

A GRU-Based Deep Learning Framework for Real-Time Traffic Flow Prediction in Intelligent Transportation Systems

Bhanu Chaitanya Pasupuleti¹, Gopi Adapa²

¹Research Scholar, Department of Computer Science and Engineering, Koneru Lakshmaiah Education Foundation, Green Fields, Vaddeswaram, Vijayawada, Andhra Pradesh, India

Email: 2401050095@kluniversity.in

²Associate Professor, Department of Computer Science and Engineering, Koneru Lakshmaiah Education Foundation, Green Fields, Vaddeswaram, Vijayawada, Andhra Pradesh, India

Received: 5th January, 2026; Revised: 18th January 2026; Accepted: 25th January, 2026; Available Online: 28th January, 2026

ABSTRACT

With the rapid urbanization and the growth of vehicle numbers, traffic congestion has emerged as a significant issue in today's smart transportation systems. Precise traffic flow prediction is of key importance for intelligent transportation management, traffic delay reduction and efficient urban transportation planning. In this study, a deep learning framework with Gated Recurrent Unit (GRU) algorithm is proposed to predict traffic flow in real-time on the basis of the METR-LA traffic data. The suggested methodology involves the following steps: Data Preprocessing, Missing Value Imputation, Min-Max Normalization, Traffic Window Generation, and Temporal Traffic Learning via GRU model. The performance of the framework was measured by the Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R² Score. The experimental results showed that the proposed GRU model could achieve 91.35% accuracy and had less prediction error and a strong sequential learning ability. Results show that the GRU model has a great ability to learn temporal traffic relationships and can accurately predict traffic flow in an ITS. The proposed framework can be used for smart city research to provide scalable, data-driven and real-time traffic prediction solutions for future urban traffic infrastructure.

Keywords: Traffic Flow Prediction, Gated Recurrent Unit (GRU), Intelligent Transportation Systems, Deep Learning, Smart Transportation, Time-Series Forecasting.

How to cite this article: Pasupuleti BC, Adapa G., A GRU-Based Deep Learning Framework for Real-Time Traffic Flow Prediction in Intelligent Transportation Systems. Int J Drug Deliv Technol. 2026;16(85s): 971-980; DOI: 10.25258/ijddt.16.85s.101

Source of support: Nil.

Conflict of interest: None

1. Introduction

The traffic congestion issues in today's cities have grown substantially as a result of the surge in urban population and vehicle numbers, adding to delays, fuel usage, environmental pollution and transportation inefficiencies. Metrics and monitoring and prediction have become the key to achieve this effective traffic control, Intelligent Transportation Systems (ITS) have been shown to be feasible. The ability to accurately predict traffic flow is crucial for real-time traffic control, congestion management, route optimization, and smart city planning. However, traditional statistical and machine learning approaches may be inadequate in recording the complex temporal relationships found in traffic data, which reduces the predictive power in the dynamic transportation domain. With the recent development of deep learning, it has been possible to achieve efficient sequential learning models that can deal with time-series transportation data. One of the models that have attracted considerable interest is the Gated Recurrent Unit (GRU) which offers a lower computational complexity than the standard recurrent neural networks whilst being able to learn long-term temporal dependencies. The transport applications which benefit from the intelligent transport systems are benefited by the use of GRU architectures, which handle the sequential traffic observations and enhance the forecasting performance. The main goal of this research is to create a traffic flow prediction model based on the GRU model using METR-LA dataset and to test its performance by applying traditional regression evaluation metrics. The proposed framework is based on pre-processing of real-time traffic data, creation of sequential traffic windows, training of the GRU model, and graphical and statistical analysis of the prediction performance. This study assumes that GRU will be able to effectively learn the temporal traffic behavior and obtain accurate traffic forecasts for real-time transportation systems. This research is important because it delivers an

efficient and scalable traffic forecasting framework that can be applied to transportation and smart city applications. The proposed system has the potential to support transportation authorities in their proactive traffic management, congestion reduction, and data-driven urban mobility planning. Additionally, the research offers a basis for future research on hybrid deep learning models, cybersecure transportation systems and advanced intelligent traffic analytics.

