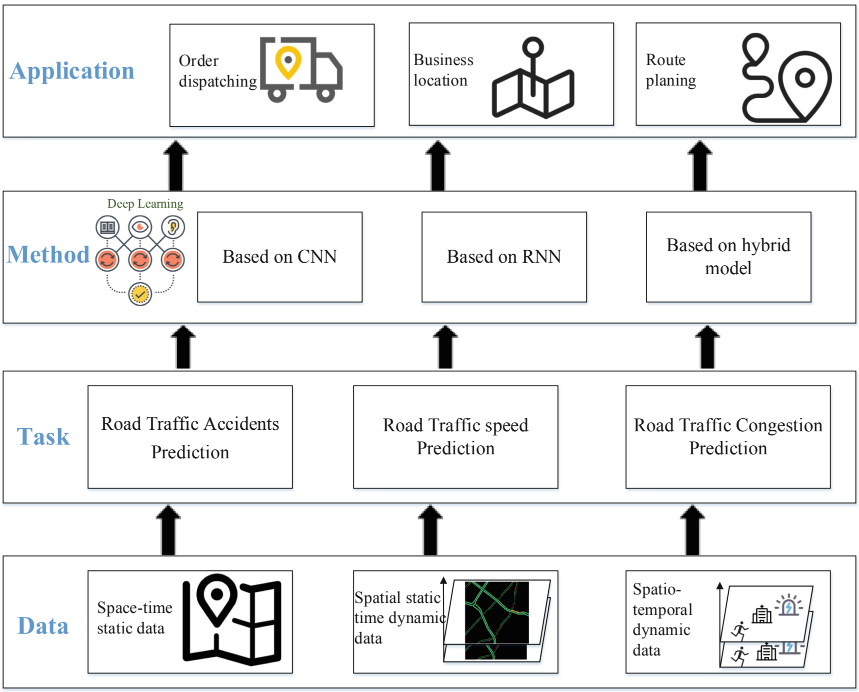

Fig. 1. The overview of traffic prediction

2 Classification of Traffic Data

In this section, we will summarize 56 literature and the methodologies used to predict traffic. We only consider recent papers from 2014 to 2021, which provided sufficiently novel methods and contributions to the field.

In our lives, we unconsciously participate in the collection, transmission and application of big data. With the increase of people's attention to travel conditions, the complexity and diversity of data are an improvement. According to different sources of data in ITS, traffic data are classified into the following categories from the perspective of time and space: spatio-temporal static data, spatial static temporal dynamic data, spatio-temporal dynamic data, point data, network data. The collected data are shown in Table 1. In this table, the STSDS stands for spatio-temporal static data, the SSTDD stands for spatial static temporal dynamic data, the STDD stands for spatio-temporal dynamic data, the PD stands for point-data, and the ND stands for network data.

Table 1. Data statistics for different types

Tasks	Techniques	Example	STSD	SSTDD	STDD	PD	ND
Flow	CNN	[1–3]	×	×	√	×	√
		[4, 5]	×	×	√	√	√
		[6, 7]	×	√	×	×	√
	RNN	[8–10]	×	√	×	×	√
		[11–16]	×	×	√	√	√
	Hybrid model	[17, 18]	×	√	×	√	√
		[19–22]	×	√	×	×	√
		[23–28]	×	×	√	√	√
Speed	CNN	[29, 30]	×	√	×	×	√
	RNN	[31]	×	×	√	×	√
		[32–36]	×	√	×	×	√
	Hybrid model	[37, 38]	×	×	√	√	√
		[39, 40]	×	×	√	×	√
		[41, 42]	×	√	×	×	√
Accident	CNN	[43]	×	×	√	√	√
	RNN	[44–46]	×	×	√	√	√
	Hybrid model	[47]	×	×	√	√	√
Congestion	CNN	[48]	×	×	√	×	√
	RNN	[49, 50]	×	√	×	×	√
		[31, 51–53]	×	×	√	×	√
	Hybrid model	[54–56]	×	×	√	×	√

2.1 Spatial Static Time Dynamic Data

Compared with the space-time static data, with the change of the time dimension, the spatial static time dynamic data will produce. For example, sensors are placed on the fixed points to collect the passing vehicle information. The spatial dimension is stationary, but each point's time is changing. These data are widely used in traffic forecasting, such as traffic flow forecast, traffic speed forecast, traffic congestion forecast, and traffic demand forecast, and so on.

