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A Review of Traffic State Prediction (TSP) Methods in Intelligent Transportation Systems (ITS)

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Abstract

In today's world, traffic congestion is a major problem in almost all metropolitans. This problem is even becoming more crucial due to increasing numbers of vehicles. Mobility of people, travel time duration, quality of life, transportation planning systems and traffic management are examples which bear the effects of traffic congestion The modern smart technology such as Artificial Intelligence (AI) has reduced traffic congestion by improving traffic monitoring and management technologies. These technologies require sufficient and accurate traffic data such as flow, velocity, and traffic density. Several machine learning-based methods have been proposed to predict the traffic state. Providing accurate prediction is an important stage in the successful implementation of Intelligent Transportation Systems (ITS). In this paper, we summarize the latest approaches in enhancing traffic state prediction, and possible developments in future, which potentially can transform many aspects of traffic management.

Keywords: Artificial Intelligence, Traffic State Estimation, Intelligent Transportation Systems, Machine Learning, Review Paper.

Introduction

Intelligent transportation systems (ITS) have been receiving a growing interest since early 1970s. It is an infrastructure for a transportation system which is constructed by integrating information of cars, people, and roads. ITS utilizes advanced technology techniques such as electronic sensor technologies, data transmission technologies, and intelligent control technologies to manage a transportation system with the aim of providing an efficient services for drivers and travelers in transportation systems (An et al., 2011). In today's world, one of the major problems in ITS is traffic management. Monitoring and managing traffic has a major role in traffic congestion reduction. Among its effects could be the reduction of road fatalities, increased road safety, reduced fossil fuel consumption and increased driving quality (Dimitrakopoulos & Demestichas, 2010).

There is a massive amount of traffic data available due to pervasive technologies in telecommunication and transportation systems. There are two main categories for collecting traffic data. The first category includes video cameras, inductive loop detectors and other static sensors which can be installed at fixed locations on roads for detection of traffic state (such as traffic, density, speed, and flow). While data collected from these devices are accurate and sufficient to be used for traffic management, these traditional techniques cannot cover all roadways since they necessitate a large-scale infrastructure deployment, and a large amount of upkeep and maintenance costs. The second category uses the technology of cellular network data (GPRS, UMTS, GMS, CDMA) It has created a convenient platform for receiving traffic information from vehicles that can be used to identify traffic (volume of traffic, traffic flow), calculation of time and route of movement, and creation of the right and momentary reports (Yu, et al., 2019). Floating Car Data (FCD) is a convenient and cost-effective method of the second category which gathers traffic condition information. It does not need any specific device and offers good coverage across road networks with a defined penetration rate. However, GPS signals are prone to errors because of urban canyons and tall buildings which affected the traffic estimation and prediction results (Newson & Krumm, 2009). Sometimes, these GPS enabled devices update their locations and other information in a long-time interval which make their exact location and speed unknown. The latter issue is known as data sparsity or missing data.

Figure 1 illustrates a sample of traffic flow in Kuala Lumpur. Traffic state (i.e., traffic flow, speed, density, etc.) is important for urban traffic control. Traffic State Prediction (TSP) aims to forecast the traffic state variable within a certain time period. TSP is more prominent stage in mitigating traffic congestion which can predict traffic characteristics such as speed.

