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Spatial Data-Driven Traffic Flow Prediction Using Geographical Information System

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ABSTRACT

Today, traffic is one of the biggest problems of urban management. There are two general methods for traffic management, soft and hard methods. In the hard method, physical changes are applied to the road network, and in the soft method, the existing conditions are optimized. Traffic forecasting is one of the soft methods for traffic management. Traffic forecasting is usually done based on the time of existing traffic conditions, while the effect of location and neighborhood, which is one of the concepts of GIS science, is less seen in predictions. In this research, variables affecting traffic were first identified. Then, five machine learning methods were used to predict traffic on all city roads. KNN method was selected as the best one with accuracy and Kappa of 96.14% and 0.95 respectively. Finally, the prediction map was prepared by applying the superior model and Geographic Information System (GIS). One of the advantages of the traffic prediction map is easy for users and administrators to manage traffic.

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1. Introduction

Traffic is one of the most important issues we face in our daily lives. Today, traffic has been associated with complexities in big cities, especially in metropolitan areas. Due to the many facilities, and cultural conditions of cities, we have witnessed an increase in migration from rural to urban areas. This has led to the growth of the urban population and urbanization. On the other hand, the increasing population and the lack of proper passages in cities have increased the number of vehicles and created a traffic problem in cities.

The increase in traffic causes other problems such as air pollution, noise pollution, environment destruction, care accidents, high fuel consumption and long travel time [1]. Accordingly, it is important to address the issue of traffic and its solution. Therefore, the authorities are trying to reduce traffic with various methods.

In intelligent transportation systems, traffic prediction is a basic component of many control and monitoring systems. Traffic prediction is a necessary step to achieve time optimization in the urban traffic control system. Hence, traffic prediction is an important research area for intelligent traffic control and traffic guidance. Therefore, using effective methods to predict traffic flow with high accuracy is very important.

Urban transportation planning officials are constantly trying to predict the future state of traffic on a network to take precautionary measures. If there was no prediction, we would see high traffic congestion and low service.

Traffic flow forecasting has a fundamental role in various issues such as traffic light management, route planning, and so on. For example, knowing the flow of traffic gives drivers the ability to make better decisions. Drivers can decide instantly according to the traffic situation and choose alternative routes to reach the destination.

In the past years, various types of research have been conducted on traffic forecasting, vehicle speed, and other traffic parameters. However, less success has been achieved in reaching the goals with higher precisions [2]. In this paper, we propose a solution to predict vehicular traffic using Machine Learning (ML) techniques. In this paper, variables that affect traffic are identified. Here five methods Decision Tree (DT), K-Nearest Neighbor (KNN), Discriminant Analysis, Naive Bayes, and Neural Network (NN) are used to learn the effect of the parameters on the traffic situation. Then, the most accurate method is selected based on the knowledge extracted from the learning. Finally, the future traffic of the city can be predicted by entering the new data into the model. A traffic map of the city's future can also be prepared by using GIS. The main purpose of this study is to increase the accuracy of traffic forecasting and also display forecast traffic maps. This study can help travelers and traffic officials in the decision-making process whether for travel or management purposes.