Many studies use spatial static time dynamic data from different sources to collect. For example, Ma et al. [32] in the process of using the deep learning method of LSTM NN for traffic speed prediction, use travel speed data from traffic microwave detectors in Beijing. Zhao et al. [24] propose the EnLSTM-WPEO, which uses the six traffic flow data sets from the highways of Seattle, includes the traffic flow from north to south, west to east, south to north, and east to west. In [57] the built model is based on the traffic flow dataset extracted from the Wisconsin Traffic Operation and Safety Laboratory at the University of Wisconsin Madison. All available data came from the locations of nine detectors in this study.

In these works, the spatial static time dynamic data of Beijing by remote traffic microwave sensors is relatively more popular. We summarize the top-3 most popular main datasets in Table 2, which include 40% of the literature works we surveyed.

Table 2. Popular spatial static temporal dynamic data

Main dataset	Task	References
Beijing dataset	Flow, Speed, Accident, Congestion	[3, 23, 41, 42, 58]
PEMS dataset	Flow, Speed, Accident, Congestion	[12, 28, 40, 52]
Spain dataset	Flow, Speed	[34, 59, 60]

2.2 Spatio-Temporal Dynamic Data

Time and space dimensions are changing constantly, which constitute the spatio-temporal dynamic data, and belongs to the point data of space and time change too. Spatio-temporal dynamic data is the main research hot spot of traffic prediction from the present to the future. With the rise of "sharing", people always unconsciously participate in the collection of spatio-temporal data. In short, many people using Mobike at the same time in different places, or there are different people in the same place using Mobike.

According to current studies, most models are build based on a dataset of PeMS, which is collected from the transportation system of England. PeMS is a typical spatio-temporal dynamic data. In this paper, we explore 60 papers, this dataset is used the ten of them. For example, the most cited papers in this field through the PeMS [27], which include 2501 traffic roads of England. In many papers, traffic forecasting is dependent on external factors, such as weather, holidays, policies and so on. All in all, spatio-temporal dynamic data is the most widely used data type in traffic forecasting. The

Table 3. Popular spatio-temporal dynamic data

Main dataset	Task	References
PEMS dataset	Flow, Speed, Accident, Congestion	[11, 13, 23, 27, 58]
Beijing dataset	Flow, Speed, Accident, Congestion	[2, 20, 31, 44]
Another dataset	Flow, Speed, Congestion	[4, 8]

spatio-temporal dynamic data are shown in Table 3, which includes 35% of the literary works we surveyed.

In addition to the above two kinds of data, spatio-temporal data also includes spatio-temporal static data. In the process of traffic prediction, the spatio-temporal static data plays a very important role as the foundation of in the whole traffic big data. In ITS, spatio-temporal static data (or point data) is fixed and immobile from the beginning of construction, such as building position, floor area, floor height and so on.

3 Deep Neural Networks for Traffic Prediction

With the rapid development of ITS, a large number of deep learning models have been adopted to traffic forecasting recently. Deep learning plays an important role in ITS, which becoming more and more popular in many tasks of traffic forecasting. The main function of deep learning methods is modeling for a large amount of traffic data, then providing the right decisions for people's travel. Since 2014, deep learning is beginning to be used in traffic prediction by Lv et al. [59], which usually use a separate method to predict traffic condition in the future. In 2016, Fu et al. [28] proposed the hybrid deep learning methods to model traffic data jointly. Until 2018, many scholars have been involved in the research of deep learning on traffic prediction, and then in many papers have explored and supplement. The development process of deep learning applied to traffic prediction is shown in Fig. 2.

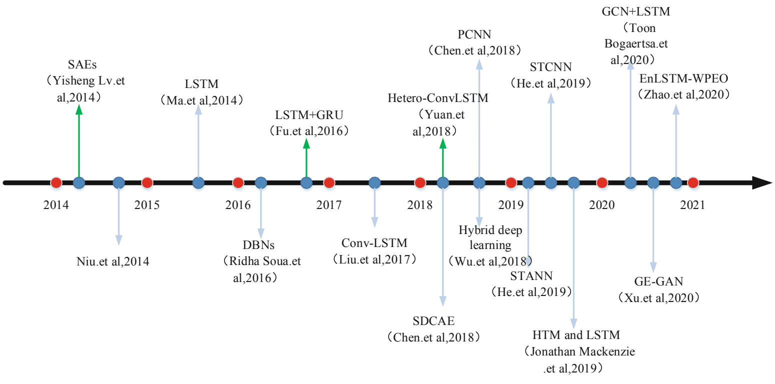

Fig. 2. The development of traffic prediction based on deep learning.

