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MODELING OF TRAFFIC IN INTELLIGENT TRANSPORTATION SYSTEMS

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Modeling of the effective environment in the Republic of Tatarstan using transport data

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Automated urban traffic monitoring systems are widely used to solve various tasks in intelligent transport systems of different regions. They include video enforcement, video surveillance, traffic management system, etc. Effective traffic management and rapid response to traffic incidents require continuous monitoring and analysis of information from these complexes, as well as time series forecasting for further anomaly detection in traffic flow. To increase the forecasting quality, data fusion from different sources is needed. It will reduce the forecasting error, related to possible incorrect values and data gaps. We implemented the approach for short-term and middle-term forecasting of traffic flow (5, 10, 15 min) based on data fusion from video enforcement and video surveillance systems. We made forecasting using different recurrent neural network architectures: LSTM, GRU, and bidirectional LSTM with one and two layers. We investigated the forecasting quality of bidirectional LSTM with 64 and 128 neurons in hidden layers. The input window size (1, 4, 12, 24, 48) was investigated. The RMSE value was used as a forecasting error. We got minimum RMSE = 0.032405 for basic LSTM with 64 neurons in the hidden layer and window size = 24.

Keywords: transport modeling, video enforcement, traffic flow forecasting

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Транспортные данные для моделирования эффективной транспортной среды в Республике Татарстан

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Автоматизированные системы мониторинга городского трафика широко используются для решения различных задач в интеллектуальных транспортных системах различных регионов. Такие системы включают комплексы фотовидеофиксации, видеонаблюдения, управления дорожным трафиком и т. д. Для эффективного управления транспортным потоком и своевременного реагирования на дорожные инциденты необходимы непрерывный сбор и анализ потока информации, поступающей с данных комплексов, формирование прогнозных значений для дальнейшего выявления аномалий. При этом для повышения качества прогноза требуется агрегирование данных, поступающих из различных источников. Это позволяет уменьшить ошибку прогноза, связанную с ошибками и пропусками в исходных данных. В данной статье реализован подход к краткосрочному и среднесрочному прогнозированию транспортных потоков (5, 10, 15 минут) на основе агрегирования данных, поступающих от комплексов фотовидеофиксации и систем видеонаблюдения. Реализован прогноз с использованием различных архитектур рекуррентных нейронных сетей: LSTM, GRU, двунаправленной LSTM с одним и двумя слоями. Работа двунаправленной LSTM исследовалась для 64 и 128 нейронов в каждом слое. Исследовалась ошибка прогноза для различных размеров входного окна (1, 4, 12, 24, 48). Для оценки прогнозной ошибки использована метрика RMSE. В ходе проведенных исследований получено, что наименьшая ошибка прогноза (0.032405) достигается при использовании однослойной рекуррентной нейронной сети LSTM с 64 нейронами и размером входного окна, равном 24.

Ключевые слова: транспортное моделирование, фотовидеофиксация, прогнозирование транспортного потока

1. Introduction

Every year the number of vehicles on city roads is increasing. A significant increase in cars on roads inevitably leads to increasing the number of different problems including traffic jams and traffic accidents. That leads to delays in emergency and operational services, emission of harmful substances, increased fuel consumption, etc. There are several approaches to enhance road capacity by designing and building new multi-level junctions but this is a time- and cost-consuming approach. On the other hand, there are a lot of existing ITS solutions in modern cities, which produce a lot of data to be analyzed, and the capacities of these solutions are often not fully used in practice. To enhance traffic management decision-making solutions, we should increase the capabilities of these solutions including data fusion from multiple sources and its further processing/analysis.

There are many ITS solutions installed in the city of Kazan, the capital of the Republic of Tatarstan, including different traffic management (TMS), video enforcement, and surveillance systems. They produce a lot of additional data that could be used for solving many additional tasks. In this paper, we implemented data fusion from video enforcement and surveillance systems and use this data for improved traffic flow forecasting in the Republic of Tatarstan. We use and compare different artificial neural network models for forecasting.