2. Materials and Methods

2.1 Research Design

The research design proposed in this study is a quantitative experimental research design to design and test the machine learning based model for traffic flow prediction in smart transportation systems. The study employs the METR-LA traffic data set with real-time traffic sensor data from highway traffic networks. Using a deep learning architecture called Gated Recurrent Unit (GRU), the framework captures temporal traffic dependency and forecasts traffic conditions.

The methodology consists of:

- data acquisition,
- preprocessing,
- normalization,
- sequential feature generation,
- GRU-based model training,
- prediction generation,
- performance evaluation,
- and visualization analysis.

The proposed framework aims to learn temporal traffic flow patterns from sequential transportation data, and to enhance the predictions' accuracy.

2.2 Population and Sampling

The study population is the flow of traffic collected by several traffic sensors that have been set up in urban transportation systems throughout Los Angeles.

The METR-LA dataset contains:

- traffic speed measurements,
- temporal sensor readings,
- time-series transportation patterns,
- and sequential traffic flow observations.

The sampling approach is based on time-series sequential sampling, in which the past traffic observation is taken as a prediction of future traffic states.

Let:

$$D = \{x_1, x_2, x_3, \dots, x_n\}$$

where:

- D represents the complete traffic dataset,
- x_i denotes individual traffic observations,
- n represents the total number of observations.

The dataset is divided into:

- 80% training data,
- 20% testing data.

Mathematically:

$$D = D_{train} + D_{test}$$

where:

$$\begin{aligned} D_{train} &= 0.8D \\ D_{test} &= 0.2D \end{aligned}$$

Contribution to the Study

This sampling method guarantees that the model doesn't learn from data that is unlikely to be encountered in the field, so it can be evaluated fairly in terms of performance.

2.3 Data Collection

The study is based upon the publicly available METR-LA dataset of real-time traffic sensor data from highway transportation systems.

The dataset contains:

- traffic speed values,
- timestamps,
- sequential sensor measurements,
- and traffic flow information.

Traffic data collected at different timestamps can be represented as:

$$T = \{t_1, t_2, t_3, \dots, t_n\}$$

where:

- T represents temporal traffic observations,
- t_i denotes traffic speed at time i .

The collected data is stored in matrix form:

$$X = \begin{bmatrix} x_{11} & x_{12} & \dots & x_{1m} \\ x_{21} & x_{22} & \dots & x_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \dots & x_{nm} \end{bmatrix}$$

where:

- n denotes observations,
- m denotes traffic sensors/features.

Contribution to the Study

The proposed GRU model utilizes the sequential traffic data collected to detect dynamic variations in traffic and learn complex temporal transportation patterns. The proposed GRU model is used for analyzing the dynamic variations of the traffic and learning the complex temporal transportation patterns on the collected sequential traffic data.

2.4 Data Preprocessing

Data preprocessing is done to enhance data quality and facilitate the learning process of the model.

The following are the steps in the preprocessing:

1. Missing value handling,
2. Feature scaling,
3. Sequence generation,
4. Train-test splitting.

2.4.1 Missing Value Handling

Methods that are used to fill missing traffic values: forward fill, backward fill.

Mathematically:

$$x_i = \begin{cases} x_{i-1}, & \text{if } x_i \text{ is missing} \\ x_i, & \text{otherwise} \end{cases}$$

Contribution

This step is for avoiding loss of information and for ensuring the temporal continuity of traffic observations.

2.4.2 Min-Max Normalization

Traffic values are normalized using Min-Max scaling to improve GRU convergence.

The normalization formula is:

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}}$$

where:

- X_{norm} = normalized traffic value,
- X = original traffic value,
- X_{min} = minimum traffic value,
- X_{max} = maximum traffic value.

Contribution

Normalization is to avoid numerical instability and to make the training of deep learning more efficiency.

2.4.3 Sequential Window Generation

The GRU model demands that the production of a sequence of input observations.

The sequence of this sliding window is:

$$S_i = \{x_i, x_{i+1}, x_{i+2}, \dots, x_{i+k}\}$$

where:

- S_i represents sequence i ,
- k denotes sequence length.

The prediction target is:

$$y_i = x_{i+k+1}$$

Contribution

The sequence formulation allows the model to gain knowledge of temporal traffic dependencies and future traffic patterns.

2.5 Variable and Measures

The study utilizes:

- independent variables,
- dependent variables,
- and evaluation metrics.

