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Improving the accuracy of short-time traffic prediction in intelligent transport system based on machine learning algorithms

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Abstract

Intelligent traffic management systems, urban planning, and the reduction of traffic congestion all depend on traffic flow prediction. In this research, a method based on machine learning based on neural network combination and feature selection based on genetic algorithm is presented for predicting short-time traffic flow. The genetic algorithm-based approach seeks to find a model's optimal parameters globally. Inner-city traffic constantly changes and can be unpredictable. This is because traffic patterns repeat over time (have periodic characteristics) but also swing wildly from moment to moment (high fluctuations). As a result, it's very hard to guess what traffic will be like in the future. Thin operators have been used duo to it good performance for short-time traffic prediction in neural networks system. In Isfahan gathered traffic data to see how well a new model, called LSTM, predicts traffic flow. We compared LSTM's performance against other established methods like wavelet neural networks (WNN) and multilayer perceptron (MLP). the proposed neural network prediction model and genetic algorithm results have %97 accuracy, %97 correlation coefficient, 14.67 less average absolute error, higher signal-to-noise ratio, 0.97 entropy value, and 3.95 standard deviation. Compared to other methods, it has shown its superiority, such as ordinary neural networks. This model excels at finding the best solution quickly and accurately, even with noisy or complex data.

Keywords: *Artificial intelligence (AI); machine learning (ML); Intelligent transportation system (ITS); Traffic prediction (TP); wavelet neural networks (WNN); multilayer perceptron (MLP).*

1. Introduction

The main goal of this research is to provide an accurate method for predicting the time series of traffic data, or in other words, predicting short-time traffic based on machine learning methods [1-9]. In this research, a new method will be proposed to increase the accuracy of short-time traffic prediction with the help of machine learning. In which for high accuracy approximation, different data model is created using thin feature graph based on the types of data distribution [10-18]. Thin feature selection is a new feature selection method that has been considered in many fields of application such as image processing, data mining, and machine learning [19-25]. In thin feature selection, a graph of features is formed, the vertices of this feature graph and the edges of these features are correlations between features. The features extracted with the help of thin methods have a good correlation. These features will be used to train the network [26-40].

2. The importance and necessity of research

Imagine a transportation system that can predict traffic jams before they happen! That's the power of traffic flow prediction, a key part of intelligent transportation. By accurately guessing how many cars will be on the road at a specific time and place, traffic forecasting helps ease congestion, making travel safer and cheaper for everyone [41-44].

3. Innovative aspect of research

Traffic in cities as a dynamic and completely variable phenomenon is a very big challenge. With the increase in the volume of cars and the population, its problems are increasing day by day [45-49]. Traffic forecasting, which is part of the intelligent transportation system, can help in optimizing and solving the traffic problem. So far, many researches have been presented to predict short- time traffic, but there is a long way to arrive at a suitable answer. In this research, in order to

improve the parameters of short-time traffic prediction, a new method based on neural networks in machine learning is proposed. In the proposed method. In summary, the innovations of this research are as follows:
• Using thin feature graph to improve genetic algorithm in feature selection in time series forecasting
• Improving the accuracy of predicting traffic time series

4. Research objectives

The main goal of this research is predicting short-term traffic based on machine learning methods. In this research, in which for high accuracy approximation, different data model is created using thin feature graph based on the types of data distribution. In thin feature selection, a graph of features is formed, the vertices of this feature graph and the edges of these features are correlations between features [50-53]. The features extracted with the help of thin methods have a good correlation. These features will be used to train the network. They predicted short-term traffic by using deep neural networks. The data used in this research is the data collected in ten months from 170 streets of Seoul city in South Korea. Although deep learning-based methods are highly accurate in identifying and predicting traffic and speed, they require a large amount of data for training. The goal was to reduce the need for data processing resources as little as possible while maintaining an accuracy rate of no less than 80%, but by using the proposed algorithm an accuracy rate of 97% was achieved. I also saved the need for processing resources so that it became possible to use a laptop to process traffic intersection data [54-57].

4.1 Sub questions

Will the speed of short-time traffic forecasting with the help of graphs increase? Will the thin feature graph in short-time traffic prediction increase the convergence speed of the desired neural network in machine learning?

4.2 Genetic algorithm

In computer science, a genetic algorithm is a search method used to obtain an approximation for an answer to optimization and search problems. A particular kind of evolutionary algorithm called a genetic algorithm makes use of biological processes like inheritance and mutation. Darwin's theories of natural selection are applied via genetic algorithms to determine the best formula for identifying or matching the pattern. These algorithms are frequently a viable option for coincident prediction methods. Put otherwise, a genetic algorithm is a programming method that employs the model of genetic evolution for problem-solving [58].