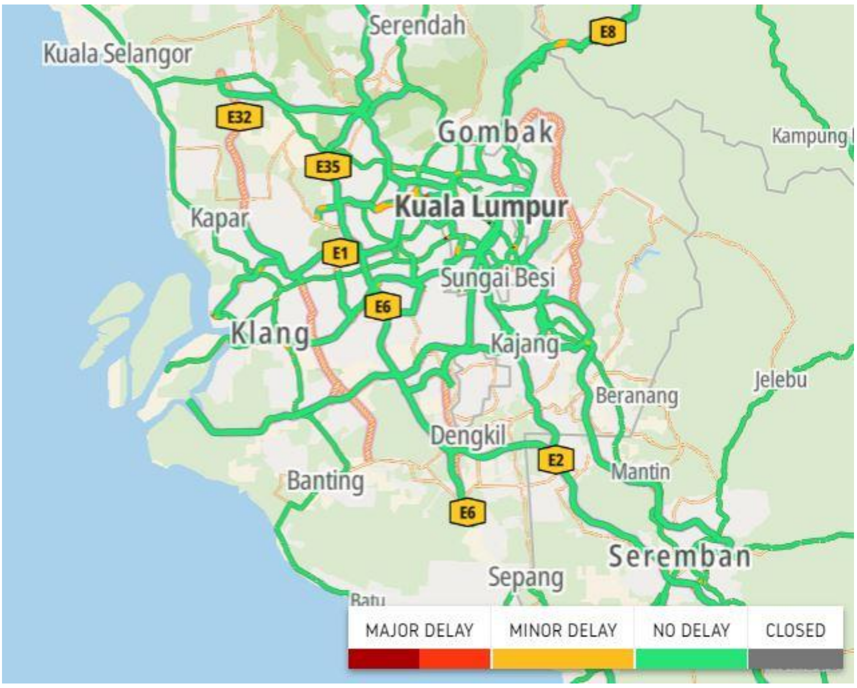

Figure 1: Sample of Traffic Flow in Kuala Lumpur
(Source: https://www.tomtom.com/traffic-index/kuala-lumpur-traffic/)

Providing accurate and sufficient traffic data plays an important role in the accuracy of traffic sate prediction. Simple and traditional ML algorithms such as Artificial Neural Network (ANN), Regression Model, Decision Tree and play a key role in traffic state prediction.
The aim of this review is to provide a review of existing traffic state prediction approaches, explain the use of each approach in ITS, and inspire the researchers in the related field.

Traffic State Prediction in Car Data

Prediction of traffic state provides information for travelers before commencing their trips, and helps ITS to control traffic intelligently, and therefore reduces the traffic congestion.
Prediction approaches are a set of methods which predict the traffic states, according to observations. There are 3 major approaches for modelling of traffic state prediction using Artificial Intelligence (AI) including, 1) Probabilistic Reasoning, 2) Shallow Machine Learning, and 3) Deep Learning, which are explained in the following section (Figure 2).

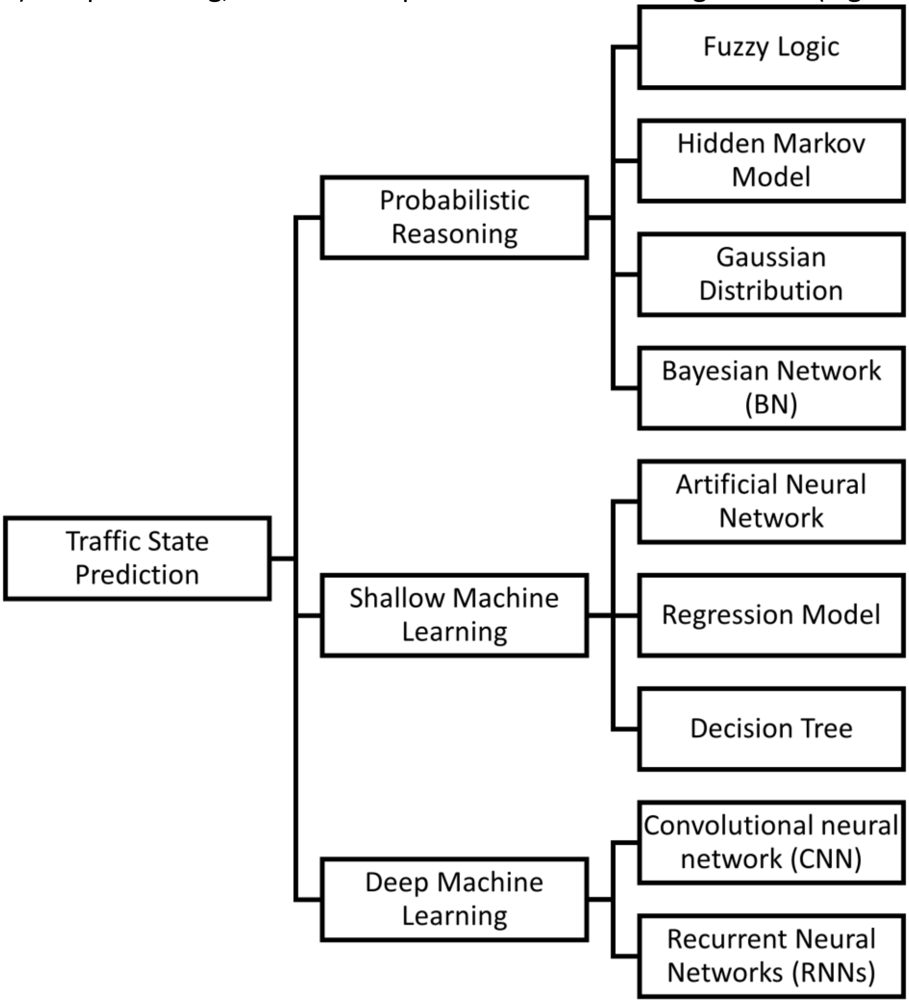

Figure 2: Traffic State Prediction Approaches

Probabilistic Reasoning

Probabilistic reasonings are approaches that involve the use of probability and logic to deal with uncertainty. Several algorithms in this field are applied in traffic state prediction. These approaches are not categorized in machine learning models but are included in AI models.

