Grenze International Journal of Engineering and Technology, Jan Issue

A Systematic Review of Deep Learning Architectures in Traffic Congestion Prediction

Mrs.B.Karthika[1] , Dr.N.UmaMaheswari[2] and Dr.R.Venkatesh[3]
[1]Assistant professor, Dept of Information Technology, PSNA college of engineering and Technology,Dindigul. 624622
Email: karthika@psnacet.edu.in
[2]Professor, Dept of Computer science and Engineering, PSNA college of engineering and Technology,,Dindigul. 624622
Email: numamahi@gmail.com
[3]Professor, Dept of Information Technology, PSNA college of engineering and Technology,Dindigul. 624622
Email: rvenkatit@psnacet.edu.in

***Abstract*—The traffic data is increasing day by day. Data produced by traffic sensors, GPS equipped vehicles; loop detectors are used in intelligent transport systems. These data may include traffic volume, speed, density, local events, geospatial data, accident information and weather data. The collected data can be used in predicting the traffic flow, speed, congestion prediction. The more accurate prediction of congestion can increase the capacity of the road. In this paper, a review about congestion prediction is done with deep learning algorithms, metrics for classification and congestion.**

***Index Terms*— traffic data, deep learning, congestion prediction.**

I. INTRODUCTION

With high urbanization and more number of vehicles, the traffic congestion level increases. The high congestion can be solved by increasing the transportation infrastructure. But it is an expensive method. The traffic congestion levels are congested, medium or free. These are used to make better driving choices. Forecasting models are focused on the prediction of traffic parameters such as speed, volume, and density. There is less/no data about small rural roads and intersection roads. So data can be collected from urban area and used for analysis. Feng Mao et al. proposed that the travel has a certain temporal periodicity [7]. The periodicity can be the people go for work during week days and on weekends they go to entertainment places. The high traffic can be found during peak hours in morning [7-10 AM] and evening[4-7].The traffic flow will have a different distribution on weekdays and weekend. Guande Qi et al. considered three areas [8]: They are long-distance bus/train stations, entertainment areas and scenic spots. The data gathered from taxi dataset, an accurate volume of taxis moving inside and outside an entertainment can be predicted. Nicholas Jing Yuan et al. proposed that based on the people movement , urban cities can be categorized into residential areas, entertainment areas, and industrial areas[9]. Z. Abbas et al. used LSTM mdoel for short-term road traffic density prediction [10]. R. Fu et al. used a hybrid model that combines LSTM and gated recurrent unit (GRU) neural network methods to predict short-term traffic flow [11]. Toncharoen Ratchanon et al presented a CNN model to predict the traffic state [11]. Song Changhee et al. proposed a CNN-based model to predict information about traffic [12]. Toon Bogaerts et al. proposed a deep neural network that automatically captures the spatial information using a graph convolution network and its temporal features by LSTM. Linjiang Zheng et al. presented a new feature to