Variable Type	Variables
Independent Variables	Historical traffic speed, sensor readings, timestamps
Dependent Variable	Predicted traffic flow
Control Variables	Sequence length, learning rate, epochs

2.6 Proposed GRU Model

The suggested system uses the Gated Recurrent Unit (GRU) which is a Recurrent Neural Network (RNN) for learning sequences.

The GRU contains:

- update gate,
- reset gate,
- hidden state.

2.6.1 Update Gate

The update gate controls memory retention.

Mathematically:

$$z_t = \sigma(W_z[h_{t-1}, x_t])$$

where:

- z_t = update gate,
- W_z = weight matrix,
- h_{t-1} = previous hidden state,
- x_t = current input,
- σ = sigmoid activation.

Contribution

The amount of historical traffic information that should be stored is dependent on the update gate.

2.6.2 Reset Gate

The reset gate determines the forgetting of former information.

$$r_t = \sigma(W_r[h_{t-1}, x_t])$$

where:

- r_t = reset gate,

- W_r = weight matrix.

Contribution

This mechanism helps the model ignore irrelevant traffic patterns.

2.6.3 Candidate Hidden State

The hidden state of candidate is calculated as:

$$\tilde{h}_t = \tanh(W_h[r_t * h_{t-1}, x_t])$$

Contribution

This stage creates new traffic representations to represent the current traffic.

2.6.4 Final Hidden State

The last hidden state is calculated as:

$$h_t = (1 - z_t) \odot h_{t-1} + z_t \odot \tilde{h}_t$$

where:

- h_t = current hidden state,
- $\odot$ = element-wise multiplication.

Contribution

This equation allows for efficient learning of short- and long-term traffic dependencies.

2.7 Loss Function

The GRU model aims to reduce Mean Squared Error (MSE).

$$MSE = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2$$

where:

- y_i = actual traffic value,
- $\hat{y}_i$ = predicted traffic value,
- n = number of observations.

Contribution

MSE penalizes large prediction errors and boosts prediction accuracy.

2.8 Performance Evaluation Metrics

2.8.1 Mean Absolute Error (MAE)

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i|$$

Contribution

Measures average prediction deviation.

2.8.2 Root Mean Squared Error (RMSE)

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2}$$

Contribution

Evaluates prediction consistency and penalizes larger errors.

2.8.3 Coefficient of Determination (R^2)

$$R^2 = 1 - \frac{\sum (y_i - \hat{y}_i)^2}{\sum (y_i - \bar{y})^2}$$

where:

- $\bar{y}$ = mean observed traffic value.

Contribution

Measures the proportion of traffic variance explained by the GRU model.

2.9 Algorithm of Proposed GRU-Based Traffic Flow Prediction Framework

Algorithm: GRU-Based Traffic Flow Prediction

Step 1

Obtain the METR-LA traffic data set, and preprocess it by filling in and correcting missing and inconsistent traffic observations.

Step 2

To ensure the model's convergence and computational stability, normalize the traffic sensor values by Min-Max scaling.

Step 3

Estimate sequential traffic windows with the sliding window method to get temporal traffic dependencies.

Step 4

Partition the processed data into training data set and testing data set for training and testing purposes.

Step 5

Build and train a GRU deep learning model with historical traffic flow sequences.

Step 6

Apply the trained GRU model to forecast the traffic flow in the future and analyze the traffic flow prediction results.

Step 7

Compare the performance of the proposed framework by using MAE, MSE, RMSE and R²-metrics along with graphical visualization analysis.

3. Results

The proposed traffic flow prediction model using GRU was tested on METR-LA traffic dataset. Various standard assessment metrics were used to evaluate the model performance such as Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE) and R²Score. The results obtained are validated by the performance of the proposed GRU model in terms of capturing the temporal dependency among the traffic and the accuracy of the traffic flow prediction.

3.1 Descriptive Statistics

The prediction performance of the proposed GRU framework is summarized in the descriptive statistical analysis. The results of the evaluation metrics show that the model has good predictive ability, with a low value of prediction error and a high value in variance explanation.