a. Fuzzy Logic

The fuzzy logic method has been applied for traffic state prediction in several studies. The fuzzy rule-based system (FRBS) is a commonly applied method in traffic engineering studies, and it uses fuzzy logic system for inference. Fuzzy logic system establishes a set of fuzzy logic rules and membership functions. The fuzzy logic rules logically model the input with corresponding output variables. In real-world traffic data, fuzzy logic rules are capable of managing large and complex data through simple rules representation of the data. A study by Zhang and Ye (2008) applied fuzzy system which used the fuzzy logic rules and MFs to generate inputs and fuse them to produce more accurate traffic flow predictions. In research by Onieva et al (2012), the traffic states the fuzzy logic rules combine the relations among different traffic states to detect the resulting traffic states. As data complexity increases, the total number of rules increases as well, reducing the overall system's accuracy, and making it computationally costly. In the study by Onieva et al (2016), the performance of evolutionary fuzzy rule learning (EFRL) and crisp rule learning (ECRL) are computed in order to predict traffic congestion of the roads. It was seen that ECRL models outperformed EFRL in terms of number of rules and average accuracy. However, it was computationally expensive. The severity changes in congestion is used as a congestion measurement in roads using Mamdani fuzzy system (Cao & Wang, 2019). One of the main advantages of the fuzzy logic system is its ability to produce several congestion states as the outcome. One of the drawbacks of fuzzy logic models in traffic state prediction is the lack of practical logic on how the membership functions are selected.

b. Hidden Markov Model (HMM)

The next algorithm category in probabilistic reasoning is hidden Markov model (HMM). A Markov chain is a model that identifies probabilities of sequences of state variables, and commonly applied for modelling time-series data. HMM have been used in several studies to recognize traffic pattern in congestion prediction (Zaki et al., 2019, 2020; Zhao, 2015). Zaki et al. (2019) discussed the use of HMM and the Adaptive NeuroFuzzy Inference System (ANFIS) in congestion prediction. Four processing steps known as initialization, recursion, termination, and backtracking are implemented to achieve optimal state transition. The Viterbi algorithm is used to calculate current state probability. The accuracy was measured using MAE, which achieved 6%. Another study by the same author proposed a year later which predicted traffic using HMM (Zaki et al., 2020) . It proposed a hybrid model composed of HMM and contrast measure to predict traffic states of roads. While contrast measure can be applied as a useful statistical technique to capture traffic state variation, HMM's generalization is not strong enough. The prediction result is measured using MAE, which is 10.

c. Gaussian Processes (GPs)

Another group of probabilistic reasoning model are Gaussian processes (GPs), which are flexible non-parametric models (Rodrigues et al., 2019). GPs can be used to model complex time-series. A study by Lin et al (2018) applied three sources of data including, trajectory data, speed data, and traffic related tweets to predict road traffic speed. While incorporating three sources of data is interesting, the model structure is complex. Moreover, did not mention the exact values of final prediction results and only sketched algorithms performance in figures. Another study presented the probability of traffic state distribution (Zhu et al., 2019). It applied EM algorithms to select variance parameters and mean of gaussian distribution. The first step generated the log-likelihood expectation for the parameters, whereas the last step maximized it. Sun et al (2019) approximated the error in GPS location in the road with Gaussian Distribution, taking mean 0. The error was calculated from the actual GPS point, matching point on the road section, and standard deviation of GPS measurement error.

From the abovementioned studies, it is seen that the Gaussian distribution model has a useful application in reducing feature numbers without compromising the quality of the prediction results or for location error estimation while using GPS data.

d. Bayesian Network (BN)

The last category of Probabilistic reasoning algorithms is Bayesian network (BN). BNs are directed graph models which are capable of presenting conditional independencies among random variables. Graph theory and probability theory are combined and build BN to deal with main issues in engineering (complexity and uncertainty) and applied mathematics (Akhtar & Moridpour, 2021; Sun et al., 2006).