According to the main research methods of current traffic forecast, which can be divided into three types: CNN-based, RNN-based and hybrid model-based. In the following subsections, we will discuss different deep learning methods of traffic prediction.

3.1 A Traffic Forecasting Method Based on CNN

In deep learning, the convolutional neural network (CNN, or ConvNet) is a class of deep neural network, most commonly applied to analyze visual imagery [3]. A CNN consists of several "convolution" and "pooling" layers. Convolution's purpose is to extract features from the input, whereas pooling's purpose is to reduce the dimensionality of each feature map and preserve the most important information. Typical CNN architecture is shown in Fig. 3.

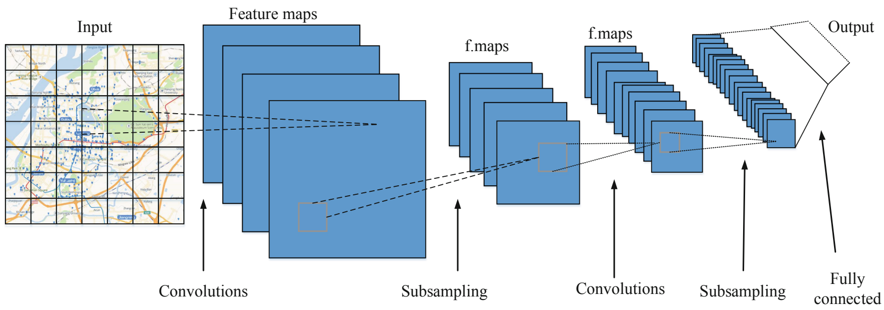

Fig. 3. Typical CNN architecture.

Therefore, many researchers in the domain of traffic forecasting try to take advantage of CNN techniques to solve related to images problems. According to [59], a classic road traffic flow prediction model using deep learning analytics is shown in Fig. 4, this is the first time that a deep architecture model using auto-encoders as building blocks to predict the traffic flow features. It is currently the most cited paper in the field of traffic forecasting. The original traffic data is preprocessed in the first, then we can get the usable data set. Using the deep learning method, which considers the spatial and temporal correlations inherently. Using a stacked autoencoder model to learn usual traffic flow features, and it is trained in a greedy layerwise fashion.

Many scholars have studied traffic flow prediction using deep learning. For example, Chen et al. [1] use 3D CNNs to abstract the spatio-temporal correlation features jointly from low-level to high-level layers for traffic data. Similarly, Chen et al. [4] propose novel spatio-temporal CNNs to extract spatio-temporal features simultaneously from low-level to high-level layers, and propose a novel gated scheme to control the spatio-temporal features that should be propagated through the hierarchy of layers. Deng et al. [6] try to transform the spatio-temporal traffic data analysis problem into the task of image-like analysis, for jointly exploring spatio-temporal relations. To traffic speed prediction, Byeonghyeop Yu et al. [29] adopt the graph convolution models in the field of traffic forecasting, which improve the forecasting accuracy and saved more training time. To

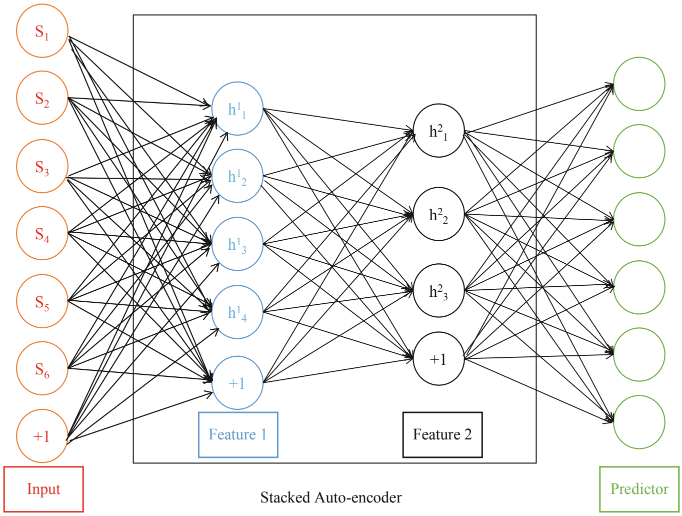

Fig. 4. A typical traffic flow prediction model [59].

traffic accident prediction, Zheng et al. [43] propose the feature matrix to gray image (FM2GI) algorithm, which strengthens the traffic accident severity performance. Chen et al. [48] propose a novel method based on a deep convolutional neural network named PCNN, which models periodic traffic data for short-term traffic congestion prediction.