4.3 Review of previous works

Traffic forecasting, which is a part of the intelligent transportation system, can help in optimizing and solving the traffic problem. Method Different methods for traffic prediction have been presented by researchers, and researches about this research topic are still ongoing. In the continuation of the results of the method There are various short-time traffic forecasts. At [59]A paper entitled "Short-time traffic speed prediction model for a parallel multi-lane arterial road using data monitored with GPS Based on Deep Learning Approach". This research tackles a powerful technique called Long Short-Term Memory (LSTM) network. At [60] in an article titled "Survey of Urban Traffic Flow Prediction Techniques" The review also identifies the types of data commonly used for traffic flow prediction, and compares how accurate different techniques. At [61] in an article titled "Prediction of traffic density in the city based on GPS using the combined CNN-RNN and C3D model", the researchers combined patterns of traffic flow as well as their weight to demonstrate the model both temporal and spatial characteristics. At [62] in an article titled “A hybrid deep learning model with attention-based conv- LSTM networks for short-term traffic flow prediction,”. This article explores a new method for predicting traffic flow. The method combines several deep learning techniques. Attention- based Conv-LSTM.

5. Suggested method

In order to predict short-time traffic in time series in machine learning, there are pre- processing stages, feature extraction from time series, feature selection and finally prediction. In the method proposed in this research, the time series data will be pre-processed using normalization. Then, using the genetic algorithm and a thinning method, the best features will be selected for prediction [63-66]. Then it will be predicted with the help of a method based on neural network or other methods. In this research family of methods based on neural network is used. Figure 1 displays the proposed method's overview. The steps of the suggested method will be described in the paragraph that follow.

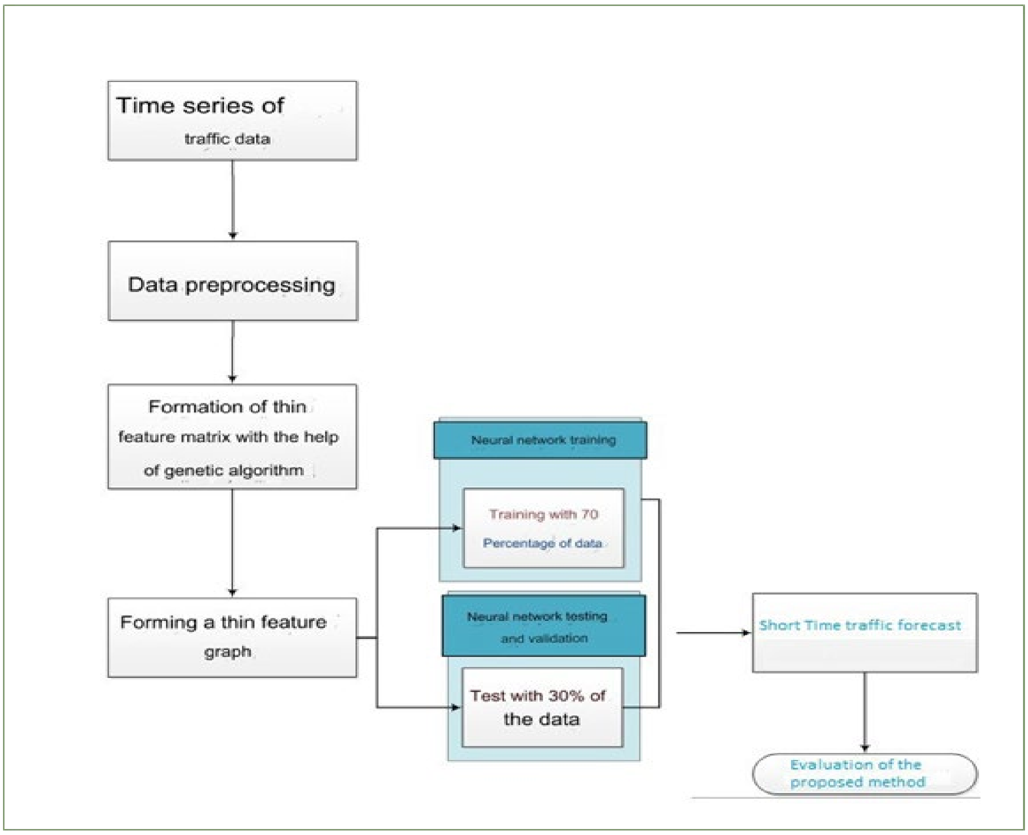

Fig. 1: Comparison of accuracy in different networks and prediction in all three sensors

The proposed system works in small cities where the number of intersections in the road network is relatively small, or part of a large city, because one of the goals of the system is the possibility of processing data using a portable calculator while maintaining the required prediction accuracy [67-70].

6. Improving the quality of time series data

Before using the collected data to solve the problem of traffic forecasting, the data must be pre- processed because the data in this research are the data that are actually collected by the sensors in the city. Due to the real nature of these data, there are missing values and also noise in these data [71-73]. Therefore, in the pre-processing stage, in addition to improving the quality of data by placingdata in different ways such as K nearest neighbor [74] and then normalization, quality data is provided for processing and prediction. The bleaching normalization method has been used in this research. In this method, if Xminand Xmax are the minimum and maximum data recorded by the sensor, respectively [75]. In this case,in the range of y min and y max, which is the minimum and maximum desired value in normalization. The following relationship expresses normalization in a data.

$$Y_i = Y_{min} + (Y_{max} - Y_{min})\frac{(X_i - X_{min})}{X_{max} - X_{min}} \tag{1}$$

Since in this research $Y_{\max} = 1,\ Y_{\min} = 0,$ and relation (1) can be reconstructed as relation (2) to be:

$$Y_i = \frac{X_i - X_{min}}{X_{max} - X_{min}} \tag{2}$$

Since this transformation is linear, the distribution of the data does not change slow as shown in the figure 2 below.