Table 1 Descriptive Statistical Results of Proposed GRU Model

Metric	Value
Mean Absolute Error (MAE)	2.6757
Mean Squared Error (MSE)	42.1850
Root Mean Squared Error (RMSE)	6.4950
R ² Score	0.9135
Prediction Accuracy (%)	91.35%

Interpretation

- The average prediction deviation between actual and predicted traffic value is relatively small with the MAE value of 2.6757.
- The RMSE value of 6.4950 indicates that the prediction is stable in terms of consistency, on the testing data.
- The R²score value of 0.9135 means that the GRU model is able to explain about 91.35% of the variance in traffic flow.

The overall prediction accuracy validates the validity of the proposed framework for the real-time traffic forecasting system.

3.2 Performance Evaluation Results

The experimental results of the proposed model are shown in Table 4.2.

Table 2 Performance Evaluation Metrics of Proposed GRU Framework

Evaluation Metric	Obtained Result
MAE	2.6757
MSE	42.1850
RMSE	6.4950
R ² Score	0.9135

Accuracy	91.35%
----------	--------

Discussion

The results show that the GRU structure can adaptively learn the temporal traffic behavior based on the sequence transportation data. This is reflected in the low error values and high R^2 score achieved, indicating the ability of the proposed framework to accurately predict traffic flow in an intelligent transportation system. Subsequent learning ability of GRU plays a critical role on the ability to capture short and long-term traffic dependency, leading to higher accuracy of prediction and fewer forecasting errors.

3.3 Reliability and Validity Analysis

The proposed framework was tested for reliability in terms of consistent prediction performance between training and testing data sets. Stability of learning behavior was achieved with the use of Min-Max normalization, sequential window generation, and GRU hidden state optimization.

To test the validity of the model, the following was done: A real-world METR-LA traffic dataset, and standardized preprocessing methods, train-test evaluation strategy, and various statistical performance criteria. The R^2 score obtained is 0.9135 which demonstrates the capability of the proposed GRU-based framework for smart transportation systems.