2. Survey of smart video solutions in the Republic of Tatarstan

2.1. Adaptive traffic management system

The adaptive traffic management system has been operating in the city of Kazan since 2012. This system provides the user with the following information:

- The state of traffic flow, meteorological condition, and the condition of a road surface on the autobahn.
- Video stream from sections of the road network and autobahns.
- Information on the operating mode of control objects.

At the moment more than 140 intersections in Kazan are connected to this system. This makes it possible to increase the road capacity in Kazan up to 25% and to implement adaptive prioritization of public and emergency services.

2.2. Video enforcement systems

Video enforcement systems have been used in the Republic of Tatarstan since 2008. At present, more than 890 stationary, 170 mobile, and 10 car video enforcement systems are used in the Republic of Tatarstan. The locations of stationary and mobile systems are presented in Figure 1. At present, more than 80% of the total number of speed violations are detected by these cameras.

Another approach for video enforcement has been implemented in the Republic of Tatarstan since 2019. A new video enforcement system allows detection of the vehicle speed on the entire length of Republican roads, combining the capabilities of all three types of video enforcement systems and providing an economically acceptable compromise between performance and costs. Within the project, 100 systems, operating in automatic mode, were installed to control 290 road sections with a length of 920 kilometers. These systems are connected and detect the instant and average speed of the vehicle between the sensors, providing continuous control on the entire route.

Video enforcement systems provide the following information about vehicles during their use: instant and average speed, plate number, date/time/place of the vehicle’s speed detection, and the direction of movement.

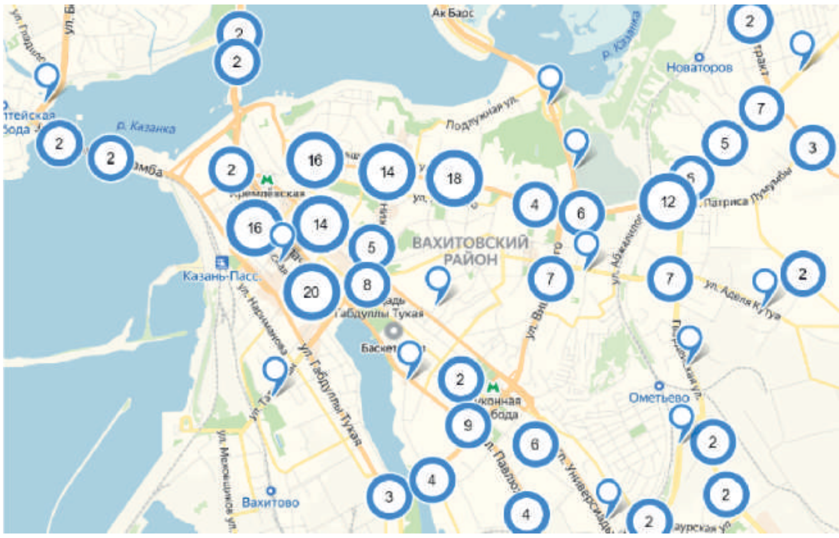


Figure 1. Locations of video enforcement cameras in Kazan

2.3. Video surveillance

The “Safe City” project was started in the Republic of Tatarstan in 2005. To date, more than 50 thousand surveillance cameras have been installed on the streets as part of this project. Some of these cameras provide surveillance of the traffic situation on city roads.

2.4. Increasing the capabilities of smart video solutions

Video enforcement and video surveillance systems generate a lot of data, which could be easily used for solving some additional tasks based on the well-prepared infrastructure of the city of Kazan. For example, we can use information from video enforcement cameras to get additional data about vehicle average speed, current road capacities, traffic density, and traffic jams. For example, we can monitor traffic density, average speed, and traffic jams in different places/different directions in the city of Kazan based on such data that enhance the basic functions of video enforcement cameras (Fig. 2).