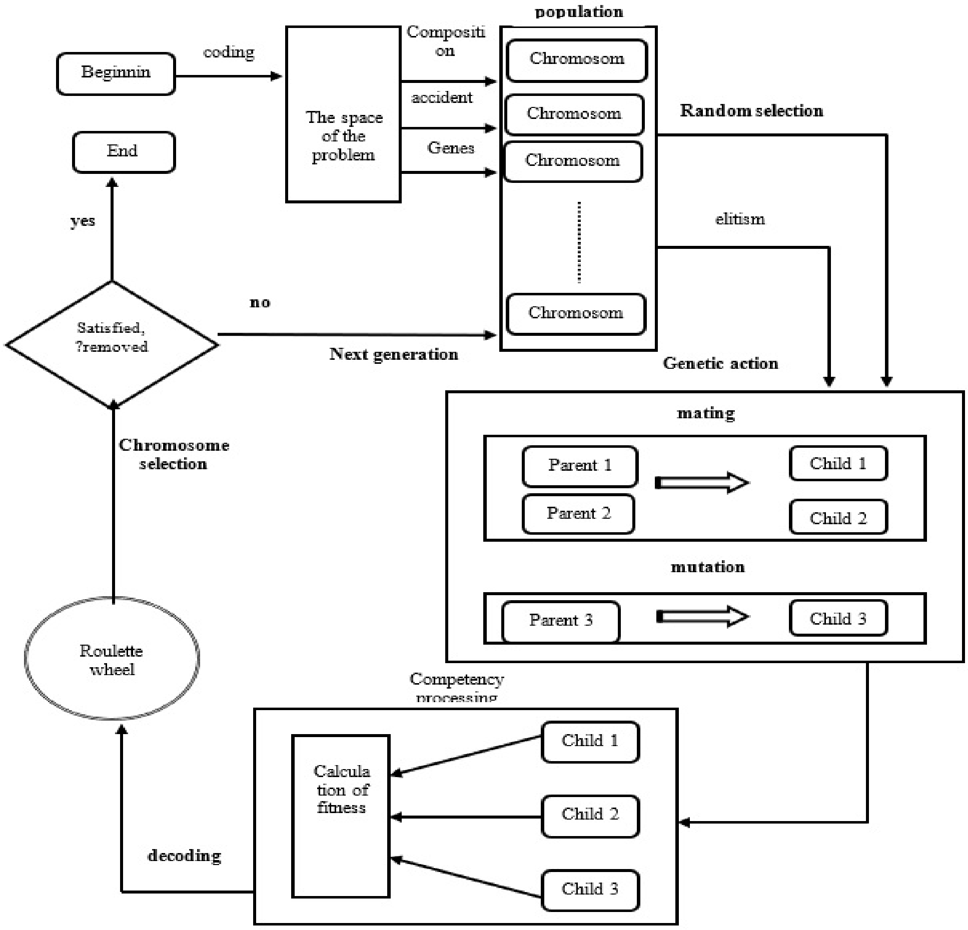

Fig. 2: Roulette wheel selection

7. Evaluation Criteria

1. The suitability of an algorithm or method for prediction depends on the obtained results. But it seems that, in general, there are two types of quantitative criteria used to evaluate these algorithms.
2. Criteria that evaluate each predicted value from the modeling with the corresponding value that is already available gives like a correlation coefficient, signal to noise ratio, peak signal to noise ratio, square root error and absolute error.
3. Criteria that measure the obtained information, such as entropy, mean gradient, spatial frequency, average, standard deviation, cross entropy [76-78].

8. Result

The necessary predictions in the proposed method have been made in the desired networks in three sensors. Tables 1, Table 2 and Table 3 are respectively the results of the evaluation criteria of the first group including C.C correlation, MAE absolute error value, SNR signal-to noise ratio, PSNR peak signal-to-noise ratio and RMSE square root error, and shows the prediction in all three sensors. The results in the tables are based on the best results obtained.

Table 1: The results of the evaluation criteria of the first type in the network Different sampling and prediction of the first sensor

criteria / method	CC	MAE	SNR	PSNR	RMSE
MLFNN	0.3370	34.8870	23.9390	20.8410	38.5276
WNN	0.5248	33.3922	25.9174	20.6828	37.8341
FNN	0.6013	25.2398	31.7659	23.5621	34.5698
RBFNN	0.8210	31.3956	34.4551	24.9820	31.0661
RNN	0.8437	29.3098	37.6216	29.0291	28.1408
CNN	0.9110	19.6510	38.1918	31.9900	26.8900
LSTM	0.9786	14.6263	40.3999	42.0072	22.1893

Table 2: The results of the evaluation criteria of the first type in different networks of sampling and prediction of the second sensor

criteria / method	CC	MAE	SNR	PSNR	RMSE
MLFNN	0.3370	26.5387	23.4853	21.4390	41.5087
WNN	0.5547	27.1105	25.8478	21.4459	34.4890
FNN	0.6127	24.5690	30.2707	24.9963	31.1097
RBFNN	0.7526	33.6519	34.2998	28.9766	29.6280
RNN	0.8505	25.7761	38.2027	29.9681	25.1408
CNN	0.9211	20.6168	36.0103	31.1714	27.1714
LSTM	0.9780	15.9176	39.6338	44.9245	21.2809

