AUT Journal of Civil Engineering

AUT J. Civil Eng., 5(4) (2021) 715-726
DOI: 10.22060/ajce.2022.21090.5791

Traffic Level of Service Prediction by Support Vector Machine, Deep Neural Network and Long Short-Term Memory Models

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ABSTRACT: Short-term prediction of traffic parameters and informing them to travelers and transportation operators is a useful tool for advanced traveler information systems. Also, as an advanced traffic management system, it helps to make or maintains the balance between travel demand and supply for the near future. This paper predicts the hourly traffic level of service, which has easily understandable information for all users. Data used in this study is related to 5 sections of a critical suburban road in the north of Iran. This data was collected for five years, and due to its high volume, it is considered big data. Long short term memory and deep neural network as two deep learning algorithms and support vector machine as a well-known classifier are trained by the first four years records. Results show that in average long short term memory predictions are more accurate for all sections, which compared to the second precise model, long short term memory predictions are higher between 1 and 14%. Using long short term memory for predicting level of services A and C, support vector machine for predicting level of services B and D and deep neural network for predicting E and F, bring the highest accuracy for each level of service.

Review History:

Received: Feb. 09, 2022
Revised: Apr. 26, 2022
Accepted: Apr. 27, 2022
Available Online: May, 05, 2022

Keywords:

Big data
Short-term prediction
Support vector machine
Deep neural network
Long short-term memory.

1- Introduction

The increase in urbanization and mobilization in most large cities and on the other hand, the limitations of resources to construct and widen the roads cause insufficient supply for all travel demands. The imbalance of travel supply and demand leads to traffic congestion occurrence [1]. This is also true not only in urban areas but also on high-traffic suburban roads. Traffic congestion causes a waste of energy, time, and money. In such a situation, the deployment of intelligent transportation systems can be useful to improve the performance of the existing transportation network. For this purpose, based on previous experiences, using advanced traffic management systems (ATMS) and advanced traveler information systems (ATIS) can be a success [2]. The main component of such systems is the short-term prediction of traffic parameters shortly. Informing these predictions will help travelers and professionals to reduce traffic congestion. Also, these systems have several economic advantages. Reducing traffic congestion and fuel consumption, air pollution reduction, decreasing the demand for constructing new roads, and decreasing operational costs are some economic advantages, which lead to saving tens of billions of tomans.

The research on short-term traffic prediction can be grouped based on these three questions. What traffic parameters are predicted? What data are used for prediction? What method is used for prediction?

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Predicting traffic volume and average speed are widely studied in previous studies [3-5]. Since the travel time is difficult to be directly measured, it is less studied than the other two traffic parameters [2, 6]. Each of these three parameters has a continuous nature. Little attention is put on predicting traffic level of service (LOS). This qualitative parameter has more significant information for users who do not know the specific parameters of the transportation network [7]. Another advantage of predicting LOS is that the problem is changed into a classification problem, which can be expected to be more accurate [7].

Regarding data sources, traffic data can be collected by loop detectors, mobile sensors like GPS and Bluetooth, traffic monitoring cameras, and Remote Traffic Microwave Sensors (RTMS) [7, 8]. Due to the emergence of these systems, a large amount of real-time and historical data becomes available at high spatial and temporal resolutions [9], and traffic data are exploding [10]. Therefore, the prediction problem requires data-driven models more than ever [9, 10]. Predictions are more valid and accurate using big data, but some models do not have the potential to use such data [11].

Prediction methods can be divided into two general categories of parametric (statistical) and non-parametric (machine learning) [11, 12]. Smoothing [13], ARIMA [14], and Kalman filtering [15] are well-known parametric prediction methods. These models have a well-established theoretical background [11]. It is possible to interpret the marginal effect and signs and investigate elasticity and estimator properties

[16, 17]. One of the main disadvantages of parametric models is the concentration on mean and losing extreme peaks [11]. Needing prior assumptions decreases their flexibility [11]. Also, by increasing the volume of data, these models significantly require more time and processing power to do mathematical calculations [16, 18]. In contrast, non-parametric models have no or fewer primary assumptions. These models consider outliers, missing, and noisy data [11]. Non-parametric models can depict nonlinear and high dimensional relationships and are more compatible with the high volume of traffic big data [11]. Although these models are not very interpretable and their main purpose of them is to increase the prediction accuracy [16]. Neural network [19] and non-parametric regression [20] are the most applicable non-parametric models [11].