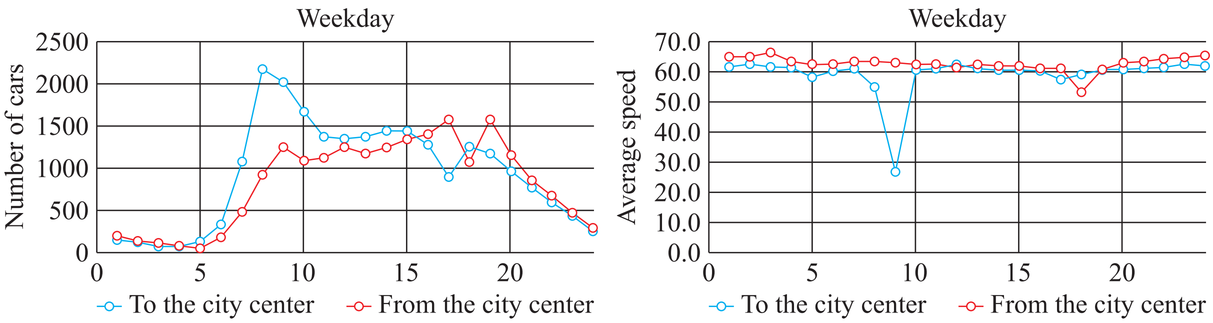


Figure 2. Traffic density and average speed in different places/different directions, the city of Kazan

Therefore, the existing ITS infrastructure in the city of Kazan generates a lot of different data. Data fusion from multiple sources and its further processing enable us to solve some additional tasks with higher accuracy. For example, we can perform traffic flow forecasting without installing additional sensors, based only on existing video enforcement and surveillance systems. Further, we can use existing infrastructure to identify the areas of concern, plan road works, manage traffic lights, and inform citizens about road situations. Logistics companies can use this information to manage the delivery process. The situational center of the Republic of Tatarstan, which represents the united transport environment (intelligent processing and analysis of video streams, optimization of traffic flows, and automated detection of traffic congestion) will receive emergency information about anomalies on the road and take appropriate measures.

3. Traffic flow forecasting approach

Traffic flow forecasting is one of the vital tasks to be solved nowadays. There are many statistical and machine learning tools for solving these tasks, including adaptive autoregressive models [Arnold et al., 1998], but in recent years recurrent neural networks have shown a great efficiency in solving such tasks due to their capability to analyze in real-time large volumes of nonlinear data with arbitrary long- and short-term dependencies in the input sequences. Recent publications show a higher accuracy of recurrent neural networks in comparison with other models for solving the tasks of traffic flow data forecasting [Ermagun, Levinson, 2019, Kolidakis et al., 2019]. Nowadays artificial neural networks (ANN) with long-short term memory are widely used for time-series data forecasting [Zhao et al., 2017; Bartlett, Han, 2018] using RMSE for evaluation of the accuracy [Yang et al., 2019; Yu et al., 2018].

3.1. General idea

In this work, we propose the traffic flow forecasting approach based on data fusion from multiple sources (Figure 3).

Firstly, raw data from video enforcement and video surveillance cameras are taken for further processing. The data preprocessing module gets information about the current vehicle's speed, current time, camera location, and plate number from stationary video enforcement systems (Figure 4). Then input data is filtered to delete the personal data and gaps. Finally, the average speed of vehicles at the current location of the video enforcement camera is calculated.