Table 3: The results of the evaluation criteria of the first type in different networks of sampling and prediction of the third sensor

criteria / method	CC	MAE	SNR	PSNR	RMSE
MLFNN	0.3479	29.4410	23.9495	21.5423	41.5080
WNN	0.6083	25.6424	24.3367	23.1398	37.5685
FNN	0.7045	23.2378	31.7651	32.4900	33.1652
RBFNN	0.7297	35.8966	35.8893	28.5748	28.5724
RNN	0.8064	23.5888	37.9649	30.6835	25.6075
CNN	0.9318	21.3201	36.7168	33.7112	27.6064
LSTM	0.9742	15.3591	39.8176	44.9059	19.3016

The necessary predictions in the proposed method have been made in the desired networks in three sensors. Tables 1, Table 2 and Table 3 are respectively the results of the evaluation criteria of the first group including C.C correlation, MAE absolute error value, SNR signal-to noise ratio, PSNR peak signal-to-noise ratio and RMSE square root error, and shows the prediction in all three sensors. The results in the tables are based on the best results obtained.
In order to evaluate more and with higher accuracy, the obtained results are also shown in the form of graphs. CNN convolutional neural network has similar results to LSTM. Although RNN has obtained good results compared to other neural networks, but due to the weakness in the memory and feedback unit, it has provided weaker results than LSTM.as shown in figure 3,4,5,6 and 7 The superiority of the LSTM method can be attributed to the memory units and their optimal use in the selected features in the proposed method.

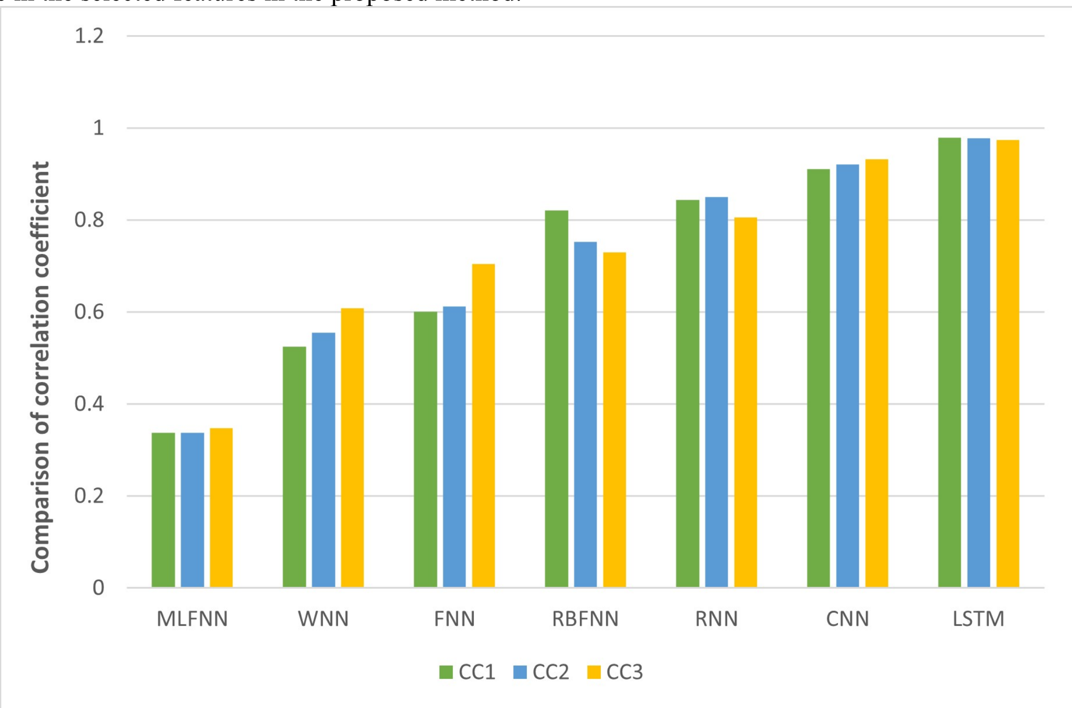

Fig. 3: Comparison of correlation coefficient in different networks and prediction in all three sensors

In a predictive model, the lower the mean absolute error, the more accurate the model's predictions.

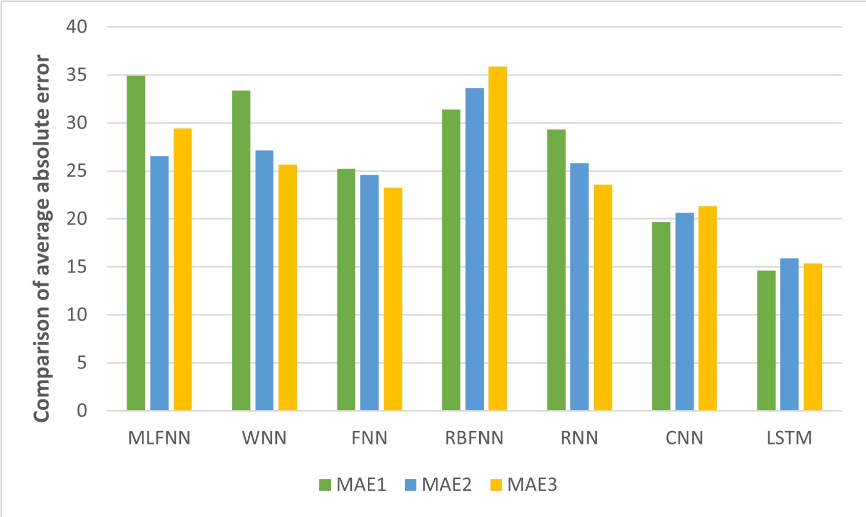

Fig. 4: Comparison of average absolute error in different networks and prediction in all three sensors