Grenze ID: 01.GIJET.8.1.512_2

prediction by adding a grid to the map and the density threshold of the grid cells are set. Based on density threshold, they extracted the hotspot grid cells to find hotspots of the city [15]**.** Gui, Zhiming et al. used a MapReduce-based DBSCAN method for finding the traffic hotspots of the city. The method detects the dense part as a hotspot [16]. Y. Shen discovered an improved DBSCAN algorithm for finding the hotspots , which is very useful in finding hotspots[17]. Xu, Zhimin et al[18]. presented spatio-temporal hotspot by identifying the road segment in which the vehicle is travelling . They found travel speed and hotspot. In probability-based map-matching algorithms, the first they compute the emission probability, the transition probability, and Viterbi algorithm is used for calculating the result**.** Francia, M et al. anticipated an enhanced map-matching algorithm with a hidden Markov model for predicting traffic congestion[21]**.** Qi, H et al. described a junction matching algorithm which improves the prediction by using road widths, angles and other information [22]**.** Mohammed Quddus et al. presented the stMM algorithm where the difference between the distance along the shortest path and the distance along the vehicle trajectory are calculated for predicting the congestion level[23]. Zhang Yong-chuana et al. proposed a traffic congestion method uses taxi trajectory data where the data has been cleaned, speed estimation, and congestion classification are done to extract information. Shuming Sun et al. proposed a map-matching algorithm based on an HMM to predict traffic congestion [25]. Yuankai Wu et al. presented a DNN-BTF model where temporal and spatial data are considered [26]**.** Nicholas G. Polson et al. proposed that uses neural network with L1 regularization to predict short-term traffic flow [27]. It identifies spatio-temporal relations first and nonlinear relations are identified for better prediction**.** Yu Bing et al. proposed a STGCN [28] is a hybrid combination of GCN and GLU to predict the traffic flow. Di Zang et al. proposed a multi-scale spatio-temporal feature learning network (MSTFLN) which is combination of convolutional long short-term memory and convolutional neural networks to predict the speed. It creates a speed matrix and time scale matrices for prediction. Yuanli Gu et al. presented a new model which is hybrid combination of LSTM neural network and GRU neural network to predict the traffic speed [30]. Jingyuan Wang et al. proposed a (eRCNN) [31] the traffic speeds are considered as an input matrix to predict the traffic congestion . Loan N.N. Do et al. used an attention mechanism where temporal and spatial characteristics of data are analyzed to improve prediction [32]. H.Xiong et al. observed that traffic congestion and proposed PPI Fast algorithm [33]. Zhou, Xun proposed the local gathering events are also added as prediction feature that cause congestion [34]. They proposed the SmartEdge algorithm to discover the top-k G-graphs**.** Khezerlou, Amin Vahedian et al. proposed a novel simulation-based evaluation approach which can be used to predict many gathering events, such as traffic accidents, concerts and sports events in addition to traffic congestion. Michael A.P.[35] Taylor described traffic congestion sources are occurrence of incidents and next is peak periods.

II. Objectives

The objectives of traffic data are follows

1. To find out traffic volume on selected road (urban or rural).
2. To predict the traffic speed of the road.
3. To minimize the traffic congestion through different deep learning algorithms.
4. To predict the bus arrival time at station.
5. To find the passenger flow at airport/railway station

III. Data Sources

Nowadays vehicles are equipped with sensors such as Radar, Ultrasonic, Camera, LIDAR to help intelligent transport systems in planning congestion free road. These sensor provide information like speed, density, object detection in performing tasks such as traveling time delay and traffic flow prediction. Radar and LIDAR sensors are used for object detection and collision avoidance respectively. Piezoelectric sensor gathers traffic data by changing mechanical energy into electric energy. The device is used to count the number of vehicles connected with sensors and mounted in nearby areas.

Microwave Doppler RADAR sensors are used to detect vehicles in motion. Vehicles are moving relative to each other which is the fundamental principle of Doppler effect. Also, this sensor is capable of detecting distant objects. Microwave radar detectors are capable of working in all weather conditions. This is also used to measure speed of the vehicle. Inductive loop sensors used to count the number of vehicles and speed as well. infrared and acoustic sensors are used to collect traffic data.[1].

The sources of data are Historical data, GPS equipped taxis, Maps, social media data, Weather data, API Data.

IV. Deep Learning Architecture

Deep learning is the subset of Artificial intelligence (AI).The AI is found to be useful in solving well defined problems but it also fails to solve complex problems such as object detection, language translation, picture captioning etc. Many subsets of AI were invented to solve complex problems. These subsets are Natural language processing, Fuzzy Logic, Machine learning, Deep Learning. Machine learning algorithms are capable of learning from data, identify patterns and make decisions with minimal human intervention. Machine learning approaches are broadly classified into two categories, i.e., Supervised Learning and Unsupervised Learning.