So far, various studies have been done on this subject, for example, Smith and Demetsky developed four historical means, neural network, time series, and nonparametric regression models to test freeway traffic prediction. The results showed that the nonparametric model performs better [3]. Zuo et al. created a new method for developing the weights of the k-NN model [4]. Akbari et al. suggested a cluster k-NN model to prevent discontinuous data interference in the database [5]. In 2015, Meng et al. proposed a two-step method based on the balanced binary tree and Advanced K-Nearest Neighbor (AKNN) techniques for predicting short-term traffic flow. The result showed that the k-NN model has a good result in predicting short-term traffic [6]. Xingyin Duan et al. studied the five urban areas using 1.4 billion GPS taxi records and gray correlation analysis to find factors that affect traffic congestion. They finally predicted traffic congestion through the BP neural network [7]. Su Su Hlaing et al. proposed RF theory and NN methods to simulate complex and nonlinear processes to predict traffic flow and road traffic accident based on historical traffics data [8]. Aditya Rao et al. proposed a dynamic traffic system that calculated the percentage of congestion and allocated the timer to each signal [9]. The proposed system used image processing techniques to process the video. Pavan Chhatpar et al. conducted a traffic forecast study in 2020. They provided predictive analysis of traffic in a given area using supervised learning techniques such as Back Propagation Neural Network (BPNN) [10]. They also designed an Android application to predict the traffic densities of the entire map areas in an offline mode using real-time traffic data. Zhang Tao et al used the non-parametric regression method of K-nearest neighbors to predict short-term traffic flow. The result showed that the non-parametric regression method has high precision[11]. In 2002, Tan Guozhen et al. constructed an intelligent neural network model based on the neural network using linear independent and sigmoid functions with tunable parameters. They found that the prediction convergence speed and accuracy are greatly improved compared with the traditional BPN [12]. Thammasak Thianniwet et al. used a decision tree learning algorithm to categorize GPS data. In this study, the level of traffic congestion was also determined by recording road traffic images [13]. Cynthia Jayapal et al. introduced a way to predict traffic for mobile users. Mobile phones are equipped with traffic applications that use GPS to identify locations. This data is sent to a remote server that predicts traffic congestion. The traffic is then transferred to the end user's phone [14]. In 2020, Gaurav Meena et al. used machine learning algorithms, Decision Trees (DT), Support Vector Machine (SVM), and Random Forest (RF) to predict traffic, while the RF algorithm performed better than the others [15]. Sharmila and Velaga (2020) used machine learning techniques such as Artificial Neural Networks (ANN) and SVM to estimate corridor-level travel time. They considered various factors such as road geometry, traffic variables, location information from the GPS receiver, and other spatiotemporal parameters that affect travel time. A k-fold cross-validation technique was then used to determine the optimum model parameters in the ANN and SVM models [16]. Srikanth and Mehr used a VISSIM microscopic traffic simulation model to generate traffic flow data. They compared the Adaptive Neural-Fuzzy Inference System (ANFIS), ANN, and Multiple Linear Regression (MLR) models to predict the number of passenger cars. The results showed that the ANFIS model estimates are closer to the real data compared to MLR and ANN models [17]. In 2022, Ghasempoor and Behzadi predicted the traffic in the coming days using the neural network algorithm based on the collected traffic data. Traffic forecasting was done using basic neural network methods, Feed-forward Levenberg-Marquardt, Conjugate Gradient Neural Networks, and Bayesian Neural Networks. The results showed that the Feed-forward Levenberg-Marquardt method predicts traffic data with 81.59% accuracy, which had the most accuracy among other methods [18]. Andrew Moses and Parvathi R proposed a solution to predict vehicular traffic using machine learning techniques. In their study, vector regression support, linear regression algorithms, decision tree, and random forests were used, and finally, random forests had a better performance than other methods [19].

Given the serious problem of traffic in most cities and its harmful effects, it is necessary to find solutions to solve this problem. Tehran is one of the densely populated cities where the traffic problem is the main problem of urban management. The high population and lack of proper transportation have caused traffic congestion in this city. In this research, all the main roads of the city are considered as the study area. Presenting the future traffic situation in the form of a map is very efficient for users, which is done in this research using GIS. In the present study, the introduction and background of the research are stated first. The second part introduces the methods and theories and examines the effectiveness of the proposed model. In the end, the result of the research and future research opportunities are presented.

2. Methodology

There are different methods to predict the traffic flow of a city. Most of which are very expensive and time-consuming. In this research, traffic forecasting was done using computational intelligence algorithms. At first, the required data were identified and collected. Then the necessary pre-processing was done on the data. Next, the most suitable algorithm was selected by examining different ML algorithms. Figure 1 shows the flowchart of the proposed model.