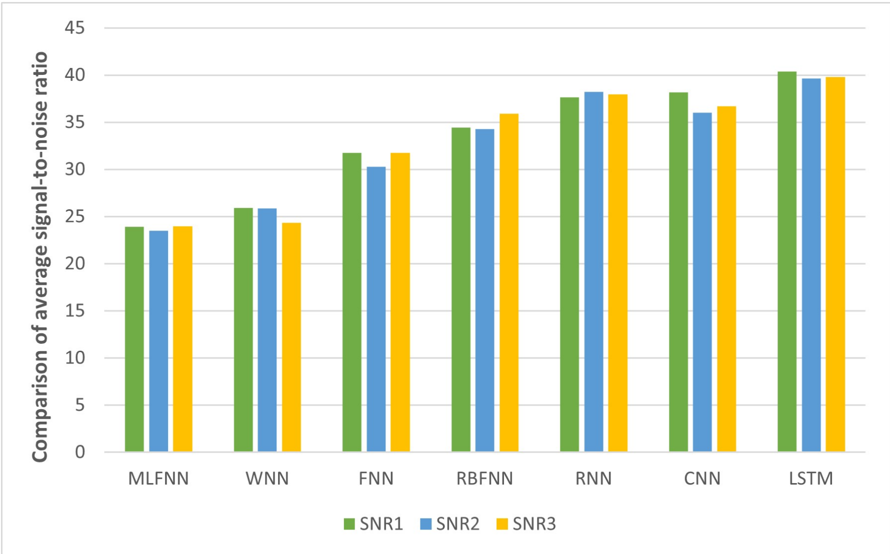

Fig. 5: Comparison of average signal-to-noise ratio in different networks and prediction in all three sensors

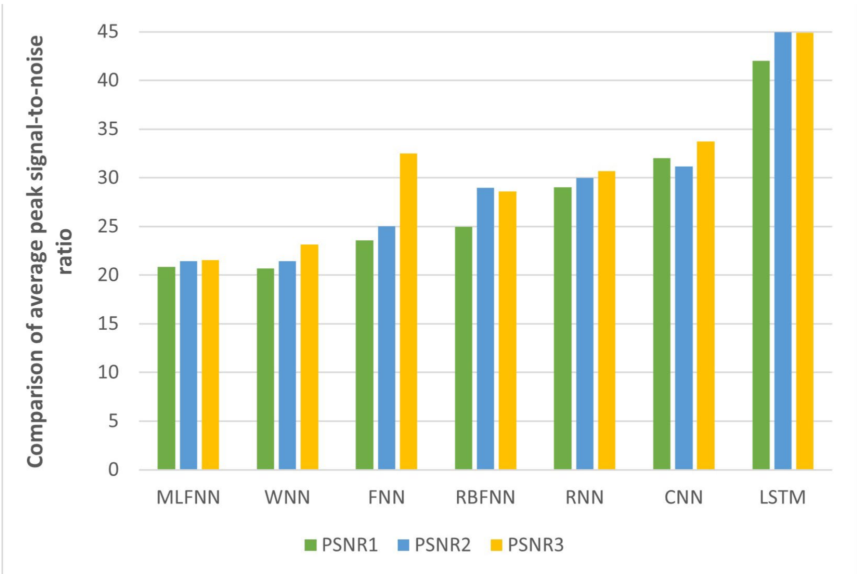

Fig. 6: Comparison of average peak signal-to-noise ratio in different sampling and prediction networks of all three sensors