Supervised Learning techniques require input data which is a labeled that describes the naming of data. It performs two primary tasks, i.e classification and regression. In unsupervised learning, the user needs to find patterns and distributions among the given data sets. It includes the tasks of clustering and density estimation. Popularly used supervised learning techniques include ANN, Support Vector Machine (SVM) Bayesian methods and k-Nearest Neighbor (k-NN) whereas popular unsupervised learning techniques include k-means, Principal Component Analysis (PCA) etc. For each dataset, a set of features are extracted to feed as input to the model. However, in some domains such as – natural language processing, computer vision it is difficult to find the right features due to the very large size of the dataset.

Deep learning is a subset of machine learning which imitates the thinking process of the human brain that extracts features in an automatic fashion. Deep learning techniques have gained much attention in recent years. Deep Learning has originated from cognitive theories that create complex neural network structures. TensorFlow, PyTorch, MxNet, DyNet, Keras are some of the popular Deep learning platforms used currently. Deep learning constructs a computational model with multiple processing layers to support high-level data abstraction. It has automatic feature extraction from data, to explore hidden data relationships among different attributes of the data set with less or no human intervention. These models have shown accurate results compared to other traditional machine learning methods. Deep learning models use the underlying architecture of neural networks. The structural building block of a neural network is a single neuron called perceptron that takes several inputs, processes it by a weights and bias function. Then the result passes through an activation function which gives the output. While training a model, the whole data set is categorized into training, testing and validation sets.

A. Design of neural networks

In designing a neural network model, the neurons are arranged in hierarchical layers. Except for the input and output layers, models also have hidden layer neurons. Neurons of two different layers are connected by weights which are updated during the training of the model. The weights can be adjusted to minimize loss function. There are many loss functions in deep learning networks. They are cross entropy loss, mean bias error, MSE etc. Loss function calculates the error in the prediction . This is calculated by finding the difference rate between actual and predicted values. Different loss functions may generate a different error for the same prediction. To minimize the loss function/cost function, the backpropagation (BP) technique is used that updates the bias and weights of neurons at each layer by propagating the current error backward to the previous layer. These are some commonly used activation function rectified linear unit (ReLU), sigmoid function, and hyperbolic tangent function.

More is the number of hidden layers, deeper is the NN gets. The whole process is repeated until the minimum of the loss function is reached. The weights can be adjusted using a function called the optimization function. Optimization function generally computes the stochastic gradient descent (SGD) which is a partial derivative of loss function with respect to weights. In summary, MLP involves two essential computations, i.e., forward pass and backward pass. In the forward pass, training data set is passed through the network and as per the model; output error value is computed whereas in the backward pass, the computed error value is used to adjust weights in the network. Most of the literature study is based on applying BP method with gradient descent as a training algorithm.

B. Metrics for classification

The evaluation measures are precision, recall, f1-score and accuracy.
Precision =TruePositive/(TruePositive + FalsePositive).
Recall =TruePositive/(TruePositive + FalseNegative).
f1- score =2*Precision*Recall/(Precision · Recall).
Accuracy =True Positive + True Negative/Total

C. Loss function

Categorical entropy loss function is used for multi class classification problems.

V. CONGESTION MEASUREMENT METRICS

1. Speed: The traffic speed of the road affects the quality of traffic at the time. Whereas high speed leads to road traffic accidents, while low speed in the urban area indicates congestion. The congestion level (C.L.) is categorized based on the average speed of the road, given in the below form.
   C.L. = Free if $v > 25$km/hr
   Slow if 10km/hr $\leq v \leq$ 25km/hr
   Jam if $v <$ 10km/hr --------------------------------- (1)
   Where v is the speed of the vehicle.
2. Speed Reduction Index is a measure representing the ratio of the decline in speeds from free flow conditions.
3. Speed performance index value ranges from 1 to 100 can be defined by the ratio between vehicle speed and the maximum permissible speed.
   SPI = (avg/max) × 100------- (2)
   where SPI denotes the speed performance index, avg indicates the average travel speed, and max denotes the maximum permissible road speed.
4. Travel time Congestion is a travel time delay in excess of the normally incurred under light or free flow travel conditions.
5. Travel rate refers to the rate of motion for a particular roadway segment or trip that can be represented by the ratio of the segment travel time by the segment length.
   Trr = Tt /Ls--------------------- (3)
   where, Trr denotes the travel rate, Tt is the travel time, and Ls indicates the segment length.
6. Delay Rate The delay rate is the rate of time loss for vehicles operating during congestion for a specific roadway segment or trip.
   Dr = Trac - Trap----------------- (4)
   where, Dr is the delay rate, Trac is the actual travel rate, and Trap is the acceptable travel rate.
7. Delay Ratio The delay ratio can be calculated by the ratio of delay rate and the actual travel rate
   D = Dr /Trac-------------------(5)
   where D denotes the delay ratio, Dr is the delay rate, and Trac is the actual travel rate.