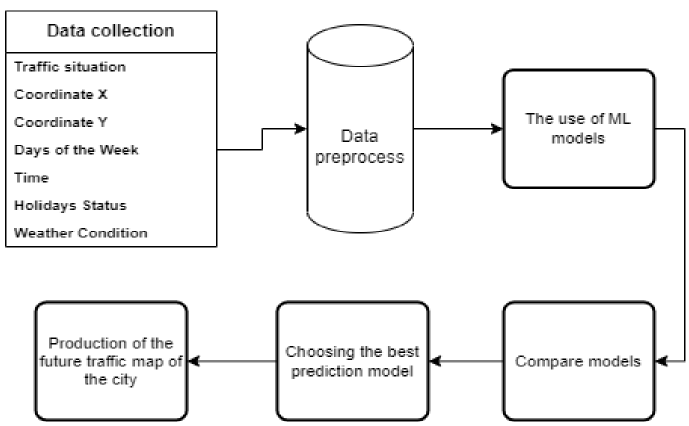

Fig. 1. The flowchart of the method.

There are various variables that affect traffic congestion. This data is provided by a Web GIS system designed by [20]. The designed website collects the traffic data of the entire study area once every 15 minutes. The collected data is from 4 to 10 April 2020. The study area is Tehran city, which is located from 51° 07′ 10″ E to 51° 30′ 14″ E longitude, and 35° 36′ 01″ N to 35° 48′ 27″ N latitude at an altitude of 1495.9 m Mean Sea level (MSL). Traffic data is collected in point format. Each point has a longitude and latitude, both of which are designated as input variables [21,22]. Various variables affect traffic, which has different effects on traffic. Variables such as time, day, holiday or non-holiday, and weather are among the most important variables [23].

The traffic pattern is diverse on different days. For example, the day of the week plays a significant role in the amount of traffic. So it is determined as one of the variables (the numbers 0 as Saturday and 6 as Friday). Time is another variable that affects traffic. The time of collected data is 24 hours a day (0:00 to 23:59), which is shown as a number. Holidays are also another variable that affects traffic. On holidays, most people usually rest, which causes a sharp decrease in traffic. The holiday is shown as a binary variable. If the desired day is a holiday, the number is one; if not, the number is zero. Another important variable that affects traffic is the weather. Rainy weather, thunderstorms, snow, etc. increase traffic congestion. Tehran weather data is stored 24 hours a day. In this article, weather conditions are divided into three categories: 1, 2, and 3. Storms, thunder, and snow increase traffic. These weather conditions are shown by the number 3 in these situations. Light rain, rain, drizzle, rain shower, and fog are shown with number 2, and other weather conditions that do not affect traffic intensity are shown with number 1. Table 1 shows the different weather conditions with their categories.

Table 1
Categories of different weather conditions.

Category	Condition	Category	Condition
2	Showers in the Vicinity	1	Partly Cloudy
2	Light Rain with Thunder	1	Fair
3	T-Storm	1	Fair/Windy
3	Thunder	1	Mostly/Cloudy
1	Fog	1	Cloudy
1	Wintry Mix	2	Light Rain
2	Drizzle	2	Light Rain Shower / Windy
2	Light Drizzle	2	Rain Shower / Windy
3	Thunder in the Vicinity	2	Rain
3	Snow	2	Rain Shower

In this system, a class is assigned to each point, which indicates the traffic situation at that point. These collected traffic data are divided into five classes: no traffic (1), low traffic (2), medium traffic (3), high traffic (4), and very high traffic (5). Two million record samples are collected during one week. Table 2 shows a view of the collected data.

Table 2
Sample traffic data.

NO	Traffic situation	Coordinate X	Coordinate Y	Days of the Week	Time	Holidays Status	Weather Condition
1	1	531637.216	3951732.410	0	6.15	0	1
2	3	538180.386	3944881.363	0	5.23	0	2
3	5	531523.288	3947692.771	2	16.40	0	1
4	2	537917.365	3950958.017	3	16.37	0	1
5	4	544537.347	3950760.197	4	14.37	0	1
6	1	532012.245	3951173.183	5	12.10	0	1
7	5	532770.493	3946938.622	5	19.4	0	1
8	4	542575.722	3949435.199	6	12.65	1	3
9	2	531617.096	3946225.768	6	21.70	1	1
10	3	542158.483	3953776.624	6	22.18	1	1

The possibility of incorrect or inconsistent data in Big Data is very high. These outlier data disrupt data mining analysis. In this stage, data is prepared for the data mining process. Therefore, the quality of the output results will be increased. Figure 2 shows the total data collected in five classes after data preprocessing. This figure shows traffic data in all the streets of the city.