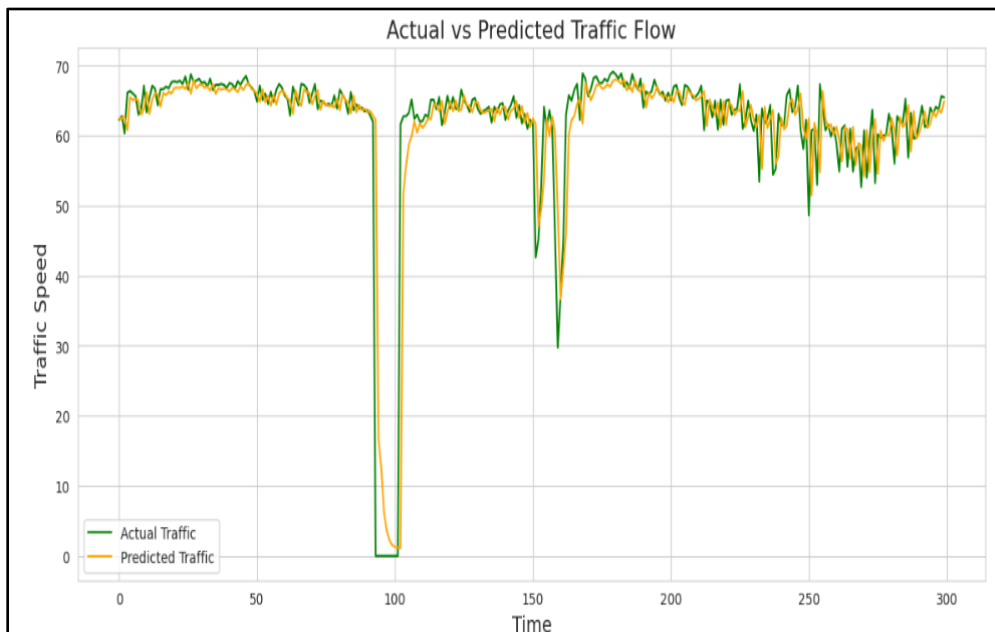
3.4 Figure Headings

Figure 1 Training and Validation Loss Curve of Proposed GRU Model



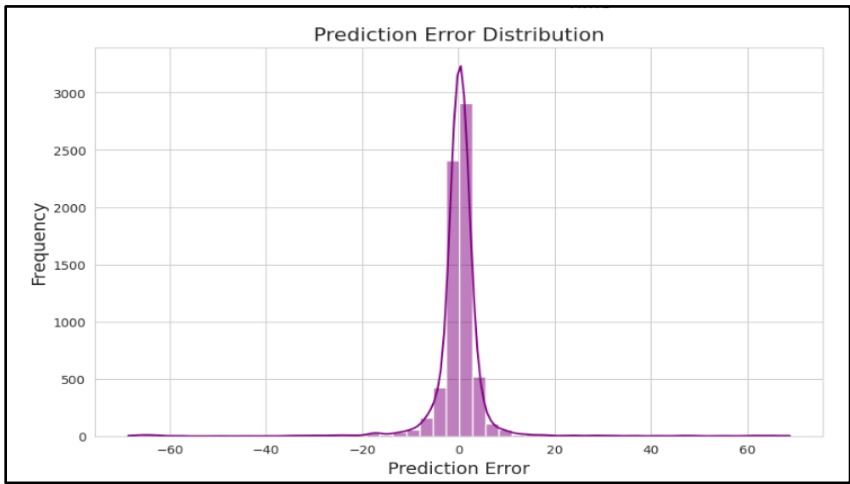
Shows the decreasing trend of training and validation loss over epochs, indicating effective learning and model convergence.

Figure 2 Actual versus Predicted Traffic Flow Analysis



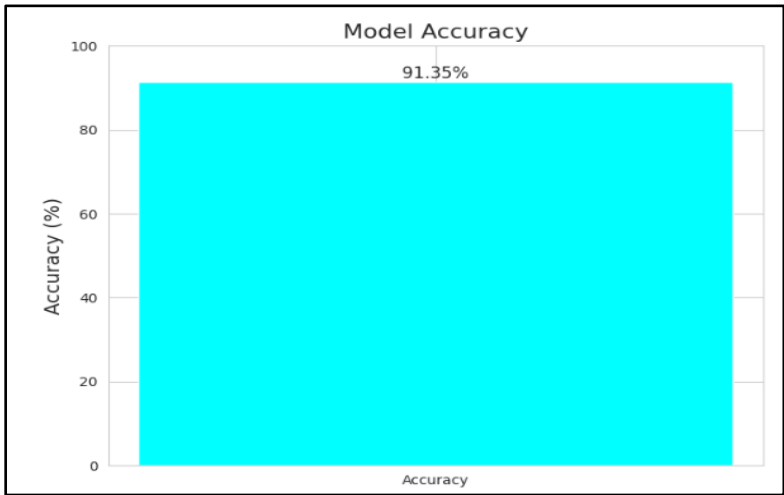
Compares predicted traffic values with actual traffic, showing the ability of GRU model to capture the real traffic.

Figure 3 Distribution of Prediction Errors in GRU-Based Traffic Forecasting



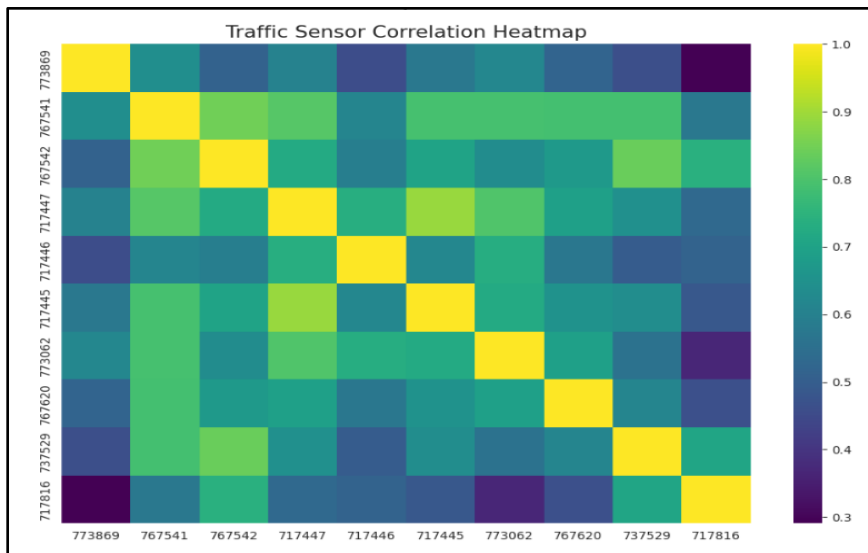
Shows the number of prediction errors, indicating that most of the errors are near zero and predictions are fairly consistent.