Kim and Wang (2016) utilizes BN to detect and predict traffic congestion. The study applied three sources of data Loop detector, incident data and weather information in the proposed method. It presented 40 scenarios based on congestion occurrence probabilities.

ii. Shallow Machine Learning (SML)

Traditional and basic ML algorithms are included in Shallow Machine Learning (SML). In this category of algorithms, features cannot be extracted from the input, and it is necessary to define them in advance. After extracting the feature, can perform model training. In this section, the application of SML in TSP will be discussed.

a. Artificial Neural Network (ANN)

In recent years artificial neural networks (ANNs) have become popular and helpful models for classification, clustering, pattern recognition and prediction in many disciplines. ANNs are one type of model for machine learning (ML) and has become relatively competitive to conventional regression and statistical models regarding usefulness (Dave & Dutta, 2012). The great potential of ANNs is the high-speed processing provided in a massive parallel implementation and this has heightened the need for research in this domain (Abiodun et al., 2018).

The basic structure of ANN is demonstrated in Figure 3. ANN consists of an input layer to take the data, hidden layer to process the data, and output layer to provide the solution, and each layer includes neurons. ANN is one of the commonly used algorithms in traffic state prediction because of its ability for efficient forecasting and ease of implementation. Several studies successfully applied ANN-based algorithms such as FeedForward Neural Network (FNN), and BackPropagation Neural Network (BPNN) in traffic management.

Yang et al (2019) proposed a method using BPNN to predict traffic flow and obtain the congestion grade judgment. The generated data was based on SUMO traffic simulation data, and the proposed congestion evaluation algorithm based on road occupancy (CRO) was compared with three other evaluation methods namely as congestion evaluation based on mileage ratio of congestion (CMRC), road speed (CRS), and vehicle density (CVD). The results indicated that the method accurately expresses the congestion degree of roadways with less training cost and low processing time of real-time processing. In another study Nadeem and Fowdur (2018) proposed a hybrid NN by combining an adaptive prediction algorithm

(Adaptive RMSE) with BPNN. The data in this paper is based on real-time GPS data, which updates the database, but the effect of data increment in the accuracy was not discussed.

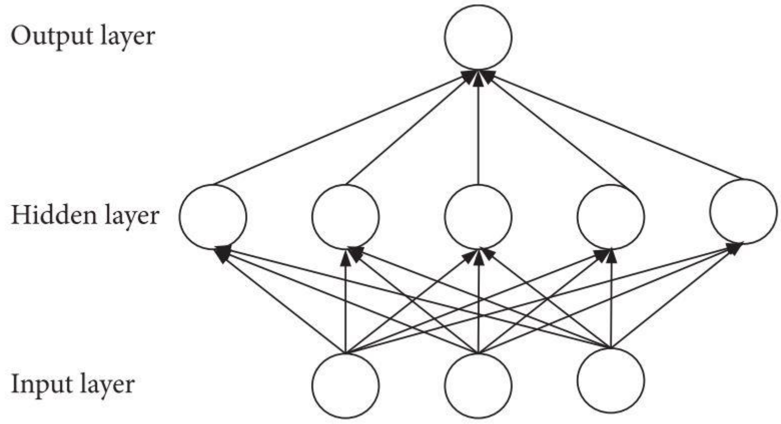

Figure 3: Basic structure of ANN

One of the benefits of using ANN algorithms is the flexibility in data analysis, and ability to deal effectively with multidimensional problems. The artificial neurons of each layer can be changed based on the input data. ANNs are effective in modelling and recognizing patterns for variety of road types due to the flexible structure that allows to capture complex nonlinear behaviors. However, to increase the performance of ANN large datasets are required, which increases the complexity.

b. Regression Model

Regression is a statistical method that models the relationship between input and output numerical variables. Two of the most common models are Simple Linear Model with one input, and Multiple Linear Regression with multiple inputs. Regression has been used in data science and ML for varies tasks such as prediction, forecasting, and time series modelling. There are various types of regression such as linear regression, and logistic regression.

Navarro-Espinoza et al (2022) applied multiple machine learning algorithms such as Linear Regression, Gradient Boosting, and Random Forest to predict the traffic flow. The algorithms were performed on public dataset derived from induction loops. The algorithms achieved similar results, and Linear Regression had the lowest performance accuracy while required less training time compared to other models. Despite achieving promising results, using more features could possibly increase the traffic flow prediction accuracy.

Zhang and Qian (2018) proposed a framework to predict traffic congestion by exploring correlation among energy usage and roadway congestion. The results indicate that electricity use patterns have both positive effect (in morning) and negative effect (at night) on congestion on highways. LASSO regression is used to find the correlations between the pattern features and select the most critical features that are linearly related to the response.