This paper aims to make four contributions. First, this paper defines and predicts the qualitative LOS, which measures the performance of the transportation links. Second, we used traffic big data which is collected for five years. Also, new features related to the solar and lunar calendar, holidays, time of day, and blockage by police or accident are extracted and used. Third, the short-term prediction problem is investigated for a suburban road in Iran as a developing country. Many studies focus on urban traffic prediction. Since the destination of this suburban road is a tourist city, the majority of trips are recreational and non-routine. Forth, methodologically, we used deep machine learning methods, including Long Short Term Memory (LSTM) and Deep Neural Network (DNN), and also the Support Vector Machine (SVM) to predict LOS. The accuracy of these models is compared. This comparison shows the superior performance of the proposed models for each section of the road.

2- Previous Studies

Since the 1980s, researchers have begun to study the short-term prediction of traffic parameters [21]. By increasing computational power and evolution of prediction methods, the focus of studies on the prediction of traffic parameters such as traffic speed and flow and travel time was increased. In this section, previous studies are reviewed based on predicted traffic parameters, used methods, and data.

Various statistical methods have been employed in traffic parameters prediction such as the autoregressive integrated moving average (ARIMA) [22], probabilistic graphical methods such as Markov chain [23], Markov random fields (MRF) [24], and Bayesian network [25]. For example, Xu et al. [26] predict LOS using a combined ARIMA and Kalman filter. The prediction error of the combined method is lower than the pure ARIMA and Kalman filters. Jayan and Anusha [27] collect travel time by Bluetooth and RFID (Radio Frequency Identifier) sensors under mixed traffic conditions. They predict travel time using the ARIMA model. Yang et al. [28] investigate floating car speed prediction by using a combined wavelet-ARIMA model. First, the wavelet solves missing data and noise disturbance problems, and then ARIMA predicts speed.

Neural networks (NNs) [29, 30], SVM [31], K-nearest neighbourhood (KNN) [32], Locally weighted learning (LWL) [33] and deep learning methods such as LSTM [34] are well-known time series prediction methods. Wu et al. [35] develop a deep neural network-based traffic flow prediction model (DNN-BTF) that can mine spatial-temporal features of traffic flow. The proposed method outperforms states of the art methods such as the traditional shallow back-propagation neural network (BPNN) and stacked autoencoder (SAE) in terms of prediction error. Ma et al. [36] predict traffic speed by learning traffic as an image. A convolutional neural network (CNN) based method is employed to extract traffic feature and predict traffic speed. Tian et al. [37] predict traffic flow by using an LSTM-based model. They employed multi-scale temporal smoothing to infer missing data. To capture more information from traffic flow data Tan et al. [38] propose a novel method based on dynamic tensor completion (DTC). Compared to ARIMA, the accuracy of the designed algorithm is improved, especially under missing data. Yao et al. [39] consider dynamic spatial dependencies between locations and the daily and weekly temporal dependency to predict traffic flow. They propose a novel spatial-temporal dynamic network (STDN) and verify its effectiveness. Although machine learning methods can model nonlinear relationships, Li et al. [40] refer to requiring a large amount of data and lack interpretability as two main deficiencies of them and investigate the accuracy and efficiency concepts. They predict LOS by an algorithm based on partial least square (PLS). To predict LOS Liu et al. [41] propose a fully convolutional model based on semantic segmentation technology, which is appropriate for grid-based Spatio-temporal LOS prediction in dense urban areas. Xu et al. [42] present an algorithm based on kernel K-nearest neighbors (kernel-KNN) to predict LOS.

Some studies combined different methods and show that hybrid methods' performance is better than pure methods. Wang et al. [43] predict vehicle-type specific traffic speed using hybrid empirical mode decomposition (EMD) and ARIMA (EMD-ARIMA). The proposed model outperforms the traditional ARIMA, the Holt-Winters, the NN, and a naive model. Lue et al. [44] combine the KNN and LSTM to predict traffic flow. KNN can capture spatial features of traffic flow, and LSTM is used for mining temporal variability and prediction of traffic flow.

The short-term prediction is applied to diverse transportation research. Jiang et al. [45] predict online car-hailing services demand using the least squares support vector machine (LS-SVM) model. By using a DNN model that consists of a CNN and LSTM Petersen et al. [46] predict bus travel time. Liu et al. [47] employ a deep learning-based algorithm to predict metro passenger flow. Tu et al. [48] present a novel deep belief network method to predict flight delay.