Figure 4 Prediction Accuracy Analysis of Proposed Traffic Prediction Framework



Describes the model accuracy overall, showing that the GRU framework is able to provide stable and accurate traffic forecasting.

Figure 5 Traffic Sensor Correlation Heatmap of METR-LA Dataset



Identifies relationships between the sensors, captures trends in sensor readings that help the GRU's predictions.

3.5 Overall Discussion

Experimental results show that the proposed traffic flow prediction framework based on GRU network has excellent forecasting ability with less prediction error and has good time series learning ability. The traffic variations are well modelled and good traffic predictions are made which are conducive for intelligent transportation and smart city applications. The high level of accuracy (91.35%) obtained demonstrates that GRU deep learning architecture can be used for real-time traffic-flow prediction problems with large-scale transportation data.

4. DISCUSSION

The experimental results demonstrate that the proposed traffic flow prediction framework for GRU is effective. framework based on GRU has the ability to model the temporal traffic patterns and achieves reliable traffic forecasting from the METR-LA dataset. The prediction accuracy of 91.35% and the R^2 score near 1, show that the GRU model is capable of learning the traffic dependency in a sequential manner with minimum prediction error. The GRU architecture offers advantages over conventional machine learning methods, particularly for real-time traffic prediction tasks, as it excels in temporal learning and computational efficiency. The results of this study can be used for intelligent transportation research, enabling smart traffic management, congestion monitoring, and potential future applications in smart cities. Moreover, the suggested framework has practical implication for authorities in transportation sector as it allows forecasting and flexible urban mobility planning based on data. The visualization results also showed that the predicted traffic values are more or less aligned with the real traffic behaviour, which indicates the stability and robustness of the proposed model. The use of sequential deep learning also enhanced the capability of the framework to analyze the dynamic changes in traffic at different time intervals. Overall, the proposed GRU framework has been efficient in learning performance and can be a reliable solution to future intelligent transportation systems.

5. CONCLUSION

This study aimed to design a GRU based deeplearning architecture for the prediction of traffic flow based on the METR-LA real-time transportation dataset. The methodology involved data preprocessing, data normalization, a sequential traffic window generation, training of GRU model and testing of GRU model performance using MAE, MSE, RMSE and R^2 metrics. The simulated results validated that the proposed framework was able to effectively predict the results with 91.35% accuracy and good temporal learning ability. The research has been helpful in the field of IST because it can be easily scaled and can be useful to predict traffic flow for smart transportation systems in real-time scenarios. The study was conducted on a single traffic dataset and primarily aimed at sequential traffic prediction, but the use of hybrid deep learning models, cyberattack detection mechanism, graph neural networks, and multi-source traffic datasets can further improve the accuracy of traffic prediction and provide intelligent transportation security in the future. The proposed framework also exhibited lower prediction error and better forecasting consistencies when evaluated in the experimental phase. The embedding of GRU deep learning architecture facilitated efficient extraction of temporal traffic features from

sequential transportation data. The embedding of GRU deep learning architecture facilitated efficient extraction of temporal traffic features from sequential transportation data. Hence, the proposed system can also contribute to the future smart city infrastructures, which includes intelligent traffic monitoring, congestion reduction, and data-driven transportation management.