VI. CONCLUSION

Many deep learning approaches are used to classify traffic congestion. The unusual factors such as accidents, weather, and planned events are main reasons for congestion. For example, if the rainfall intensity increases, then speed and flow both decrease. These data are very important to predict congestion. Metrics also play an important role in congestion. Imbalanced classification refers to classification tasks where the number of examples in each class is unequally distributed. Choosing the dataset, deep learning model, loss function, metrics is very crucial in prediction. The more advanced deep learning graph techniques can be used to solve congestion problems.

REFERENCES

[1] Arzoo Miglani, Neeraj Kumar,"Deep learning models for traffic flow prediction in autonomous vehicles: A review, solutions, and challenges", vehicular communications 2019,https://doi.org/10.1016/j.vehcom.2019.100184.

[2] Yan Shi,Haoran Feng,Xiongfei Geng,Xingui Tang,Yongcai Wang,"A Survey of Hybrid Deep Learning Methods for Traffic Flow Prediction",ICAIP 2019 3rd International Conference on Advances in Image Processing, November 8–10, 2019,DOI: 10.1145/3373419.3373429

[3] Ugo Fiore,Adrian Florea,Gilberto Pérez Lechuga,"An Interdisciplinary Review of Smart Vehicular Traffic and Its Applications and Challenges", journal sensor and actuator networks,2019, https://doi.org/10.3390/jsan8010013.

[4] Amudapuram Mohan Rao,Kalaga Ramachandra Rao,"MEASURING URBAN TRAFFIC CONGESTION – A REVIEW",International Journal for Trac and Transport Engineering, 2012, 2(4): 286 – 305, DOI: http://dx.doi.org/10.7708/ije.2012.2(4).01.

[5] P. S. Castro, D. Zhang, C. Chen, S. Li, and G. Pan, ''From taxi GPS traces to social and community dynamics: A survey,'' ACM Comput. Surv., vol. 46, no. 2, pp. 1–34, 2013.