Lonare and Bhramaramba (2020) integrated the spatiotemporal correlation and compared linear regression model and LSTM model in traffic speed prediction. According to the results, LSTM model provided better performance.

Regression techniques have shown promising results in forecasting timeseries problem such traffic forecasting and traffic management. Although linear time series are effective, these models usually leave certain aspects of data unexplained. Therefore, these models are not reliable for nonlinear datasets.

c. Decision Tree (DT)

A decision tree is a supervised learning method for classification and prediction. Decision tree uses a set of if-then-else conditions to learn from data. It uses all features present in data to make a series of decisions. In some cases, instead of a single tree, multiple decision trees can produce effective results, which is also known as Random Forest. Random Forest randomly creates decisions trees and aggregate the results to provide the final decision based on the majority.

The study by Navarro-Espinoza et al (2022) used Random Forest to predict traffic speed. This method has shown better results than Linear Regression model. Liu and Wu (2018) proposed a model based on random forest, where a combination of Classification and Regression Trees, known as CART, was applied to predict traffic congestion. They used several features such as weather conditions, time, road quality and holiday in the model.

Decision tree classifies the data by learning simple decision rules based on one or multiple input data. However, Decision tree usually creates binary results, which is not suitable for the task of traffic congestion prediction.

d. Support Vector Machine (SVM)

SVM is a well-known classification technique which can be applied to solve various research issues. It is categorized as a statistical ML method which aims to drive a higher dimensional linear space from the non-linear data. In such a space, the data can be classified linearly by the hyperplane which can be useful in traffic pattern recognition and state prediction. Tseng et al (2018) applied SVM with traffic theory using multi-source data such as traffic data, weather data and social media data. Another study applied Adaptive Particle Swarm Optimization to optimize the parameters of adaptive Multi-kernel SVM. It also introduced how to adaptively adjust the hybrid kernel function's weight according to the change tendency of real-time traffic flow. Spatiotemporal information of correlative locations is incorporated and are combined with AMSVM's autoregressive predicted value. The performance is measured using MAPE, RMSE and R which are 10.2608%, 3632% and 0.9654 respectively.

iii. Deep Learning (DL)

Deep Leaning, also called Deep Machine Learning (DML) is in fact the "deep" ANN. Indeed, "deep" indicates several hidden layers on NN. While in SML there is only one hidden layer, DL has several hidden layers. These hidden layers are units of nonlinear process units which are used for feature extraction and transformation of data. in DL, diverse traffic data can be converted into feature vectors or patterns within certain time limit (Akhtar & Moridpour, 2021). Therefore, DL has lots of strengths to be the dominant method in TSP.

with limited collection time horizon into patterns or feature vectors. From last few years, DL has become popular in traffic congestion prediction studies. In this section, DL algorithms which are used in TSP will be discussed. Figure 4 illustrates DL algorithms.

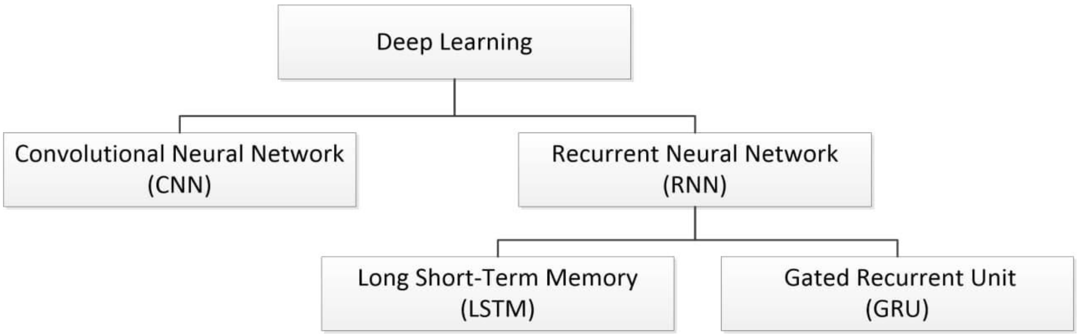

Figure 4: Deep Leaning Models

a. Convolutional neural network (CNN)