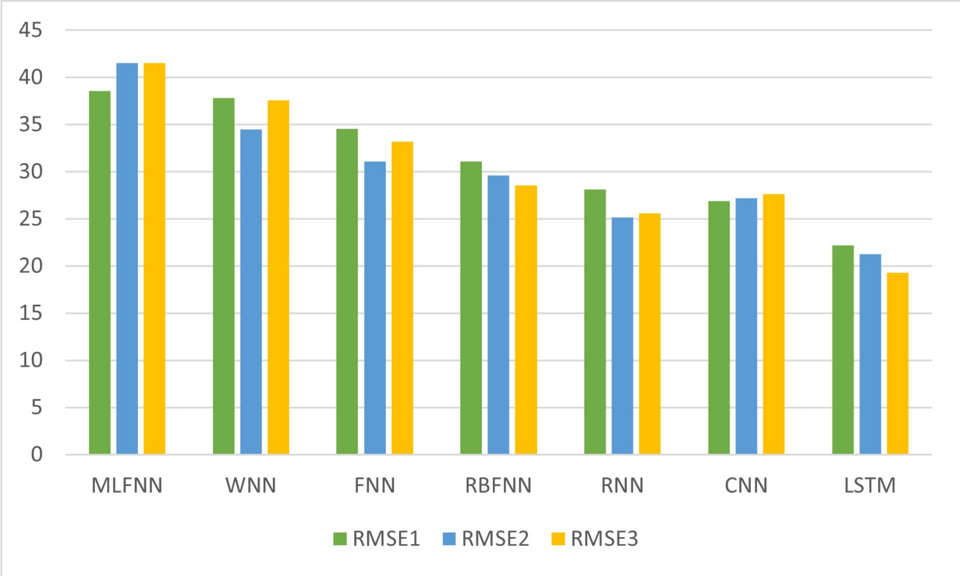

Fig. 7: Comparison of root mean error in different networks and prediction in all three sensors

Tables 4, Table 5 and Table 6 respectively show the results of the evaluation criteria of the second group including AVG average, ENT entropy, C.ENT cross entropy, AG gradient average, SD standard deviation. It shows the first, second and third sensor sampling and prediction in different networks. The results in the tables 4,5 and 6 are based on the best results obtained.

Table 4: The results of the evaluation criteria of the second type in different networks of sampling and prediction of the first sensor

criteria / method	ENT	SF	A.G	SD	ACC
MLFNN	0.8733	38.4063	19.6872	03.6265	84.45
WNN	0.9361	51.9643	27.5027	03.6767	85.29
FNN	0.914	60.3634	35.7684	03.4345	88.17
RBFNN	0.9399	63.5075	46.7142	03.7185	89.74
RNN	0.9543	66.0074	51.3860	03.7957	93.12
CNN	0.9611	67.7883	52.1256	03.8190	95.02
LSTM	0.9721	72.4148	55.8707	03.9593	97.45

Table 5: The results of the evaluation criteria of the second type in different networks of sampling and prediction of the second sensor

criteria / method	ENT	SF	A.G	SD	ACC
MLFNN	0.897	39.7077	20.3442	03.7054	85.11
WNN	0.9123	49.4052	28.8884	03.5860	85.89
FNN	0.9065	59.6551	35.7609	03.2791	87.39
RBFNN	0.9417	61.6882	45.4901	03.6713	89.90
RNN	0.9597	63.0548	47.3232	03.7609	94.50
CNN	0.9612	65.9343	50.9137	03.8811	95.77
LSTM	0.9875	69.2037	56.9786	03.9584	98.09

Table 6: The results of the evaluation criteria of the second type in different networks of sampling and prediction of the third sensor

criteria / method	ENT	SF	A.G	SD	ACC
MLFNN	0.8516	37.4872	19.1737	03.6818	84.39
WNN	0.9545	50.5959	29.3812	03.6767	89.94
FNN	0.9101	58.8910	36.9156	03.4150	90.89
RBFNN	0.8995	56.6443	46.3120	03.7230	91.5
RNN	0.9577	59.7889	46.3860	03.7390	95.01
CNN	0.9413	58.4934	51.5443	03.8331	96.19
LSTM	0.9616	66.5180	56.9960	03.9167	97.91

In order to evaluate, the results in figure 8, 9, 10, 11 and 12 obtained from tables 4, 5 and 6 are shown in the form of graphs.

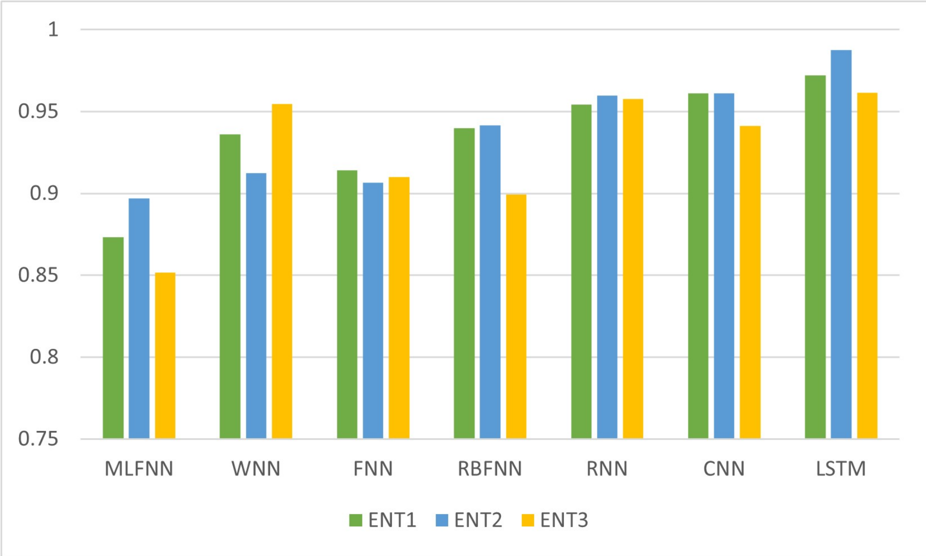

Fig. 8: Comparison of entropy in different networks and prediction in all three sensors