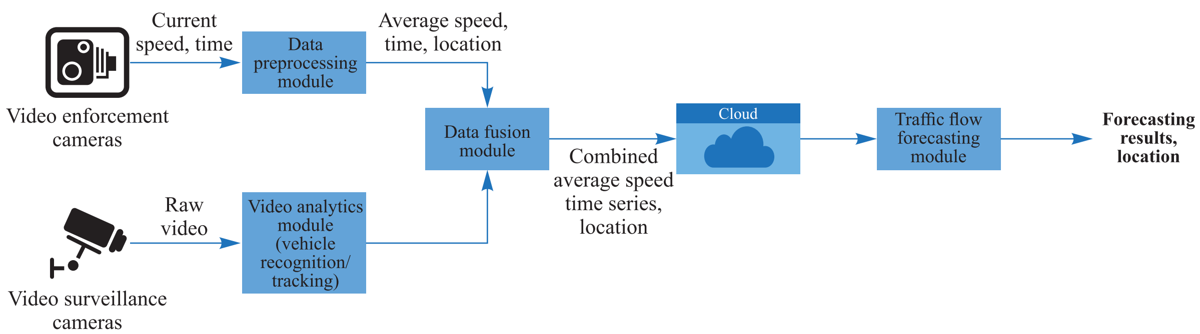


Figure 3. Suggested approach

Figure 4. Tests section for traffic flow forecasting

Also, raw videos from video surveillance cameras are taken and processed using a video analytics module (Figure 5) [Makhmutova et al., 2019]. After that vehicle detection/tracking and speed calculation are performed. Finally, we calculate the average speed of vehicles at the current location of the video surveillance camera.

The information from the data preprocessing module and the video analytics module (average vehicle's speed, time, location) is sent into the data integration module in the data center. This module combines the information from two systems and calculates the vehicle's average speed time series at different locations. This information is sent to the cloud. To combine the information from two data sources, we calculate the average value for two average speeds, received from two sources/one time and the same location. This approach makes it possible to delete possible gaps in raw data influenced, for example, by a fault of the plate recognition procedure of the video enforcement system or a fault of the car detection procedure of the video analytics module. It also makes it possible to decrease the level of errors in vehicle speed detection in comparison with the single data source.

Figure 5. Speed recognition of vehicles on surveillance camera

3.2. The ANN models used

We compare several neural network architectures (LSTM, Bidirectional LSTM, and GRU) (Figure 6) for solving traffic flow forecasting tasks. These models take an input sequence of $m + 1$ values (average speed) as input and obtain as a result the sequence of $n + 1$ predicted average speed values. The RMSE error was chosen for the estimation of the forecasting accuracy.

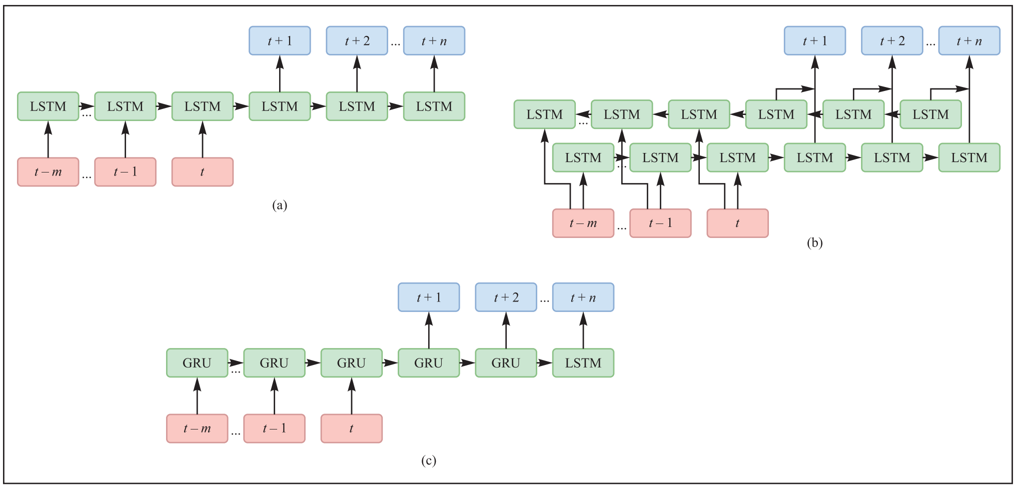


Figure 6. The neural network architectures used (a — LSTM, b — Bidirectional LSTM, c — GRU)

4. Evaluation

Evaluation of the suggested approach was performed on real data from the test section of the city of Kazan (Figure 4). We used 5-minute time series intervals for forecasting. Five months of historical data were used for training and one month of historical data for testing.