One of the common DL algorithms in TSP is Convolutional neural network (CNN). CNN has wide usage in image processing and computer vision. Considering traffic data as a time-space (2D) matrix, CNN can process traffic data well. The time-dimension features of the matrix are associated with the road's traffic information. Space-dimension features of the matrix are associated with the traffic flow information in a timestamp among all roads (Sun et al., 2019). Hence, the traffic state variables of roads can be predicted by CNN at certain timesteps. When the time-space features of the input data are extracted, traffic state prediction can be done through a full connection layer. In the study by Ma et al (2017), first matrix dimension represents the temporal feature and the second matrix dimension represent average traffic speed. It performed the false-positive rate and detection rate for different dataset partitions. However, Traffic speed is evaluated using only 3 traffic congestion levels, which are heavy traffic (0-20), moderate traffic (20-40), and free flow traffic (>40). Multiple convolutional operations is applied by M. Chen et al. (2018) to model the multiscale traffic patterns and temporal dependencies. It used video surveillance data. In this paper, the congestion level is defined as the average travel time for that segment at each timeslot, which will be compared with the PCNN congestion level prediction.

b. Recurrent Neural Networks (RNNs)

Another important algorithm in DL is Recurrent Neural Networks (RNNs). Spatiotemporal features can be learned by RNNs. Consequently, using RNN as a DL prediction model is recommended. In RNN, the output of the previous timestep is used as the input of the next timestep. Backpropagation through time is the basis of how RNN learns. RNN can have an input layer, hidden layer, and output layer.

The RNN has two variants called LSTM and GRU.

- **Long short-term memory (LSTM):** LSTM is variant of RNN. The main improvement of LSTM over RNN is adding gate structure in the hidden layer cells.
- **Gated Recurrent Unit (GRU):** The GRU model is a variant of the LSTM model. The GRU model combines the input gate and the forgetting gate into an update gate, which incorporates the cell state and the hidden state.

Cui et al (2018) proposed a deep stacked bidirectional and unidirectional LSTM called SBU-LSTM to predict the traffic speed using fixed positioned sensors. While it presented good accuracy performance for speed prediction, the traffic congestion levels are not identified. A study proposed a Res-RGNN (Residual Recurrent Graph Neural Networks) to predict traffic speed using loop detector data (Chen et al., 2019). It is a hybrid algorithm of GRU and Graph convolution which models the direct relationships between historical and future time-steps using gating mechanism. While it achieved good performance results, it still requires investigation for spatiotemporal features learned by MRes-RGNN for better interpretability. Another study predicted traffic speed using several algorithms including CNN, LSTM and GRU and used the predicted speed it to identify congestion level (Sun et al., 2019). It applied HMM-based map-matching for estimation of the average traffic speed as a pre-processing step before prediction. The LSTM model achieved the highest performance. The best performance results for window length of 8, MAE, RMSE and MSE are 1.45, 6.08 and 36.97 respectively. A research by Zhang et al (2019) proposed a traffic congestion model using attention-based LSTM using fixed position sensors. It showed how a specific traffic state is important to the entire traffic flow and implied more contextual association. Nevertheless, its emphasis on traffic flow rather than speed prediction, as an important method for congestion prediction, might be the reason of not having significant results. Another study presented a model to predict traffic speed and propagate the congestion level using LSTM (Majumdar et al., 2021). It applied loop detector data for experimentation and used RMSE to measure performance, which achieved 84–95%. The major weakness of the work is lack of numerical experiment for congestion level identification. Only visual congestion propagation was presented.

The Future of AI and Machine Learning in TSP

Precise short-term traffic speed prediction is useful in road guidance and speed inducing, which can help drivers to avoid traffic congestion and get fast, safe, and comfortable trip experience. According to research, machine learning has shown to be effective in predicting traffic state. Although there are challenges in providing accurate prediction, given the rapid advances in AI, we expect AI to enhance and provide more accurate results.

The current experimental traffic data only has location, speed, and time. As a future research direction, the researchers can combine multi-source traffic data such as traffic information updates by users in social media and weather condition data.

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References

Abiodun, O. I., Jantan, A., Omolara, A. E., Dada, K. V., Mohamed, N. A. E., & Arshad, H. (2018). State-of-the-art in artificial neural network applications: A survey. *Heliyon*, *4*(11), 938. https://doi.org/10.1016/J.HELIYON.2018.E00938

Akhtar, M., & Moridpour, S. (2021). A Review of Traffic Congestion Prediction Using Artificial Intelligence. *Journal of Advanced Transportation*, *2021*. https://doi.org/10.1155/2021/8878011

An, S. H., Lee, B. H., & Shin, D. R. (2011). A survey of intelligent transportation systems. *Proceedings - 3rd International Conference on Computational Intelligence, Communication Systems and Networks, CICSyN 2011*, 332–337. https://doi.org/10.1109/CICSyN.2011.76