In the application of traffic prediction, CNN is often as a component in a hybrid deep neural network, whose main task is to capture the spatial aspect of traffic data.

3.2 A Traffic Forecasting Method Based on RNN

Recurrent Neural Networks (RNN) is commonly applied to sequence data because their memorization capability, which learns the sequence of both long and short-term dependencies. In the process of working, the Feedforward Neural Network is based on only the current input, however, the RNN takes decisions based on current and previous inputs [4]. This visualization can be seen in Fig. 5.

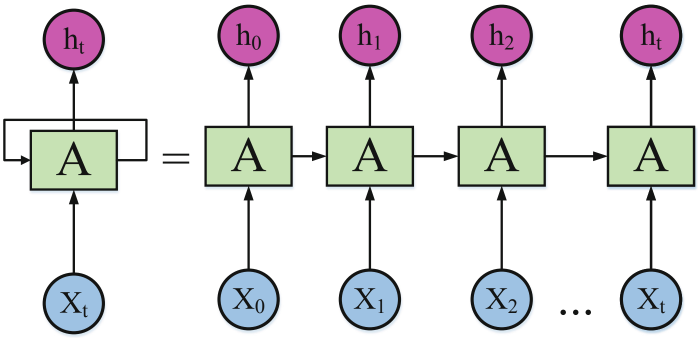

Fig. 5. A recurrent neural network [4].

Additionally, RNN is able to scale to longer sequences compared to other network architectures. Its unique capability makes it as one of the most popular deep neural networks. For example, Mou et al. [10] propose a piece of temporal information enhancing LSTM (T-LSTM) to predict traffic flow of a single road section, the model can improve prediction accuracy by capturing the intrinsic correlation between traffic flow and temporal information. Moreover, Ma et al. [32] propose Long Short-Term Neural Network (LSTM NN) captures nonlinear traffic dynamics in an effective manner. The LSTM NN can overcome the issue of back-propagated error decay by memory blocks. For traffic prediction of different tasks, RNN is beneficial to extract temporal correlation of spatio-temporal data.

3.3 A Traffic Forecasting Method Based on the Hybrid Model

Because the traffic data have the following three complex features: temporal correlations, spatial correlations, and diversity of spatio-temporal (ST) correlations. Traffic predicting accurately and timely is a challenging problem in ITS. However, Modeling for these various types of ST correlations is very difficult, so many of these existing works taken attention to the diversity of ST correlations through the hybrid model [23], details are shown in Fig. 6.

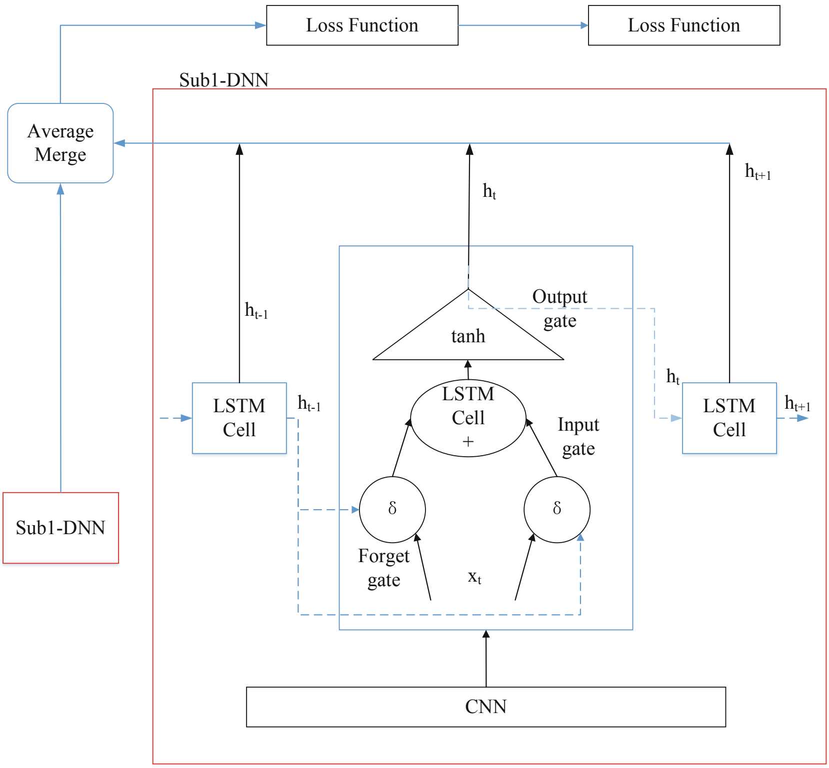

Fig. 6. The architecture of the hybrid CNN-LSTM [23].