3- Methodology

3- 1- Deep neural network

Typical NNs have three layers, an input layer, a hidden layer(s), and an output layer that full connection is applied between them. Each layer consists of several processing ele-

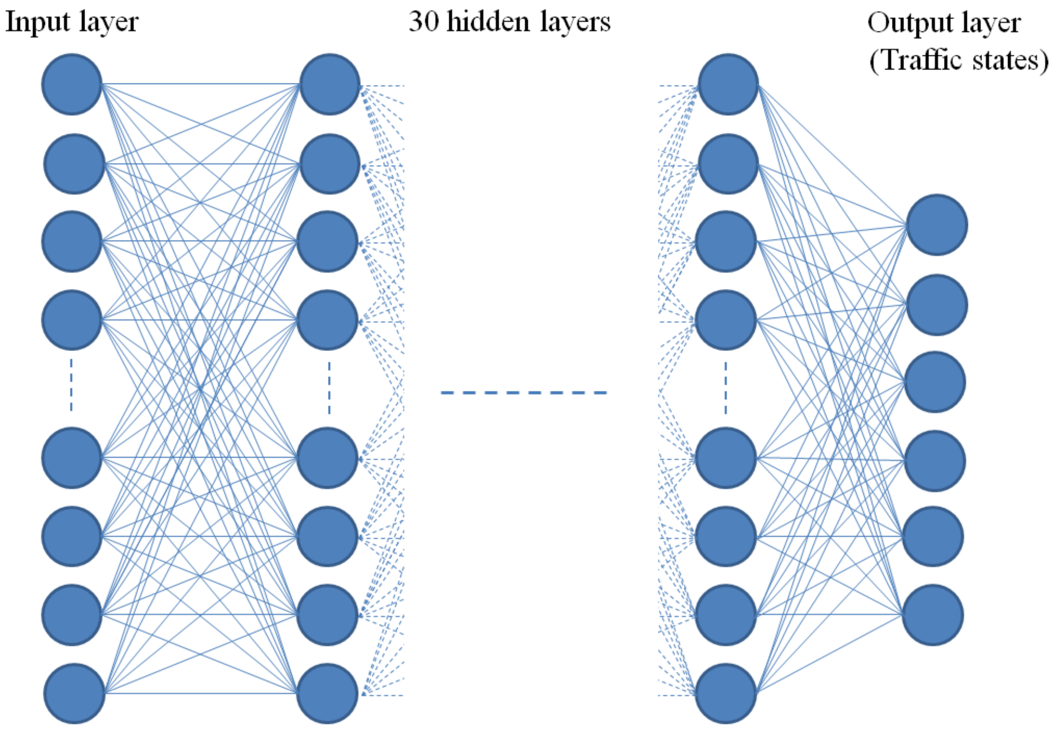

Fig. 1. The architecture of used DNN.

ments (PEs). PEs in hidden layers receive the outputs of previously connected layers and transform them into a weighted linear summation (Eq. (1)) and gives it to connected next layers as their input.

$$I_{j(k)} = \sum_{i=1}^{M} w_{ij} \sigma w_{i(k-1)} O_{i(k-1)} + \gamma \tag{1}$$

Where $I_{j(k)}$ and $O_{j(k)}$ are the input and output of the jth PE in the hidden layer k. M is the number of PEs in the previous layer. w_{ij} is the weight of connections, and γ is a bias term. $\sigma()$ is a sigmoid transform function. Step, hyperbolic tangent, and rectified linear unit are other popular functions. Eq. (2) presents sigmoid formulation:

$$\sigma(X) = \frac{1}{1+\exp(-X)} \tag{2}$$

Increasing the number of hidden layers and PEs is converted shallow NN to DNN. It is expected that the DNN model provides a more accurate prediction [35]. Deep-learning methods are representation-learning methods with multiple levels of representation [49, 50].

The fully connected DNN architecture used in this study consists of 1 input layer, 30 hidden layers, and one output layer. Fig. 1 shows the architecture of used DNN.