4.1. Data preparation

Table 1. General training parameters

Parameter	Value
Dataset size	45 169
Training set size	38 618
Validation set size	16 551
Batch size	32

At first traffic flow speed is generated from the raw video surveillance data by extracting the vehicle speed and time. The personal data is deleted. Then the values are averaged with intervals of 5 minutes. If the data preprocessing module detects the gap in the data from some source, this information is supplemented with a value for the same time in the past. At the same time, using computer vision algorithms in the video analytics module, we obtained similar information about traffic flow speed from this module. Before sending data for further processing, we combined the data obtained from two sources in the data integration module, which averages the speed values. Thus, the data set for training and testing recurrent neural network models was prepared (Figure 7).

Then, we evaluate the accuracy of forecasting.

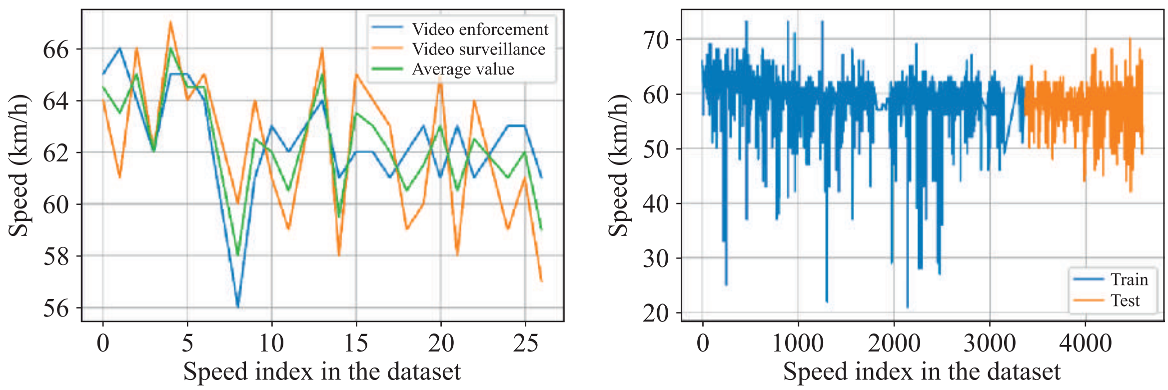


Figure 7. Averaging data obtained from two different sources (left) and splitting into training and test data sets (right)