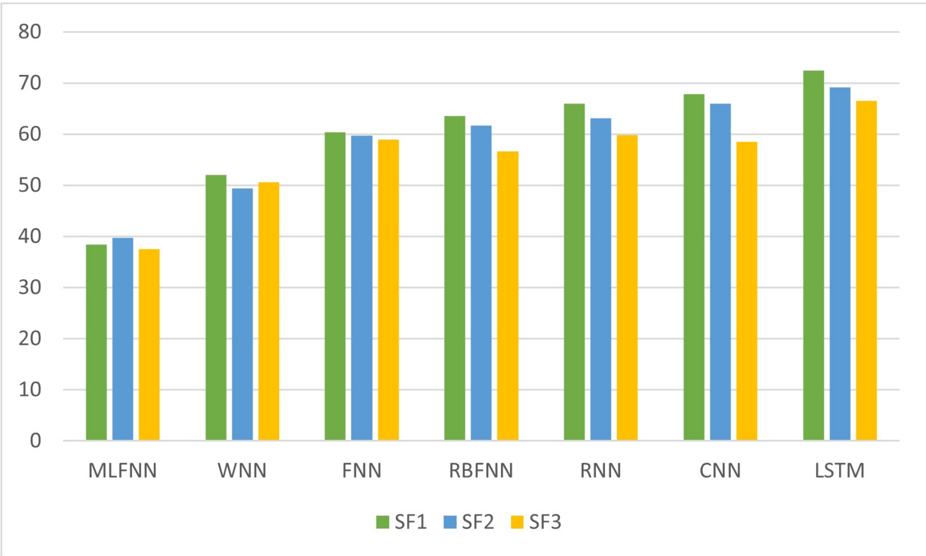

Fig. 9: Comparison of spatial frequency in different sampling and prediction networks of all three sensors

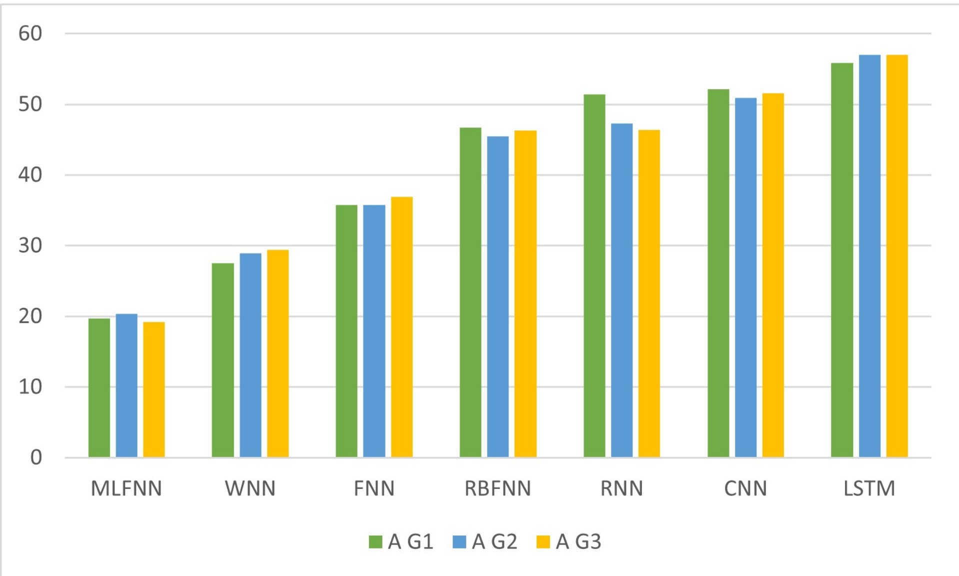

Fig. 10: Comparison of average gradient in different networks and prediction in all three sensors

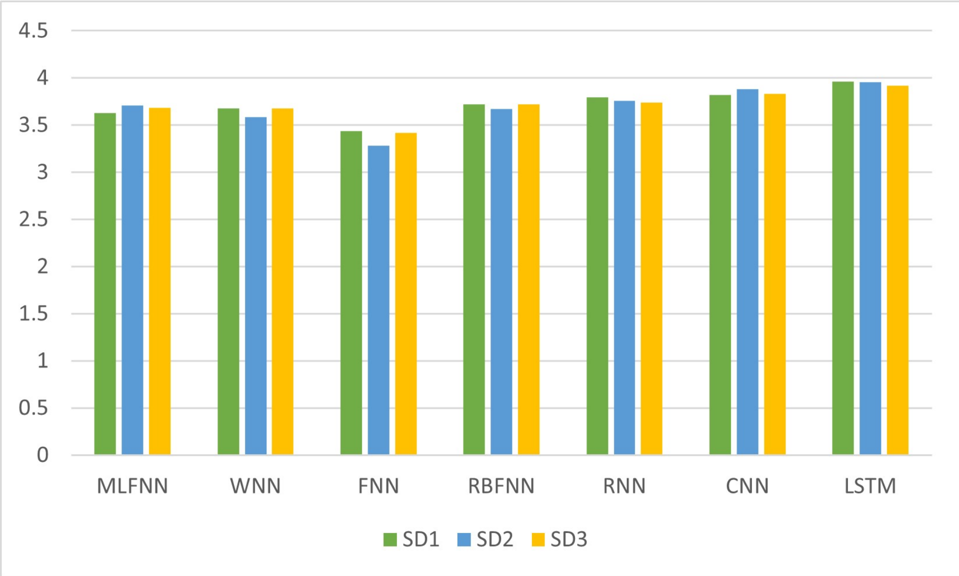

Fig. 11: Comparison of standard deviation in different networks and prediction in all three sensors