Cao, W., & Wang, J. (2019). Research on traffic flow congestion based on Mamdani fuzzy system. *AIP Conference Proceedings*, *2073*(1), 020101.

https://doi.org/10.1063/1.5090755

Chen, C., Li, K., Teo, S. G., Zou, X., Wang, K., Wang, J., & Zeng, Z. (2019). Gated residual recurrent graph neural networks for traffic prediction. *33rd AAAI Conference on Artificial Intelligence, AAAI 2019, 31st Innovative Applications of Artificial Intelligence Conference, IAAI 2019 and the 9th AAAI Symposium on Educational Advances in Artificial Intelligence, EAAI 2019*, 485–492. https://doi.org/10.1609/aaai.v33i01.3301485

Chen, M., Yu, X., & Liu, Y. (2018). PCNN: Deep Convolutional Networks for Short-Term Traffic Congestion Prediction. *IEEE Transactions on Intelligent Transportation Systems*, *19*(11), 3550–3559. https://doi.org/10.1109/TITS.2018.2835523

Cui, Z., Ke, R., Pu, Z., & Wang, Y. (2018). Deep Bidirectional and Unidirectional LSTM Recurrent Neural Network for Network-wide Traffic Speed Prediction. *ArXiv:1801.02143*.

Dave, V. S., & Dutta, K. (2012). Neural network based models for software effort estimation: a review. *Artificial Intelligence Review 2012 42:2*, *42*(2), 295–307. https://doi.org/10.1007/S10462-012-9339-X

Dimitrakopoulos, G., & Demestichas, P. (2010). Intelligent transportation systems: Systems based on cognitive networking principles and management functionality. *IEEE Vehicular Technology Magazine*, *5*(1), 77–84. https://doi.org/10.1109/MVT.2009.935537

Kim, J., & Wang, G. (2016). Diagnosis and Prediction of Traffic Congestion on Urban Road Networks Using Bayesian Networks: *Transportation Research Record*, *2595*(1), 108–118. https://doi.org/10.3141/2595-12

Lin, L., Li, J., Chen, F., Ye, J., & Huai, J. (2018). Road Traffic Speed Prediction: A Probabilistic Model Fusing Multi-Source Data. *IEEE Transactions on Knowledge and Data Engineering*, *30*(7), 1310–1323. https://doi.org/10.1109/TKDE.2017.2718525

Liu, Y., & Wu, H. (2018). Prediction of road traffic congestion based on random forest. *Proceedings - 2017 10th International Symposium on Computational Intelligence and Design, ISCID 2017*, *2*, 361–364. https://doi.org/10.1109/ISCID.2017.216

Lonare, S., & Bhramaramba, R. (2020). Traffic Flow Prediction Using Regression and Deep Learning Approach. *New Trends in Computational Vision and Bio-Inspired Computing*, 641–648. https://doi.org/10.1007/978-3-030-41862-5_63

Ma, X., Dai, Z., He, Z., Ma, J., Wang, Y., & Wang, Y. (2017). Learning Traffic as Images: A Deep Convolutional Neural Network for Large-Scale Transportation Network Speed Prediction. *Sensors 2017, Vol. 17, Page 818*, *17*(4), 818. https://doi.org/10.3390/S17040818

Majumdar, S., Subhani, M. M., Roullier, B., Anjum, A., & Zhu, R. (2021). Congestion prediction for smart sustainable cities using IoT and machine learning approaches. *Sustainable Cities and Society*, *64*(September 2020). https://doi.org/10.1016/j.scs.2020.102500

Nadeem, K. M., & Fowdur, T. P. (2018). PERFORMANCE ANALYSIS OF A REAL-TIME ADAPTIVE PREDICTION ALGORITHM FOR TRAFFIC CONGESTION. *Journal of Information and Communication Technology*, *17*(3), 493–511. https://doi.org/10.32890/JICT2018.17.3.8262

Navarro-Espinoza, A., Lopez-Bonilla, O. R., García-Guerrero, E. E., Tlelo-Cuautle, E., López-Mancilla, D., Hernández-Mejía, C., & Inzunza-González, E. (2022). Traffic Flow Prediction for Smart Traffic Lights Using Machine Learning Algorithms. *Technologies*, *10*(1), 5. https://doi.org/10.3390/TECHNOLOGIES10010005

Newson, P., & Krumm, J. (2009). Hidden Markov map matching through noise and sparseness. *Proceedings of the 17th ACM SIGSPATIAL International Conference on Advances in*

Geographic Information Systems - GIS '09, 336–343. https://doi.org/10.1145/1653771.1653818