3- 2- Long short term memory

The LSTM networks are a special type of recurrent neural network (RNN) capable of learning long-term dependencies. For the first time, these networks were introduced in 1997 by Hochreiter and Schmidhuber [51]. Traditional RNNs can model nonlinear time series relationships but are not able to train the time series with long time lags. Also, it is difficult to find the optimal time window size automatically [2]. LSTM can address these issues by incorporating memory units and learning when to forget previous memories and update memories [37].

Let denote the input time series with D variables of length T as $X = (X_1, X_1, \ldots, X_T)$. Where X_t is the t-th observation. c_t is a memory cell, contains information at time step t, and is controlled by three gates. These gates control whether to forget the current cell value (forget gate f_t, Eq. (3)), to read its input (input gate i_t, Eq. (4)), and to output the new cell value (output gate o_t, Eq. (5)) [37]. Also, $\tilde{c}_t$ (Eq. (6)) is an input modulation gates. All these gate, cell update and output are computed in the following formulas [36]:

$$f_t = \sigma\left(W_{xf} X_t + W_{hf} h_{t-1}\right) \tag{3}$$

$$f_t = \sigma\left(W_{xf} X_t + W_{hf} h_{t-1}\right) \tag{4}$$

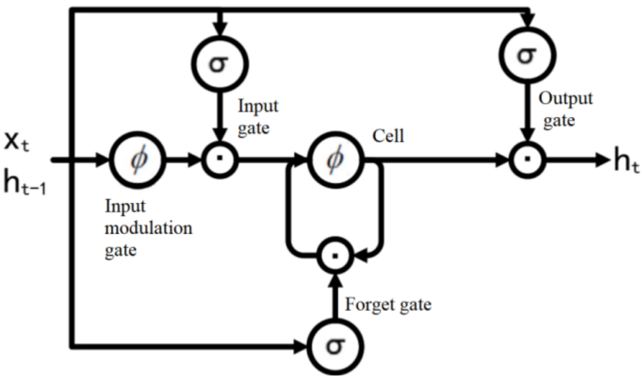

Fig. 2. The architecture of an LSTM network [37].

$$o_t = \sigma\left(W_{xo} X_t + W_{ho} h_{t-1}\right) \tag{5}$$

$$\tilde{c}_t = \varphi\left(W_{xc} X_t + W_{hc} h_{t-1}\right) \tag{6}$$

$$h_t = o_t \odot \phi\left(c_t\right) \tag{7}$$

$$c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t \tag{8}$$

Where $\odot$ indicates scalar product. W s are the network parameters matrices. h_t (Eq. (7)) is the hidden state. $\phi()$ is the hyperbolic tangent function, and $\sigma()$ denotes the sigmoid transfer function (Eq. (2)).

Fig. 2 shows the architecture of an LSTM network.

3- 3- Support vector machine

The SVM is a supervised machine learning technique that is used for both classification and regression (SVR) problems. In the case of classification, SVM finds linear boundaries between different classes. For linearly separable data, the main aim is to find hyperplanes with the largest distance from the nearest data point in each class, which are known as support vectors. After finding support vectors, the rest of the data can be discarded. Fig. 3 shows the best boundary (the black one) for classification, which has equal distances from support vectors of red and blue classes.

In many cases, data is distributed non-linearly. Before finding boundaries, it is essential to map data into a separable space by using mathematical functions, named the Kernel function (Fig. 4).

Common kernel functions are linear, polynomial, sigmoidal, and radial basis functions (RBF). This study used the widely used RBF kernel function [53]. The formulation of the RBF function is as Eq. (9) [54].

Where σ is a free parameter to be calibrated. $(X_i - X_j)^2$ is the squared Euclidean distance between the two feature vectors X_i and X_j [30, 55].

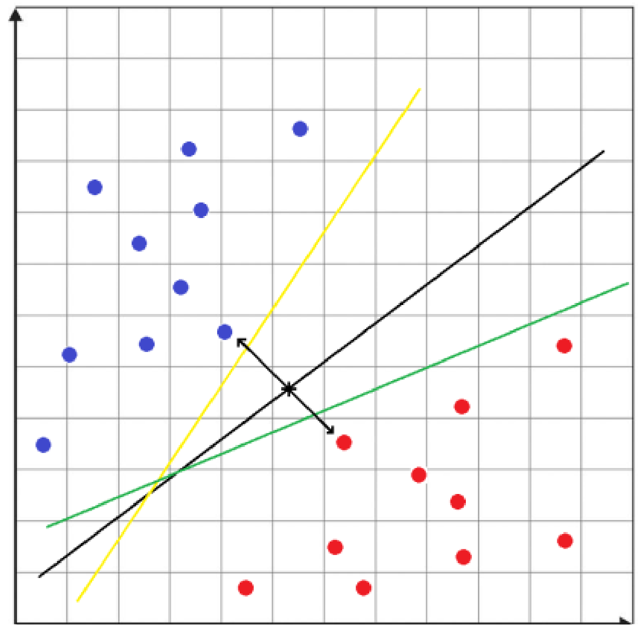

Fig. 3. The optimal boundary for separating classes [52].