REFERENCES

- [1] Cho, K., Van Merriënboer, B., Gulcehre, C., Bahdanau, D., Bougares, F., Schwenk, H., & Bengio, Y. (2014). Learning phrase representations using RNN encoder–decoder for statistical machine translation. *Proceedings of EMNLP*. DOI: 10.3115/v1/D14-1179
- [2] Zhao, L., Song, Y., Zhang, C., Liu, Y., Wang, P., Lin, T., Deng, M., & Li, H. (2020). T-GCN: A temporal graph convolutional network for traffic prediction. *IEEE Transactions on Intelligent Transportation Systems*, 21(9), 3848–3858. DOI: 10.1109/TITS.2019.2935152
- [3] Wang, S., Shao, X., & Li, J. (2022). Traffic flow prediction using bi-directional gated recurrent unit method. *Transportation Research Record*. DOI: 10.1177/03611981221127383
- [4] Ma, C., Wang, Y., & Zhang, X. (2025). Hybrid deep learning model with VMD-BiLSTM-GRU networks for short-term traffic flow prediction. *Data Science and Management*, 8(3), 257–269. DOI: 10.1016/j.dsm.2024.10.004
- [5] Zeng, W., Liu, Y., & Huang, H. (2023). Traffic flow prediction based on hybrid deep learning models with missing data. *Sustainability*, 15(14), 11092. DOI: 10.3390/su151411092
- [6] Sun, X., Zhang, J., & Li, Q. (2023). Short-term traffic flow prediction model based on a shared GRU framework. *Physica A: Statistical Mechanics and its Applications*, 626, 129079. DOI: 10.1016/j.physa.2023.129079
- [7] Gomes, B., Silva, J., & Rodrigues, A. (2023). A survey on traffic flow prediction and classification. *Machine Learning with Applications*, 14, 100511. DOI: 10.1016/j.mlwa.2023.100511
- [8] Liu, M., & Wang, H. (2020). Traffic flow prediction based on deep learning. *Journal of System Simulation*, 32(9), 1758–1766. DOI: 10.16182/j.issn1004731x.joss.19-0423
- [9] Li, Q., Zhang, Y., & Wang, X. (2023). Short-term vehicle speed prediction based on BiLSTM networks. *Physica A*, 615, 128602. DOI: 10.1016/j.physa.2022.128602
- [10] Zhang, J., Chen, H., & Liu, Y. (2025). A CNN-LSTM-GRU hybrid model for spatiotemporal traffic flow prediction. *Systems*, 13(9), 765. DOI: 10.3390/systems13090765
- [11] Singh, V., Sharma, R., & Kumar, P. (2025). A novel CNN-GRU-LSTM based deep learning model for traffic prediction. *Information Systems Frontiers*. DOI: 10.1007/s10791-025-09526-0
- [12] Kong, J., Fan, X., Jin, X., & Zuo, M. (2022). Traffic flow prediction via variational Bayesian inference-based encoder-decoder framework. *Applied Intelligence*. DOI: 10.48550/arXiv.2212.07194
- [13] Zhang, W., Li, X., Huang, X., Wang, T., & Gao, H. (2024). SGRU: A high-performance structured gated recurrent unit for traffic flow prediction. *arXiv Preprint*. DOI: 10.48550/arXiv.2404.11854
- [14] Das, L. C. (2023). Traffic volume prediction using memory-based recurrent neural networks: A comparative analysis of LSTM and GRU. *arXiv Preprint*. DOI: 10.48550/arXiv.2303.12643
- [15] Zhao, Y., Liu, Z., & Wang, H. (2022). Traffic flow prediction model based on the combination of deep learning and spatiotemporal analysis. *Frontiers in Bioengineering and Biotechnology*, 10, 804454. DOI: 10.3389/fbioe.2022.804454
- [16] Zhou, L., Chen, Y., & Wang, P. (2022). Research on short-term traffic flow prediction based on KNN-GRU. *2022 China Automation Congress (CAC)*, 1924–1928. DOI: 10.1109/CAC57257.2022.10055164
- [17] Pan, Y., Zhang, T., & Xu, L. (2025). Traffic flow prediction based on time-domain graph convolution and GRU networks. *International Journal of Intelligent Transportation Systems Research*. DOI: 10.1007/s13177-025-00511-x
- [18] Ma, C., Zhao, H., & Li, Y. (2025). GRU-LSTM model based on sparrow search algorithm for short-term traffic prediction. *Journal of Intelligent and Connected Vehicles*. DOI: 10.26599/JICV.2024.9210051
- [19] Rüther, R., Klos, A., Rosenbaum, M., & Schiffmann, W. (2020). Traffic flow forecast of road networks with recurrent neural networks. *arXiv Preprint*. DOI: 10.48550/arXiv.2006.04670
- 1) Ata, K. I. M., Hassan, M. K., Ismaeel, A. G., Al-Haddad, S. A. R., Alquthami, T., & Alani, S. (2025). A multi-layer CNN-GRUSKIP model based on transformer for spatial temporal traffic flow prediction. *arXiv Preprint*. DOI: 10.48550/arXiv.2501.07593