Therefore, many researchers propose a traffic forecasting method based on the hybrid model. For example, Zhang et al. [40] propose Spatial-Temporal Graph Attention Networks (ST-GAT). The graph attention mechanism extracts the spatial dependencies and introduces an LSTM network to extract temporal domain features, this approach is able to capture dynamic spatial dependencies of traffic networks. Duan et al. [26] propose a hybrid neural network to predict urban flow which is made up of CNN and LSTM. The CNN can statically extract the potential spatial features and the LSTM to dynamically abstract the short term and long term temporal features of urban traffic data.

In the field of traffic prediction, the forecasting method based on the hybrid model is commonly used as a component spatio-temporal data analysis of ITS. Its task is to capture the spatio-temporal patterns of traffic data.

4 Challenges

Although deep learning has made great achievements in traffic prediction, there are still many challenges have not been fully studied. We need to solve these questions in future works. This section introduces the main challenges of traffic forecasting based on deep learning as follows.

1) Traffic data characteristic and complexity: traffic data belongs to spatio-temporal data, which has spatial correlation, temporal correlation and heterogeneity. However, in most of the existing studies only extracting spatio-temporal correlation, the heterogeneity of the correlations contribution takes into account is very rarely [60]. Furthermore, we also need to solve the many external factors in the complex urban environment, such as social media data, weather data, accidents data and so on. How to improve the accuracy of traffic prediction when we consider to add the weather conditions and holidays? Or considering other types of traffic data like a truck, bus and metro, and personal phone signals data simultaneously to get better deep learning models. And then most of the existing traffic prediction data is collected by equipment such as an annular coil detector or ultrasonic sensor. These data are often missing, invalid and uncertain due to weather, sensor failure, traffic control and other reasons. This will increase the difficulty of data preprocessing.
2) The performance capacity of the model: the short-term traffic prediction works well, but with the increase of prediction time, the error gets bigger, and the accuracy of long-term prediction will become worse. With the continuous expansion of the road network, the number of intersections and sensors will increase, the road network topology will become more complex, the amount of historical traffic data will become larger, and the performance of the model will be lower. Besides, due to the limited available traffic sensors in urban areas, limiting the traffic data availability, we need to take into account the dependency of different sensors. In this case, how to effectively improve the accuracy of the long-term forecasts is a challenging and very difficult task.
3) Application of actual traffic scenarios: most of the existing traffic prediction models are based on data sets to train and test, but the application of models is extremely scarce in real scenarios. However, accurate traffic prediction of actual traffic scenarios can bring many benefits: provide convenience for traffic managers and travelers,

reduce traffic jams, realize intelligent transportation. In practical application, traffic data around the selected scene is first collected for traffic prediction, and then the predicted traffic data is used to plan travel roads and design automatic control of traffic lights.

With the rapid development of the 6G network [61], future research should focus on how to apply traffic prediction to actual scenarios, which will help traffic managers to control traffic and bring convenience to people's travel. Accurate traffic prediction is the most important part of the traffic information service system, which is beneficial to alleviate traffic congestion and reduce the occurrence of traffic accidents. In the future, various types of data can be combined with each other for better depicting the hourly traffic information and human mobility in urban areas and generating a better prediction.

5 Conclusions

Ever since IBM came up with the concept of Smarter Earth in 2018, intelligence has become the main goal of today's society development, such as intelligent transportation, intelligent medical, intelligent currency, and so on. In short, traffic forecasting is able to provide useful information use the past and present traffic data, then achieve a vision of traffic conditions in the future. However, due to the various characteristics of traffic data and the complexity of traffic networks in different regions, it is still a big challenge to achieve an accurate assessment of future traffic forecasts.

We hope the traffic prediction field will inspire more scholars to study, which can directly contribute to the improvement of traffic conditions. Deep learning will have profound impacts on the traffic forecast.