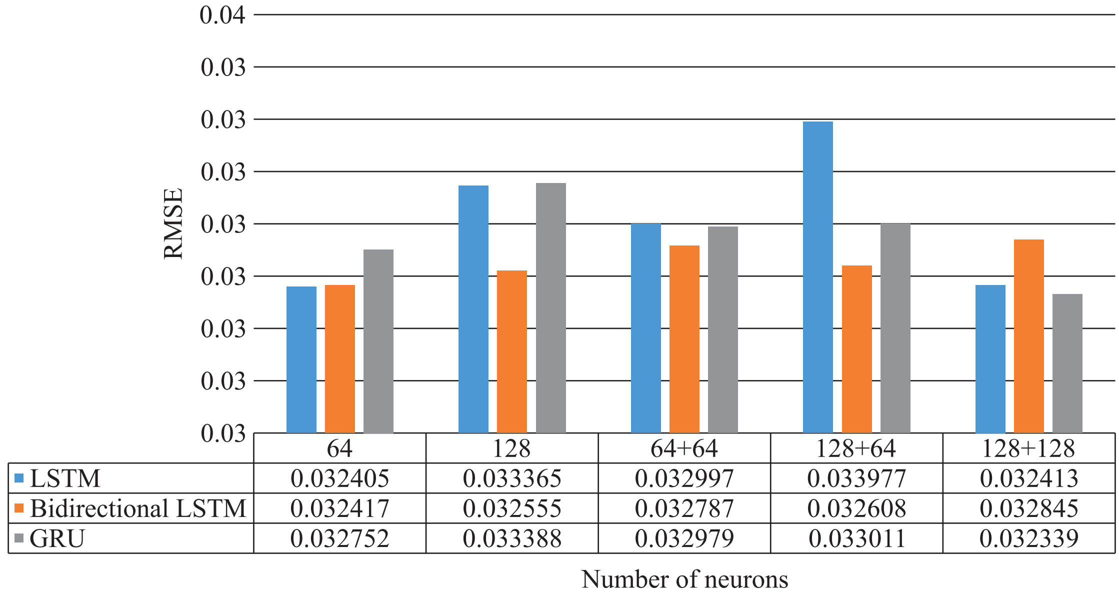
4.2. Evaluation

We considered the 5-minute time-series traffic flow forecasting task and evaluated the accuracy of such forecasting depending on the architecture of the recurrent neural network. We used recurrent neural network architectures with 1 hidden layer (64 or 128 neurons) and 2 hidden layers (64+64, 128+64, and 128+128 neurons). We used 200 epochs and Adam optimizer during the training procedure. We evaluated the forecasting accuracy for different ANN architectures (Figure 8). For these experiments, the GRU neural network with 2 layers and 128 neurons per layer architecture showed the best result. We have got the best RMSE error value = 0.032339.

We also compared the accuracy depending on the number of inputs of the recurrent neural network (window size) (Table 2). The forecasting accuracy for 10 and 15 minutes was also considered (Figure 9).

Table 2. Evaluation of the accuracy (RMSE) of traffic flow forecasting depending on GRU architecture (5-minutes)

Layers	Number of neurons	Number of inputs for the recurrent neural network (window size)				
		1	4	12	24	48
1	64	0.034600	0.034157	0.033672	0.032752	0.033461
	128	0.035507	0.032985	0.032845	0.033388	0.035120
2	64+64	0.035442	0.033666	0.033670	0.032979	0.033152
	128+64	0.034959	0.033364	0.033034	0.033011	0.032429
	128+128	0.034720	0.03300	0.032972	0.032339	0.032728



	64	128	64+64	128+64	128+128
LSTM	0.032405	0.033365	0.032997	0.033977	0.032413
Bidirectional LSTM	0.032417	0.032555	0.032787	0.032608	0.032845
GRU	0.032752	0.033388	0.032979	0.033011	0.032339

Figure 8. Evaluation of the accuracy (RMSE) of traffic flow forecasting depending on Bidirectional LSTM architecture (number of input data — 24)

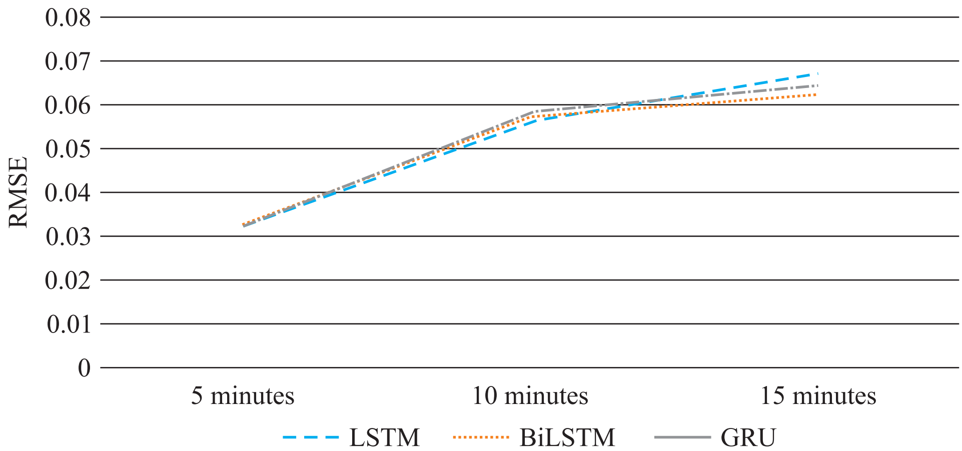


Figure 9. Evaluation of accuracy (RMSE) of traffic flow forecasting for different ANN depending on different time steps prediction outputs (number of input data — 12, output data — 3)