[6] W. Chen, F. Guo, and F.-Y. Wang, ‘‘A survey of traffic data visualization,’’IEEE Trans. Intell. Transp. Syst., vol. 16, no. 6, pp. 2970–2984, Dec. 2015.
[7] F. Mao, M. Ji, and T. Liu, ‘‘Mining spatiotemporal patterns of urban dwellers from taxi trajectory data,’’ Frontiers Earth Sci., vol. 10, no. 2, pp. 205–221, Jun. 2016.
[8] G. Qi, X. Li, S. Li, G. Pan, Z. Wang, and D. Zhang, ‘‘Measuring social functions of city regions from large-scale taxi behaviors,’’ in Proc. IEEE Int. Conf. Pervas. Comput. Commun. Workshops (PERCOM Workshops), Mar. 2011, pp. 384–388.
[9] N. J. Yuan, Y. Zheng, X. Xie, Y. Wang, K. Zheng, and H. Xiong, ‘‘Discovering urban functional zones using latent activity trajectories,’’ IEEE Trans. Knowl. Data Eng., vol. 27, no. 3, pp. 712–725, Mar. 2015.
[10] Z. Abbas, A. Al-Shishtawy, S. Girdzijauskas, and V. Vlassov, ‘‘Short-term traffic prediction using long short-term memory neural networks,’’ in Proc.IEEE Int. Congr. Big Data (BigData Congress), Jul. 2018, pp. 57–65.
[11] R. Fu, Z. Zhang, and L. Li, ‘‘Using LSTM and GRU neural network methods for traffic flow prediction,’’ in Proc. 31st Youth Acad. Annu. Conf. Chin. Assoc. Automat. (YAC), Nov. 2016, pp. 324–328.
[12] R. Toncharoen and M. Piantanakulchai, ‘‘Traffic state prediction using convolutional neural network,’’ in Proc. 15th Int. Joint Conf. Comput. Sci.Softw. Eng. (JCSSE), Jul. 2018, pp. 1–6.
[13] C. Song, H. Lee, C. Kang, W. Lee, Y. B. Kim, and S. W. Cha, ‘‘Traffic speed prediction under weekday using convolutional neural networks concepts,’’in Proc. IEEE Intell. Vehicles Symp. (IV), Jun. 2017, pp. 1293–1298.
[14] T. Bogaerts, A. D. Masegosa, J. S. Angarita-Zapata, E. Onieva, and P. Hellinckx, ‘‘A graph CNN-LSTM neural network for short and long- term traffic forecasting based on trajectory data,’’ Transp. Res. C, Emerg. Technol., vol. 112, pp. 62–77, Mar. 2020.
[15] L. Zheng, X. Zhao, Z. Jiang, J. Deng, D. Xia, and W. Liu, ‘‘Mining uban attractive areas using taxi trajectory data,’’ Comput. Appl. Softw., vol. 35, p. 1, Jan. 2018.
[16] M. Ester, H.-P. Kriegel, J. Sander, and X. Xu, ‘‘A density-based algorithm for discovering clusters in large spatial databases with noise,’’ in Proc. KDD, 1996, vol. 96, no. 34, pp. 226–231.
[17] Z. Gui and H. Yu, ‘‘Mining traffic hot spots from massive taxi trace,’’J. Comput. Inf. Syst., vol. 10, no. 7, pp. 2751–2760, 2014.
[18] Y. Shen, L. Zhao, and J. Fan, ‘‘Analysis and visualization for hot spot based route recommendation using short-dated taxi GPS traces,’’ Information, vol. 6, no. 2, pp. 134–151, 2015.
[19] Z. Xu, Z. Lin, C. Zhou, and C. Huang, ‘‘Detecting traffic hot spots using vehicle tracking data,’’ in Proc. 2nd ISPRS Int. Conf. Comput. Vis. Remote Sens. (CVRS), vol. 9901, 2016, Art. no. 99010Y.
[20] Z. Xia, Q. Lei, Y. Yang, H. Zhang, Y. He, W. Wang, and M. Huang, ‘‘Vision-based hand gesture recognition for human-robot collaboration: A survey,’’ in Proc. 5th Int. Conf. Control, Automat. Robot. (ICCAR), Apr. 2019, pp. 198–205.
[21] M. Francia, E. Gallinucci, and F. Vitali, ‘‘Map-matching on big data: A distributed and efficient algorithm with a hidden Markov model,’’ in Proc. 42nd Int. Conv. Inf. Commun. Technol., Electron. Microelectron. (MIPRO), May 2019, pp. 1238–1243.
[22] H. Qi, X. Di, and J. Li, ‘‘Map-matching algorithm based on the junction decision domain and the hidden Markov model,’’ PLoS ONE, vol. 14, no. 5, 2019, Art. no. e0216476.
[23] M. Quddus and S. Washington, ‘‘Shortest path and vehicle trajectory aided map-matching for low frequency GPS data,’’ Transp. Res. C, Emerg. Technol., vol. 55, pp. 328–339, Jun. 2015.
[24] Z. Yong-Chuan, Z. Xiao-Qing, Z. Li-Ting, and C. Zhen-Ting, ‘‘Traffic congestion detection based on GPS floating-car data,’’ Procedia Eng.,vol. 15, pp. 5541–5546, Jan. 2011.
[25] S. Sun, J. Chen, and J. Sun, ‘‘Traffic congestion prediction based on GPS trajectory data,’’ Int. J. Distrib. Sensor Netw., vol. 15, no. 5, pp. 1–18, May 2019.
[26] Y. Wu, H. Tan, L. Qin, B. Ran, and Z. Jiang, ‘‘A hybrid deep learning based traffic flow prediction method and its understanding,’’ Transp. Res. C, Emerg. Technol., vol. 90, pp. 166–180, May 2018.
[27] N. G. Polson and V. O. Sokolov, ‘‘Deep learning for short-term traffic flow prediction,’’ Transp. Res. C, Emerg. Technol., vol. 79, pp. 1–17, Jun. 2017.
[28] B. Yu, H. Yin, and Z. Zhu, ‘‘Spatio-temporal graph convolutional networks: A deep learning framework for traffic forecasting,’’ 2017, arXiv:1709.04875. [Online]. Available: http://arxiv.org/abs/1709.04875
[29] D. Zang, J. Ling, Z. Wei, K. Tang, and J. Cheng, ‘‘Long-term traffic speed prediction based on multiscale spatio-temporal feature learning network,’’ IEEE Trans. Intell. Transp. Syst., vol. 20, no. 10, pp. 3700–3709, Oct. 2019.
[30] Y. Gu, W. Lu, L. Qin, M. Li, and Z. Shao, ‘‘Short-term prediction of lane- level traffic speeds: A fusion deep learning model,’’ Transp. Res. C, Emerg. Technol., vol. 106, pp. 1–16, Sep. 2019.
[31] J. Wang, Q. Gu, J. Wu, G. Liu, and Z. Xiong, ‘‘Traffic speed prediction and congestion source exploration: A deep learning method,’’ in Proc. IEEE 16th Int. Conf. Data Mining (ICDM), Dec. 2016, pp. 499–508.
[32] L. N. N. Do, H. L. Vu, B. Q. Vo, Z. Liu, and D. Phung, ‘‘An effective spatial-temporal attention based neural network for traffic flow prediction,’’ Transp. Res. C, Emerg. Technol., vol. 108, pp. 12–28, Nov. 2019.
[33] H. Xiong, A. Vahedian, X. Zhou, Y. Li, and J. Luo, ‘‘Predicting traffic congestion propagation patterns: A propagation graph approach,’’ in Proc. 11th ACM SIGSPATIAL Int. Workshop Comput. Transp. Sci., 2018,pp. 60–69.
[34] A. V. Khezerlou, X. Zhou, L. Li, Z. Shafiq, A. X. Liu, and F. Zhang, ‘‘A traffic flow approach to early detection of gathering events,’’ in Proc. 24th ACM SIGSPATIAL Int. Conf. Adv. Geograph. Inf. Syst., 2016, pp. 1–10.