Onieva, E., Lopez-Garcia, P., Masegosa, A. D., Osaba, E., & Perallos, A. (2016). A Comparative Study on the Performance of Evolutionary Fuzzy and Crisp Rule Based Classification Methods in Congestion Prediction. *Transportation Research Procedia*, *14*, 4458–4467. https://doi.org/10.1016/J.TRPRO.2016.05.368

Onieva, E., Milanes, V., Villagra, J., Perez, J., & Godoy, J. (2012). Genetic optimization of a vehicle fuzzy decision system for intersections. *Expert Systems with Applications*, *39*(18), 13148–13157. https://doi.org/10.1016/j.eswa.2012.05.087

Rodrigues, F., Henrickson, K., & Pereira, F. C. (2019). Multi-Output Gaussian Processes for Crowdsourced Traffic Data Imputation. *IEEE Transactions on Intelligent Transportation Systems*, *20*(2), 594–603. https://doi.org/10.1109/TITS.2018.2817879

Sun, S., Chen, J., & Sun, J. (2019). Traffic congestion prediction based on GPS trajectory data. *International Journal of Distributed Sensor Networks*, *15*(5). https://doi.org/10.1177/1550147719847440

Sun, S., Zhang, C., & Yu, G. (2006). A Bayesian network approach to traffic flow forecasting. *IEEE Transactions on Intelligent Transportation Systems*, *7*(1), 124–133. https://doi.org/10.1109/TITS.2006.869623

Tseng, F. H., Hsueh, J. H., Tseng, C. W., Yang, Y. T., Chao, H. C., & Chou, L. der. (2018). Congestion prediction with big data for real-time highway traffic. *IEEE Access*, *6*, 57311–57323. https://doi.org/10.1109/ACCESS.2018.2873569

Yang, X., Luo, S., Gao, K., Qiao, T., & Chen, X. (2019). Application of Data Science Technologies in Intelligent Prediction of Traffic Congestion. *Journal of Advanced Transportation*, *2019*. https://doi.org/10.1155/2019/2915369

Zaki, J. F., Ali-Eldin, A., Hussein, S. E., Saraya, S. F., & Areed, F. F. (2020). Traffic congestion prediction based on Hidden Markov Models and contrast measure. *Ain Shams Engineering Journal*, *11*(3), 535–551. https://doi.org/10.1016/J.ASEJ.2019.10.006

Zaki, J. F., Ali-Eldin, A. M. T., Hussein, S. E., Saraya, S. F., & Areed, F. F. (2019). Time Aware Hybrid Hidden Markov Models for Traffic Congestion Prediction. *International Journal on Electrical Engineering and Informatics*, *11*(1). https://doi.org/10.15676/ijeei.2019.11.1.1

Zhang, P., & Qian, Z. (Sean). (2018). User-centric interdependent urban systems: Using time-of-day electricity usage data to predict morning roadway congestion. *Transportation Research Part C: Emerging Technologies*, *92*, 392–411. https://doi.org/10.1016/J.TRC.2018.05.008

Zhang, T., Liu, Y., Cui, Z., Leng, J., Xie, W., & Zhang, L. (2019). Short-Term Traffic Congestion Forecasting Using Attention-Based Long Short-Term Memory Recurrent Neural Network. *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, *11538 LNCS*, 304–314. https://doi.org/10.1007/978-3-030-22744-9_24

Zhang, Y., & Ye, Z. (2008). Short-Term Traffic Flow Forecasting Using Fuzzy Logic System Methods. *Journal of Intelligent Transportation Systems: Technology, Planning, and Operations*, *12*(3), 102–112. https://doi.org/10.1080/15472450802262281

Zhao, J. (2015). Research on Prediction of Traffic Congestion State. *MATEC Web of Conferences*, *22*, 01059. https://doi.org/10.1051/MATECCONF/20152201059

Zhu, L., Krishnan, R., Guo, F., Polak, J. W., & Sivakumar, A. (2019). Early Identification of Recurrent Congestion in Heterogeneous Urban Traffic. *2019 IEEE Intelligent*

Transportation Systems Conference, ITSC 2019, 4392–4397. https://doi.org/10.1109/ITSC.2019.8916966

Zhu, L., Yu, F. R., Wang, Y., Ning, B., & Tang, T. (2019). Big Data Analytics in Intelligent Transportation Systems: A Survey. In *IEEE Transactions on Intelligent Transportation Systems* (Vol. 20, Issue 1, pp. 383–398). Institute of Electrical and Electronics Engineers Inc. https://doi.org/10.1109/TITS.2018.2815678