4- Dataset

Data used in this study is related to Karaj to Chaloos suburban road in Iran. This road is a critical traffic channel in the north of Iran, and in many hours of the year, congested traffic is observed on this road. Traffic data is collected by loop detectors from March 2013 to March 2019. Each record consists of hourly traffic parameters, including hourly traffic flow, hourly average traffic speed, and hourly LOS. By knowing the ratio of the hourly average traffic speed to the road free-flow speed and the ratio of hourly traffic volume to the road capacity, the hourly LOS is defined based on Table 1. This type of LOS definition is provided by Iran road maintenance and transportation organization (http://www.rmto.ir/en). The level of service of road decreases from A to E.

Where V/C and S/S_f are the ratio of the hourly average traffic speed to the road free-flow speed and the ratio of hourly traffic volume to the road capacity, respectively.

The raw data has the following details.

As the destination of this road is a tourist city, many of the travels are non-mandatory and non-routine. It is expected that calendar-related features such as weekdays, months, and holidays have a direct effect on LOS. Also, each holiday has a different effect on LOS, so it seems to be necessary to consider the type of holidays as a feature alongside calendar-related features. This study includes both the lunar and solar calendars because some of the holidays are based on the solar calendar, and others are related to the lunar calendar. Blockage by accident and police directly affects the performance of each direction of road and parallel paths. By considering these factors, effective features are extracted and presented in Table 3.

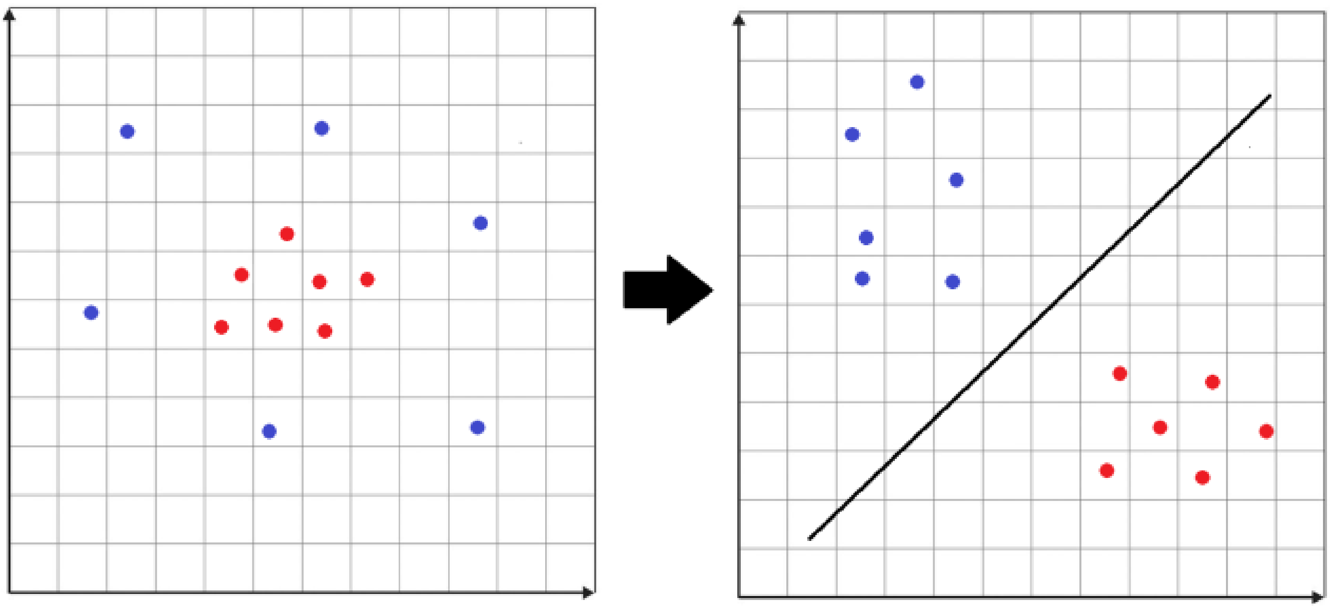

Fig. 4. Mapping data into separable space by the Kernel function [52].