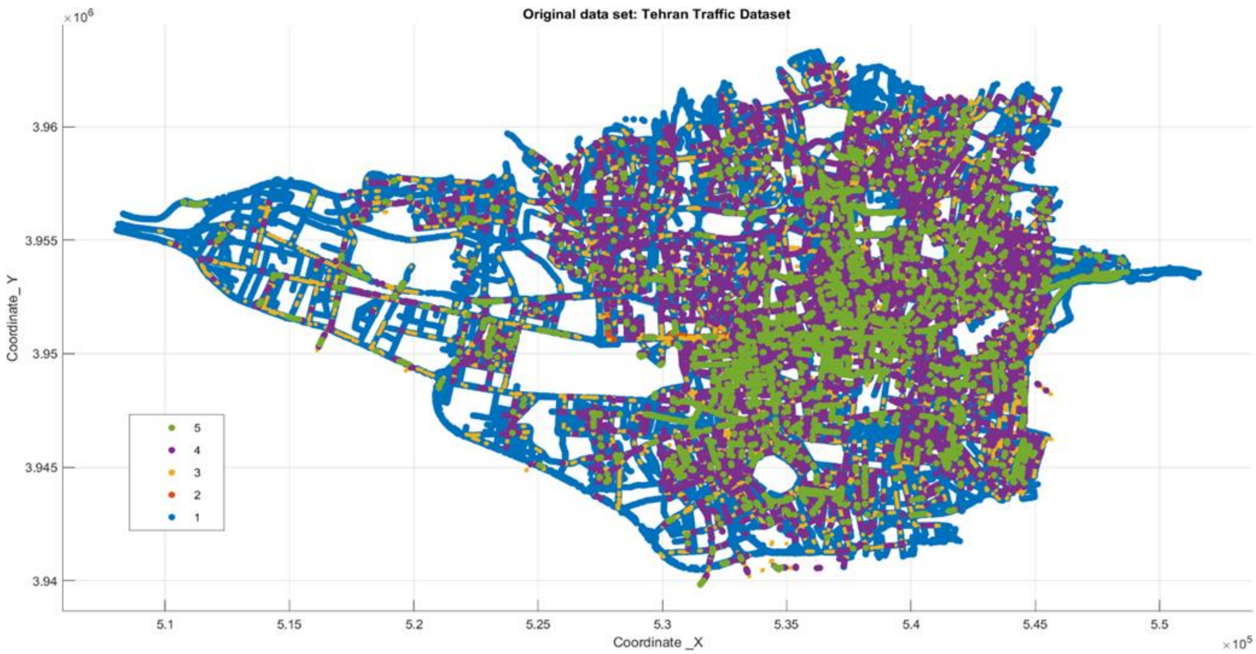

Fig. 2. Tehran City traffic dataset.

Machine learning is extensively used in many fields. The high amount of data empowers machine learning methods [19]. The goal of machine learning is to allow the computer to learn automatically without human intervention and to be able to adjust its actions accordingly [24–26]. The main purpose of machine learning algorithms is to generalize learning beyond training examples.

In the present study, five methods are used to predict traffic. The decision tree is a model that provides a tree-like structure for deciding and classifying particular data. The structure of the decision tree contains the root, the topmost node, branches which are the internal nodes, and the leaf node. The internal nodes represent a question and the branch that connects the node denotes the solution and the leaf node tries to predict the solution [27].