References

1. An, J., Fu, L., Hu, M., Chen, W., Zhan, J.: A novel fuzzy-based convolutional neural network method to traffic flow prediction with uncertain traffic accident information. IEEE Access **7**, 20708–20722 (2019)
2. Chen, C., et al.: Exploiting spatio-temporal correlations with multiple 3D convolutional neural networks for citywide vehicle flow prediction, pp. 893–898 (2018)
3. Peng, H., et al.: Spatial temporal incidence dynamic graph neural networks for traffic flow forecasting. Inf. Sci. **521**, 277–290 (2020)
4. Chen, C., Li, K., Teo, S.G., Zou, X., Li, K., Zeng, Z.: Citywide traffic flow prediction based on multiple gated spatio-temporal convolutional neural networks. ACM Trans. Knowl. Discov. Data **14**(4), 1–23 (2020)
5. Zhang, D., Kabuka, M.R.: Combining weather condition data to predict traffic flow: a GRU based deep learning approach. IET Intell. Transp. Syst. **12**(7), 578–585 (2018)
6. Deng, S., Jia, S., Chen, J.: Exploring spatial–temporal relations via deep convolutional neural networks for traffic flow prediction with incomplete data. Appl. Soft Comput. **78**, 712–721 (2019)
7. Wang, X., et al.: Traffic flow prediction via spatial temporal graph neural network, pp. 1082–1092 (2020)
8. Zhang, C., Patras, P.: Long-term mobile traffic forecasting using deep spatio-tem poral neural networks, pp. 231–240 (2018)

9. Ma, Y., Zhang, Z., Ihler, A.: Multi-lane short-term traffic forecasting with convolutional LSTM network. IEEE Access **8**, 34629–34643 (2020)
10. Mou, L., Zhao, P., Xie, H., Chen, Y.: T-LSTM: a long short-term memory neural network enhanced by temporal information for traffic flow prediction. IEEE Access **7**, 98053–98060 (2019)
11. Ryu, U., Wang, J., Kim, T., Kwak, S., U, J.: Construction of traffic state vector using mutual information for short-term traffic flow prediction. Transp. Res. Part C Emerg. Technol. **96**, 55–71 (2018)
12. Liu, Y., Zheng, H., Feng, X., Chen, Z.: Short-term traffic flow prediction with conv-LSTM. In: 2017 9th International Conference on Wireless Communications and Signal Processing (WCSP), pp. 1–6. IEEE
13. Kang, D., Lv, Y., Chen, Y.Y.: Short-term traffic flow prediction with LSTM recurrent neural network. In: 2017 IEEE 20th International Conference on Intelligent Transportation Systems (ITSC), pp. 1–6. IEEE
14. He, Z., Chow, C.Y., Zhang, J.D.: STANN: a spatio–temporal attentive neural network for traffic prediction. IEEE Access **7**, 4795–4806 (2019)
15. Shao, H., Soong, B.H.: Traffic flow prediction with long short-term memory networks (LSTMs). In: 2016 IEEE Region 10 Conference (TENCON), pp. 2986–2989. IEEE
16. Hua, Y., Zhao, Z., Liu, Z., Chen, X., Li, R., Zhang, H.: Traffic prediction based on random connectivity in deep learning with long short-term memory. In: 2018 IEEE 88th Vehicular Technology Conference (VTC-Fall), pp. 1–6. IEEE
17. Polson, N.G., Sokolov, V.O.: Deep learning for short-term traffic flow prediction. Transp. Res. Part C: Emerg. Technol. **79**, 1–17 (2017)
18. Koesdwiady, A., Soua, R., Karray, F.: Improving traffic flow prediction with weather information in connected cars: a deep learning approach. IEEE Trans. Veh. Technol. **65**(12), 9508–9517 (2016)
19. Mackenzie, J., Roddick, J.F., Zito, R.: An evaluation of HTM and LSTM for short-term arterial traffic flow prediction. IEEE Trans. Intell. Transp. Syst. **20**(5), 1847–1857 (2019). https://doi.org/10.1109/tits.2018.2843349
20. Gu, Y., Lu, W., Xu, X., Qin, L., Shao, Z., Zhang, H.: An improved Bayesian combination model for short-term traffic prediction with deep learning. IEEE Trans. Intell. Transp. Syst. **21**(3), 1332–1342 (2020)
21. Wu, Y., Tan, H., Qin, L., Ran, B., Jiang, Z.: A hybrid deep learning based traffic flow prediction method and its understanding. Transp. Res. Part C Emerg. Technol. **90**, 166–180 (2018)
22. Pan, Z., Liang, Y., Wang, W., Yu, Y., Zheng, Y., Zhang, J.: Urban traffic prediction from spatio-temporal data using deep meta learning, pp. 1720–1730 (2019)
23. Guo, S., Lin, Y., Li, S., Chen, Z., Wan, H.: Deep spatial–temporal 3D convolutional neural networks for traffic data forecasting. IEEE Trans. Intell. Transp. Syst. **20**(10), 3913–3926 (2019)
24. Zhao, F., Zeng, G.Q., Lu, K.D.: EnLSTM-WEPO: short-term traffic flow prediction by ensemble LSTM, NNCT weight integration, and population extremal optimization. IEEE Trans. Veh. Technol. **69**(1), 101–113 (2020)
25. Zheng, H., Lin, F., Feng, X., Chen, Y.: A hybrid deep learning model with attention-based conv-LSTM networks for short-term traffic flow prediction. IEEE Trans. Intell. Transp. Syst. **22**, 1–11 (2020)
26. Duan, Z., Yang, Y., Zhang, K., Ni, Y., Bajgain, S.: Improved deep hybrid networks for urban traffic flow prediction using trajectory data. IEEE Access **6**, 31820–31827 (2018)
27. Chen, Y., Shu, L., Wang, L.: Traffic flow prediction with big data: a deep learning based time series model. In: 2017 IEEE Conference on Computer Communications Workshops (INFOCOM WKSHPS), pp. 1010–1011. IEEE