Table 1. Defining hourly LOS.

S/Sf \ V/C	Under 0.1	0.1-0.3	0.3-0.5	0.5-0.7	0.7-0.9	Over 0.9
Over 0.95	A	A	B	C	D	E
0.8-0.95	A	B	C	D	D	E
0.6-0.8	B	C	D	D	E	E
0.45-0.6	C	D	D	E	E	F
0.3-0.45	E	E	E	E	F	F
Under 0.3	F	F	F	F	F	F

Table 2. Description of the raw dataset.

Name	Details
ID	Road identification code
Mehvar_id	Route identification code
Start_time	Starting date and time of periods
End_time	Ending date and time of periods
Total Car Counter	Hourly traffic volume
average speed	Hourly average traffic speed
Traffic LOS	Hourly LOS

Table 3. Description of features used in predictive models.

Feature Name	Description	Type
Season	Including spring, summer, fall, and winter	Nominal
Solar month	Including 12 solar months	Nominal
Lunar month	Including 12 lunar months	Nominal
Day of a solar month	Including 29-31 days of a solar month	Nominal
Day of a lunar month	Including 29-30 days of a lunar month	Nominal
Time of day	Including 24 hours a day	Nominal
Day or night	Including day and night	Dummy
Number of holidays	The number of sequential holidays	Continuous
Holidays	Includes 1 for holidays and 0 for other days	Dummy
Holiday type	Type of holidays	Nominal
Days before holidays	Equal to 1 if there is at least one holiday in 3 next days	Dummy
Type of ahead holidays	Including the type of holiday in 3 next days	Nominal
Days after holidays	Equal to 1 if there is at least one holiday in 3 past days	Dummy
Type of previous holidays	Including the type of holiday on 3 previous days	Nominal
Blockage	Blockage of the road by accidents or by police	Dummy
Blockage of the opposite direction	Blockage of the opposite direction by accidents or by police	Dummy
Blockage of parallel paths	Blockage of parallel paths by accidents or by police	Dummy

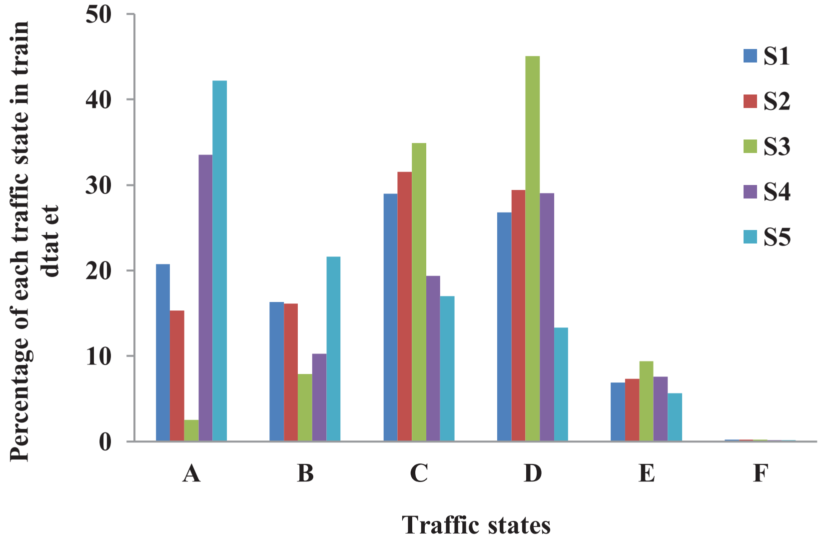

Fig. 5. The percentage of each LOS in each station.

LOS is predicted for five sections of the Karaj-Chaloos road, Named S1, S2, S3, S4, and S5. Fig. 5 shows the percentage of each LOS in each station.

Each section of this road has different attributes such as slope, number of lanes, and geometric design. These differences lead to different LOSs at the same time. Section S3 only has one lane for each direction, and in many hours of the year, LOSs, C, and D have occurred. In section S5, traffic flows are more stable because of more capacity and free flow speed compared to other stations. Attributes of sections S1, S2, and S4 are similar to each other. Also, records are not distributed equally based on LOSs. Traffic LOS E and F for all stations and LOS A for station S3 occurred rarely. This is more severe for LOS F, in which the percentages are under 1% for each section.