The KNN method is another one for classification. The KNN is a common nonparametric regression method, which is one of the simplest machine-learning algorithms. KNN is a technique that is used in data mining, machine learning, and pattern recognition. Since KNN is easy to use and implement, it is considered to be one of the best ten algorithms in the field of data mining [28]. This method is commonly used in forecast analysis to classify a point based on its neighbors [29]. In these two methods, the k-fold cross-validation method with K of 25 is used for validation. In this method, the data is divided into k sections, each of which is randomly placed in one of these k sections. Then the training and test are repeated k times; in each repetition, the k-1 part is considered as train data and one as test data. In the KNN prediction, it is important to choose the number of neighbors appropriately. The number of neighbors (K) is usually determined by using an empirical procedure. In this experiment, K is taken as 1 to 20, and the best accuracy is obtained at k = 1.

The next method is discriminant analysis, which is a multivariate statistical analysis to separate two or more groups of observations based on k variables measured on each sample and find the contribution of each variable in separating the groups [30].

Naïve Bayes classifier is another method, which is based on the Bayes theorem. A hypothesis is generated for the given set of classes. In the Naïve Bayes algorithm, the assumption of independence is raised. Bayesian theory can be used to predict the future based on the current events according to the theory of statistics and probability [27,31].

The last method is Artificial Neural Networks (ANNs) to determine the pattern of urban road traffic. These networks are modeled based on biological neural networks. ANNs can be taught to find patterns and classification information by imitating the human brain simulation [28]. ANN is used in various fields such as simulation, pattern recognition, learning, etc. [32]. In ANN, there are artificial neurons and synapses form the nodes and edges of the graph network, respectively. ANN is divided into two categories: feed-forward networks (one-way directional graphs) and feedback networks (bidirectional graphs). Feed-forward neural networks represent non-linear functional mappings between a set of input and output variables [33]. Here, a two-layer feed-forward network with hidden sigmoid neurons and smooth maximum output is used. 70% of input data are selected as the training samples. The model arranges them into a basic model for the training procedure. 15% of the data are then selected for testing, and 15% of them are selected for verification [32].

The network is trained with scaled conjugate gradient back-propagation. In the hidden layer, there are three layers of 30, 45, and 55 neurons, respectively. The number of layers and neurons is selected according to computer performance and time constraints. If the number of layers and neurons increases, the processing time is longer, while the less number of layers and neurons decreases the accuracy.

Accuracy and kappa criteria are used to compare and evaluate the models. These criteria are calculated using the confusion matrix. Accuracy is the overall accuracy of classification, which represents the ratio of correctly classified pixels to the sum of all observed pixels (Equation 1) [15,23,34].

$$\text{Accuracy} = \frac{The\ sum\ of\ the\ original\ diameter\ pixels}{the\ sum\ of\ the\ total\ pixels} \times 100 \tag{1}$$

Precision is another measure of model accuracy. Precision means the number of samples that the algorithm correctly predicted their class. Equation 2 shows the calculation of this measure [15,35].

$$\text{Precision} = \frac{(TP)}{(TP+FP)} \times 100 \tag{2}$$

The sensitivity criterion measures the number of samples that the algorithm classified in the positive category to the total number of positive samples. This criterion is obtained from Equation 3 [15,27,35].

$$\text{Recall} = \frac{(TP)}{(TP+FN)} \times 100 \tag{3}$$

Kappa is a statistical coefficient that is used to calculate inter-rater reliability for qualitative items (Equation 4) [36]. The kappa coefficient considers the probability of a random event [37].

$$kappa = \frac{n\sum_{i=1}^{k} n_{ii} - \sum_{i=1}^{k} n_{i+}n_{+i}}{n^2 - \sum_{i=1}^{k} n_{i+}n_{+i}} \tag{4}$$

Where n is the total number of observed pixels, k is the number of classes, n_{i+} is the sum of the elements of the *ith* row, and n_{+i} is the sum of the elements of the *ith* column.