We can see the results of time series forecasting in Figure 10 where a significant drop in the average speed on a road section was predicted in advance. All 3 forecasting models showed quite good results. The best accuracy indicator was obtained using a single-layer neural network with LSTM. However, the use of the GRU neural network with two layers showed a slight improvement in the accuracy indicator compared to LSTM and Bidirectional LSTM, while the test result of the one layer GRU turned out to be much worse compared to LSTM and Bidirectional LSTM.

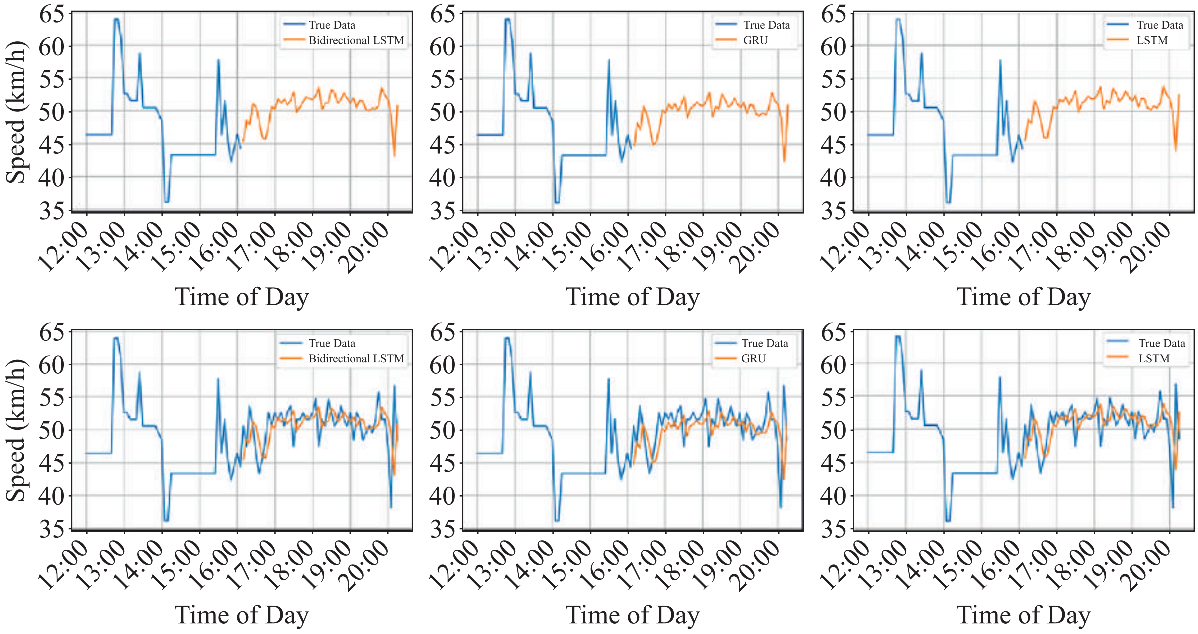


Figure 10. Forecasting results

Conclusion

Traffic forecasting is an effective tool in optimizing routes and identifying abnormal traffic patterns. In this paper, the traffic flow forecasting approach based on data fusion from two sources (video enforcement and video surveillance cameras) was suggested. This approach makes it possible to delete possible gaps in raw data influenced, for example, by the fault of plate recognition or fault of car detection. It also allows decreasing the level of errors in vehicle speed detection by the single data source. As a result of the evaluation, we obtained the evaluation accuracy (RMSE) of traffic flow forecasting on 0.032405 using a one-layer neural network LSTM with 64 neurons. Further work will be continued and used as one of the parts of the government transport strategic platform. The next important step is an optimization of the data structure for its future processing.

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