28. Fu, R., Zhang, Z., Li, L.: Using LSTM and GRU neural network methods for traffic flow prediction. In: 2016 31st Youth Academic Annual Conference of Chinese Association of Automation (YAC), pp. 324–328. IEEE
29. Yu, B., Lee, Y., Sohn, K.: Forecasting road traffic speeds by considering areawide spatio-temporal dependencies based on a graph convolutional neural network (GCN). Transp. Res. Part C Emerg. Technol. **114**, 189–204 (2020)
30. Guo, G., Yuan, W.: Short-term traffic speed forecasting based on graph attention temporal convolutional networks. Neurocomputing **410**, 387–393 (2020)
31. Wang, J., Gu, Q., Wu, J., Liu, G., Xiong, Z.: Traffic speed prediction and congestion source exploration: A deep learning method. In: 2016 IEEE 16th International Conference on Data Mining (ICDM), pp. 499–508. IEEE
32. Ma, X., Tao, Z., Wang, Y., Yu, H., Wang, Y.: Long short-term memory neural network for traffic speed prediction using remote microwave sensor data. Transp. Res. Part C Emerg. Technol. **54**, 187–197 (2015)
33. Zang, D., Ling, J., Wei, Z., Tang, K., Cheng, J.: Long-term traffic speed prediction based on multiscale spatio-temporal feature learning network. IEEE Trans. Intell. Transp. Syst. **20**(10), 3700–3709 (2019)
34. Kim, Y., Wang, P., Mihaylova, L.: Structural recurrent neural network for traffic speed prediction. In: ICASSP 2019–2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), pp. 5207–5211. IEEE
35. Wang, J., Chen, R., He, Z.: Traffic speed prediction for urban transportation network: A path based deep learning approach. Transp. Res. Part C Emerg. Technol. **100**, 372–385 (2019)
36. Zheng, Z., Wang, D., Pei, J., Yuan, Y., Fan, C., Xiao, F.: Urban traffic prediction through the second use of inexpensive big data from buildings, pp. 1363–1372 (2016)
37. Cheng, Z., Chow, M.Y., Jung, D., Jeon, J.: A big data based deep learning approach for vehicle speed prediction. In: 2017 IEEE 26th International Symposium on Industrial Electronics (ISIE), pp. 389–394. IEEE
38. Essien, A., Petrounias, I., Sampaio, P., Sampaio, S.: Improving urban traffic speed prediction using data source fusion and deep learning. In: 2019 IEEE International Conference on Big Data and Smart Computing (BigComp), pp. 1–8. IEEE
39. Zhang, Z., Li, M., Lin, X., Wang, Y., He, F.: Multistep speed prediction on traffic networks: A deep learning approach considering spatio-temporal dependencies. Transp. Res. Part C Emerg. Technol. **105**, 297–322 (2019)
40. Zhang, C., Yu, J.J.Q., Liu, Y.: Spatial-temporal graph attention networks: a deep learning approach for traffic forecasting. IEEE Access **7**, 166246–166256 (2019)
41. Ma, X., Zhong, H., Li, Y., Ma, J., Cui, Z., Wang, Y.: Forecasting transportation network speed using deep capsule networks with nested lstm models. IEEE Trans. Intell. Transp. Syst. **22**, 1–12 (2020)
42. Gu, Y., Lu, W., Qin, L., Li, M., Shao, Z.: Short-term prediction of lane-level traffic speeds: a fusion deep learning model. Transp. Res. Part C Emerg. Technol. **106**, 1–16 (2019). https://doi.org/10.1016/j.trc.2019.07.003
43. Zheng, M., et al.: Traffic accident's severity prediction: a deep-learning approach-based CNN network. IEEE Access **7**, 39897–39910 (2019). https://doi.org/10.1109/access.2019.2903319
44. Ren, H., Song, Y., Wang, J., Hu, Y., Lei, J.: A deep learning approach to the citywide traffic accident risk prediction. In: 2018 21st International Conference on Intelligent Transportation Systems (ITSC), pp. 3346–3351. IEEE
45. Yuan, Z., Zhou, X., Yang, T.: Hetero-ConvLSTM: a deep learning approach to traffic accident prediction on heterogeneous spatio-temporal data. In: Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery Data Mining, pp. 984–992
46. Bao, J., Liu, P., Ukkusuri, S.V.: A spatiotemporal deep learning approach for citywide short-term crash risk prediction with multi-source data. Accid. Anal. Prev. **122**, 239–254 (2019)