Kappa smaller than zero indicates the very poor performance of the model. Kappa between 0.00 and 0.20 shows poor performance, Kappa between 0.21 to 0.40 shows average downward performance, Kappa between 0.41 to 0.60 shows average performance, Kappa between 0.61 and 0.80 shows good performance, and Kappa between 0.81 to 1.00 shows excellent model performance [36]. The results of using the three prediction models along with the important parameters are shown in Table 3.

Table 3
Accuracy and kappa coefficient of three models.

Model	**Main Parameters**	**Accuracy**	**Precision**	**Recall**	**Kappa**
Decision Trees	Max Number of Splits: 300 Split Criterion: Gini's Diversity	54.73%	55.33%	57.14%	0.4
KNN	K = 1 Distance Metric: City Block Distance Weight: Inverse	96.14%	96.42%	96.91%	0.95
Discriminant Analysis	Discrimtype: Quadratic	41.57%	40.4%	42.52%	0.27
Naive Bayes	Kernel type: Gaussian Support: Unbounded	52.14%	52.53%	52.69%	0.38
Neural Network	Number of Hidden Nodes = 30,45,55 Epochs = 1000 Function: scaled conjugate gradient back-propagation	57.76%	58.15%	58.89%	0.45

As seen in Table 3, the Discriminant Analysis method has the least accuracy among the models. Decision Trees, Naive Bayes, and Neural Network methods are also less accurate. The KNN method performed better than the other methods with high accuracy. Therefore, the KNN method is used to predict traffic.

The traffic map shows a better view of traffic. Traffic maps have some advantages; for example, they are simple and understandable for everyone. Traffic maps can help the public to know the future traffic as well as officials and managers to manage traffic [38]. To show future traffic on the map, it is necessary to give the input 6 variables (coordinate X, coordinate Y, days of the week, time, holiday status, and weather condition). Therefore, about 80,000 new points are first created in all the streets of the city using GIS. These points are created at regular intervals from each other. Each of these points has a coordinate X and Y. The rest of the data is determined by the type of prediction problem. The result of model processing indicates the prediction of future traffic situations at any point. Using the selected algorithm, the traffic class for each point is specified as a number between 1 and 5. The numbers 1 to 5 are then displayed in green, yellow, orange, red, and dark red respectively. Figure 3 shows the predicted traffic map for the city.