Table 4. Prediction accuracy of models for each section

Models	S1	S2	S3	S4	S5
SVM	35.7%	26.9%	36.7%	60.1%	62.5%
DNN	43.5%	27.9%	28.7%	51%	62.2%
LSTM	49.9%	32.1%	37.8%	62.8%	65.2%

Table 5. Accuracy of models for each traffic state.

LOS	Models	S1	S2	S3	S4	S5	Average
A	SVM	33.1	87.2	31.6	82	89.4	64.7
	DNN	76.8	99.3	69.5	61.8	90.6	79.6
	LSTM	82.5	98	47.7	86.3	87.5	80.4
B	SVM	72.9	9	66.8	33.5	21	40.6
	DNN	35	9.9	32.5	39.3	19.2	27.2
	LSTM	45.1	0.2	64.2	31.1	30.8	34.3
C	SVM	16.3	19	32.6	37.8	8.8	22.9
	DNN	29.5	13.4	17.6	41.6	8	22.0
	LSTM	65.7	23.7	18	31.4	4.1	28.6
D	SVM	40.2	54	23.3	17.5	27.4	32.5
	DNN	37.8	37.7	28.3	13.3	17.3	26.9
	LSTM	23.8	54.2	36.1	34.3	4.8	30.6
E	SVM	20.8	11.5	15.5	0	13.5	12.3
	DNN	45.8	18.8	26.8	0	0	18.3
	LSTM	0	19.2	17.1	0	0	7.3
F	SVM	5.6	15	0	-	0	5.2
	DNN	5.6	12.9	4.1	-	0	5.7
	LSTM	0	0	0	-	0	0.0

5- Results and Discussion

First, by applying the normalization function, the data are changed so that the range of data changes is in the range [-1 1]. Records from March 2013 to March 2018 are used to train models, and the rest of the records are used for the test. Table 4 shows the accuracy of predictions for the test dataset of each road section.

LSTM outperforms SVM and DNN for all five sections. The accuracy differences are notable for sections S1 and S2. For sections S3, S4, and S5, although the LSTM has the highest accuracy, the accuracy differences are limited to 1-2%. DNN has more accuracy for S1 and S2 compared to SVM, and for the other three sections, SVM's predictions are more accurate than DNN.

To evaluate the performance of models for predicting each LOS, the prediction accuracy of LOS is calculated and presented in Table 5.

Highlighted cells indicate the most accurate model. For traffic LOS A, the LSTM has the highest average accuracy. DNN with little accuracy difference compared to LSTM predicts traffic LOS A. For LOS A; the DNN model is the most accurate model of stations, S2, S3, and S5. The SVM predicts LOS B better than other models, especially for satiations S1 and S3. Although DNN prediction accuracy is the highest for stations S2 and S4, it has the lowest accuracy of LOS B prediction on average. The performance of DNN in the prediction of light LOSs is not as well as in other models. Prediction of LOS C is more accurate by the LSTM. SVM and DNN have similar performances for this LOS. As the frequency of LOSs decrease from LOS A to LOS F, the accuracy of models is also dropped except for traffic LOS D which all three models have more accurate predictions compared to LOS C. Also, SVM prediction matches the reality more than LSTM and DNN for traffic LOS D. The performance of DNN for

Table 6. Accuracy of models for each traffic state.

Researcher	Number of LOSs	Number of observations	Method	Accuracy
Antoniou *et al.* [56]	3	705	KNN	79.7
			ANN	83.7
	4	705	KNN	86.4
			ANN	86.6
Zahid *et al.* [57]	6	-	RF	97.2
			SVM	97.8
			ANN	95.8
			Rule induction	95.8
Zhu *et al.* [58]	4	49038	Decision tree	51
			SVM	57
			ANN	72
			CNN	85
			RNN	89.5
Toncharoen *et al.* [59]	3	10800	CNN	89
			ANN	87
			KNN	87
			RF	87
Current study	6	52560	SVM	26.9-62.5
			DNN	27.9-62.2
			LSTM	32.1-65.5

rare events including LOS E and F which are related to heavy and blockage LOSs and are more critical is better than other models. Although because these LOSs is rarely observed, models cannot be trained well, and the accuracy of the predictions declined significantly. Confusion matrices are presented in the appendix.