47. Chen, C., Fan, X., Zheng, C., Xiao, L., Cheng, M., Wang, C.: SDCAE: stack denoising convolutional autoencoder model for accident risk prediction via traffic big datapp, pp. 328–333 (2018)
48. Chen, M., Yu, X., Liu, Y.: PCNN: deep convolutional networks for short-term traffic congestion prediction. IEEE Trans. Intell. Transp. Syst. **19**(11), 3550–3559 (2018)
49. Majumdar, S., Subhani, M.M., Roullier, B., Anjum, A., Zhu, R.: Congestion prediction for smart sustainable cities using IoT and machine learning approaches. Sustain. Cities Soc. **64**, 102500 (2021)
50. Di, X., Xiao, Y., Zhu, C., Deng, Y., Zhao, Q., Rao, W.: Traffic congestion prediction by spatiotemporal propagation patterns, pp. 298–303 (2019)
51. Choi, S., Kim, J., Yeo, H.: Attention-based recurrent neural network for urban vehicle trajectory prediction. Procedia Comput. Sci. **151**, 327–334 (2019)
52. Kong, F., Li, J., Lv, Z.: Construction of intelligent traffic information recommendation system based on long short-term memory. J. Comput. Sci. **26**, 78–86 (2018)
53. Chen, Y.Y., Lv, Y., Li, Z., Wang, F.Y.: Long short-term memory model for traffic congestion prediction with online open data. In: 2016 IEEE 19th International Conference on Intelligent Transportation Systems (ITSC), pp. 132–137. IEEE
54. Zhu, J., Huang, C., Yang, M., Fung, G.P.C.: Context-based prediction for road traffic state using trajectory pattern mining and recurrent convolutional neural networks. Inf. Sci. **473**, 190–201 (2019)
55. Bogaerts, T., Masegosa, A.D., Angarita-Zapata, J.S., Onieva, E., Hellinckx, P.: A graph CNN-LSTM neural network for short and long-term traffic forecasting based on trajectory data. Transp. Res. Part C Emerg. Technol. **112**, 62–77 (2020)
56. Hassija, V., Gupta, V., Garg, S., Chamola, V.: Traffic jam probability estimation based on blockchain and deep neural networks. IEEE Trans. Intell. Transp. Syst. **22**, 1–10 (2020)
57. Li, L., Qin, L., Qu, X., Zhang, J., Wang, Y., Ran, B.: Day-ahead traffic flow forecasting based on a deep belief network optimized by the multi objective particle swarm algorithm. Knowl.-Based Syst. **172**, 1–14 (2019)
58. Arif, M., Wang, G., Chen, S.: Deep learning with non-parametric regression model for traffic flow prediction, pp. 681–688 (2018)
59. Kim, Y., Wang, P., Zhu, Y., Mihaylova, L.: A capsule network for traffic speed prediction in complex road networks. In: 2018 Sensor Data Fusion: Trends, Solutions, Applications (SDF), pp. 1–6. IEEE
60. Lv, Y., Duan, Y., Kang, W., Li, Z., Wang, F.Y.: Traffic flow prediction with big data: a deep learning approach. IEEE Trans. Intell. Transp. Syst. **16**, 1–9 (2014)
61. Zhou, Y.Q., Liu, L., Wang, L.: Service-aware 6G: an intelligent and open network based on the convergence of communication. Digit. Commun. Netw. **6**, 253–260 (2020)