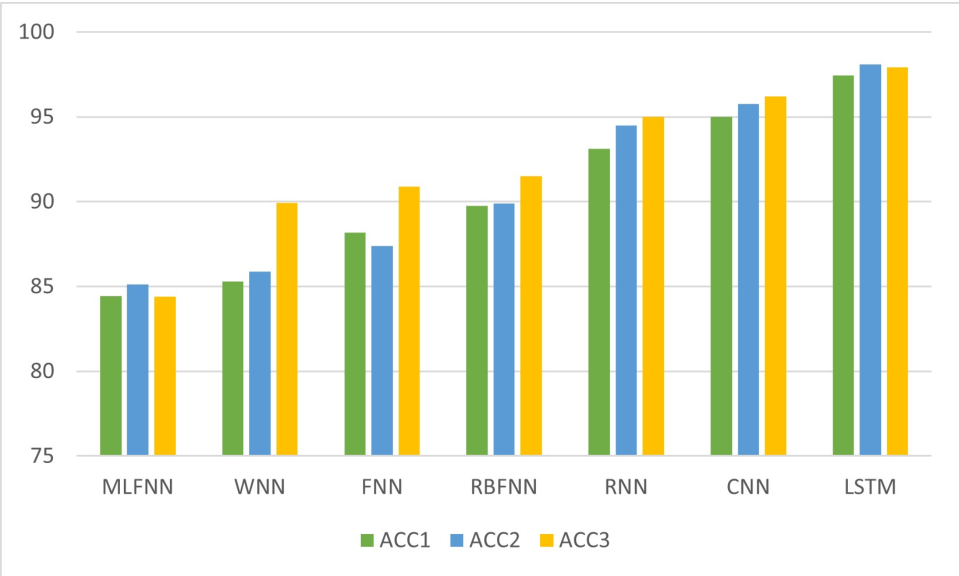

Fig. 12: Comparison of accuracy in different networks and prediction in all three sensors

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9. Conclusion

In this chapter of the research, in order to evaluate the proposed graph-based method, the sparse feature obtained from the genetic algorithm was considered as an input feature for prediction in MLFNN, WNN, FNN, RBFNN, RNN, CNN and LSTM neural networks. The parameters of the neural networks were adjusted. This adjustment was made based on experience to achieve the best result. It should be noted that the desired features cannot be used for CNN and CNN settings were done separately. It was evaluated in different criteria. The evaluation results in the discussed criteria show the superiority of the LSTM method over other neural network methods.
In this research, thin graph-based method is used to predict traffic in order to use time- spatial dependence in feature extraction from data. Random distributions can be used to determine the thin matrix. It seems that the random selection of thin matrix or even based on a distribution such as Gaussian distribution will not be powerful and reliable in determining the time-spatial dependence of the data.
Using optimization solutions can overcome this challenge. Genetic algorithm is a selection of evolutionary algorithms to determine this matrix. In this research, the thinning matrix is done with the help of genetic algorithm and based on the MSE objective function. This thinned matrix based on genetic algorithm has been used for short-time traffic prediction in various types of neural networks, including forward perceptron multilayer neural network, wavelet neural network, fuzzy, radial function, recursive and memory, as well as convolution.

The results of the simulation on the research data show the superiority of the LSTM neural network method in short-time urban traffic forecasting. The outcome shows the superiority of the proposed method in thinning the matrix in order to train the neural network. The discussed criteria, namely the MAE absolute error value, RMSE square root error and ACC accuracy all show the superiority of the LSTM method. Meanwhile, the CNN method is ranked second regardless of the need for a lot of data and computational complexity. RNN networks have also obtained similar results to CNN. By reviewing the research in order to expect short-time traffic, the following results can be achieved:
Most of the methods used in short-time traffic forecasting have disadvantages such as computational complexity, high processing cost, the need for large training data and sensitive to noise and missing values in the data.
Network usage neural networks in short-time traffic prediction than other methods- The ones used so far are more efficient be the accuracy and precision of short-time traffic prediction will increase by using neural networks. The use of neural network training algorithms in order to predict traffic has caused getting stuck in local minima.
This research has defined a thin matrix with the help of genetic algorithm. The genetic algorithm is one of the primary evolutionary algorithms that has weaknesses such as lack of convergence, being in local minima, diversity and a large number of regulatory parameters to reach a suitable answer. It seems that a newer meta-heuristic algorithm such as the gray wolf algorithm can be used to select a thin matrix. Other meta-heuristic algorithms such as Wall, the evolution of the corona virus can also help in this field.
In addition to thin matrix-based methods, the combination of traditional methods such as ARIMA and neural networks in predicting traffic time series can improve the prediction accuracy.
Deep learning methods and deep neural networks are among the methods based on modern machine learning, which have been successfully used in many fields and have shown their superiority in predicting traffic time series. have shown but a combination of thin methods and deep learning methods is a very interesting idea, which can be effective in improving prediction.

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