Finally, Table 6 compare obtained results with other researcher's results.

Based on Table 6, Although the number of LOSs and number of observations are different, but this table shows that obtained result is in an acceptable range regrading to previous studies.

6- Conclusion

LOS is a qualitative traffic parameter that shows the performance of the road and is more understandable for travelers. After informing predicted LOS travelers and transportation agencies through ATIS more sustainable transportation system can be expected. This paper aims to predict the LOS by using three machine learning techniques, SVM, DNN, and LSTM. LSTM model can capture the dependency between sequential records while SVM and DNN consider records independently. Traffic big data of 5 sections of Karaj to Chaloos as a suburban road in data collected for five years and was used to train and test models. Results show that on average, LSTM outperforms SVM and DNN for all five stations. On average, the prediction of traffic LOS A and C is more accurate by LSTM. For B and D LOSs, the highest prediction accuracy is achieved by SVM, and DNN can predict low occurrence frequency LOSs, E and F better than LSTM and SVM.

List of symbols

$I_{j(k)}$ The input of the jth PE in the hidden layer k

$O_{j(k)}$ The output of the jth PE in the hidden layer k

M Number of PEs in the previous layer

w_{ij} Weight of connections in deep neural network

γ Bias term in deep neural network

$\sigma()$ Sigmoid transform function

h_t Hidden state in LSTM

$\phi()$ Hyperbolic tangent function

σ Free parameter of SVM

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HOW TO CITE THIS ARTICLE

A. Rasaizadi, S. E. Seyedabrishami , M. S. Abadeh, Traffic Level of Service Prediction by Support Vector Machine, Deep Neural Network and Long Short-Term Memory Models , AUT J. Civil Eng., 5(4) (2021) 715-726.

DOI: 10.22060/ajce.2022.21090.5791

and Software Engineering (JCSSE), IEEE, 2018, pp. 1-6.

	SVM						DNN						LSTM					
	A	B	C	D	E	F	A	B	C	D	E	F	A	B	C	D	E	F
S1																		
A	584	146	39	13	21	1	1357	316	191	133	47	2	1458	402	130	177	259	4
B	1109	1014	1410	952	291	11	227	487	428	205	39	0	212	627	435	204	47	0
C	28	116	402	239	5	0	75	306	730	590	55	0	68	235	1623	1360	149	8
D	44	106	599	918	144	1	94	247	1035	863	114	8	29	126	283	544	132	6
E	2	9	21	162	122	4	14	35	82	476	269	7	0	1	0	0	0	0
F	0	0	0	1	4	1	0	0	5	18	63	1	0	0	0	0	0	0
S2																		
A	607	768	459	22	17	5	691	789	549	701	149	20	682	862	466	242	20	15
B	64	81	91	115	29	8	2	89	72	116	13	3	8	2	12	14	2	1
C	24	42	147	570	153	7	0	15	104	257	70	4	6	26	184	524	53	6
D	1	6	71	897	3244	152	0	1	44	701	2926	171	0	6	112	1009	3129	123
E	0	0	4	56	455	72	0	1	3	68	746	52	0	1	1	72	763	142
F	0	0	3	1	70	43	3	2	3	18	64	37	0	0	0	0	1	0
S3																		
A	110	262	77	34	9	6	242	910	547	190	32	4	166	415	113	45	24	7
B	186	1042	734	584	341	76	81	507	515	335	59	6	146	1001	853	512	127	12
C	40	210	448	370	131	15	14	109	242	400	106	7	20	106	248	317	124	1
D	7	32	107	330	136	15	9	20	60	400	318	49	13	36	153	510	360	58
E	5	13	8	72	119	11	2	13	10	65	205	52	3	1	8	30	131	45
F	0	0	1	24	30	0	0	0	1	24	46	5	0	0	0	0	0	0
S4																		
A	2699	941	105	38	8	0	2034	591	67	17	2	0	2842	1101	114	46	8	0
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C	43	415	129	62	6	0	145	609	142	91	12	0	50	315	107	48	9	0
D	0	23	20	29	7	0	12	51	27	22	10	0	0	13	16	57	12	0
E	0	0	0	0	0	0	2	7	2	3	0	0	0	0	0	0	0	0
F	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
S5																		
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