[35] A. V. Khezerlou, X. Zhou, L. Li, Z. Shafiq, A. X. Liu, and F.Zhang,‘‘A traffic flow approach to early detection of gathering events: Comprehensive results,’’ ACM Trans. Intell. Syst. Technol., vol. 8, no. 6, pp. 1–24,Jul. 2017.
[36] R. L. Bertini, ‘‘You are the traffic jam: An examination of congestion measures,’’ in Proc. 85th Annu. Meeting Transp. Res. Board, 2006, pp. 1–17.
[37] M. A. P. Taylor, J. E. Woolley, and R. Zito, ‘‘Integration of the global positioning system and geographical information systems for traffic congestion studies,’’ Transp. Res. C, Emerg. Technol., vol. 8, nos. 1–6, pp. 257–285,Feb. 2000.
[38] M. Taylor, ‘‘An extended family of traffic network equilibria and its implications for land use and transport policies,’’ in Proc. 8th World Conf. Transp. Res. World Conf. Transp. Res. Soc., vol. 4, 1999, pp. 29–42.
[39] L. Page, S. Brin, R. Motwani, and T. Winograd, ‘‘The pagerank citation ranking: Bringing order to the Web,’’ Stanford InfoLab, Stanford, CA, USA, Tech. Rep. SIDL-WP-1999-0120, 1999.