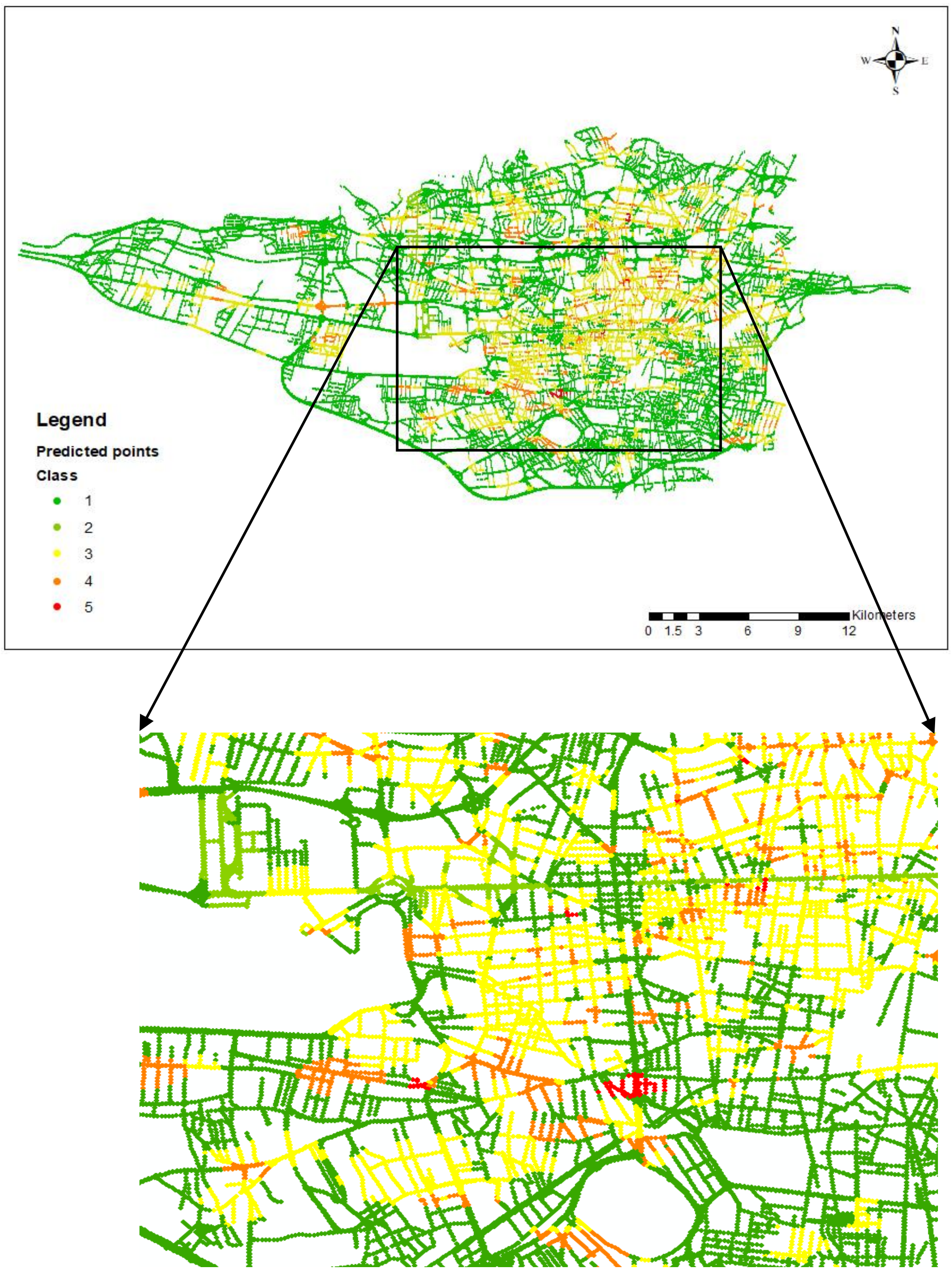

Fig. 3. The predicted traffic map of the city.

Figure 3 shows the amount of traffic anywhere. Using a traffic map allows us to see the future traffic on all the streets of the city at the selected time. As seen, the traffic condition of all roads is clear.

3. Conclusions

Urban traffic is one of the most important and complex issues that exist in most metropolises and countries. The traffic pattern may change due to issues such as weekends, school reopening, and the morning and evening rush hours. So far, various solutions and suggestions have been presented, each of which has its advantages and disadvantages.

In this article, we tried to use the traffic prediction solution for traffic control and management. Therefore, traffic data was collected and pre-processed. Five machine-learning techniques were then used for modeling the traffic. Finally, the output of these models is compared using different criteria. It was found that Decision Trees, Discriminant Analysis, Naive Bayes, and Neural Network techniques have poor performance. However, the KNN model has the best result among the models with an accuracy of 96.14% and a kappa coefficient of 0.95.

The most important limitation of the current research was the collection and control of variables affecting urban traffic. Due to the exclusivity of traffic data, it was not possible to collect raw traffic data. These data were collected indirectly using web techniques. The large volume of input data made the problem lean toward big data. Therefore, this issue requires special big data analysis. There were also different classification models and algorithms, but it was not possible to use some of them due to the special structure of some input data.

Next, a traffic map was used to show the future traffic situation of the city for a better view. Traffic maps can help the public to know the future traffic as well as officials and managers to manage traffic. One of the most important advantages of the current model is the comprehensiveness of the model for all city streets.

The proposed method is cheap and reliable. This method can predict traffic offline, which is its most important advantage. Since neighborhood and location are the main factors affecting traffic congestion, these two variables were considered in the modeling based on GIS concept. The high accuracy of the model and the preparation of a spatial map are other advantages of the current model. Future research can be used to increase prediction accuracy with long-term data or data from one or more seasons of the year.

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