International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
IJISAE
ISSN:2147-6799 www.ijisae.org Original Research Paper

Enhancing Autonomous Vehicle Navigation through Deep Learning-Based Traffic Flow Prediction

Sirisha Balla[1], A Venkata Raju[2]

Submitted: 02/09/2024 **Revised:** 18/10/2024 **Accepted:** 24/10/2024

Abstract: The phrase "deep learning-based framework for smart mobility" denotes a concept or research paper proposing a framework for traffic pattern prediction using deep learning techniques within the realm of smart mobility. The Autonomous Traffic Prediction: A Deep Learning-Based Framework for Smart Mobility initiative aims to enhance traffic prediction capabilities and develop more intelligent and efficient transportation systems by using the potential of deep learning algorithms. This paper presents a novel Improved Spider Monkey Swarm Optimized Generative Adversarial Network (ISMSO-GAN) method for predicting autonomous traffic in smart mobility. The ISMSO approach enhances the classification efficacy of the GAN. The traffic dataset from the Regional Transportation Management Center for the Twin Cities metro freeways is used to evaluate the efficacy of the proposed method. Noisy data from raw samples is eliminated using the Adaptive Median Filter (AMF). A Kernel Principal Component Analysis (KPCA) is conducted to derive the attributes from the segmented data. The study findings indicate that the proposed technique surpasses previous methods on accuracy, Mean Square Error (MSE), Mean Absolute Error (MAE), and Prediction Rate. Our suggested methodology may significantly improve traffic management and optimize resource allocation.

Keywords*: framework, Mobility, algorithms, autonomous, methodology.*

INTRODUCTION

"Autonomous traffic prediction" denotes the ability of a system or algorithm to anticipate traffic conditions and make decisions based on such data. Autonomous systems can predict traffic congestion, journey durations, and optimal routes by analyzing diverse data sources, including historical traffic patterns, real-time sensor information, climatic conditions, and social events. Diverse methodologies and tactics are used for autonomous traffic forecasting, including The technique that identifies recurring traffic congestion patterns at certain times, days, or locations by analyzing historical traffic data. Future traffic issues may be anticipated by the use of this information. Continuous data analysis is performed to predict current and future traffic situations (Shakarami et al., 2021). Weather substantially affects traffic patterns. Autonomous systems may forecast the influence of weather conditions, such as rain, snow, or fog, on traffic flow by incorporating meteorological data into their predictive models, then adjusting their plans accordingly. Traffic may be significantly affected by large-scale events, festivals, holidays, and road closures due to construction or parades. Autonomous systems may analyze information about events to predict changes in traffic patterns and provide alternative routes. Extensive traffic data may be evaluated and processed by advanced machine learning algorithms, which continuously improve their predictive capabilities. These algorithms' capacity to identify complex patterns and linkages enables the formulation of more accurate traffic predictions. Autonomous traffic prediction seeks to enable intelligent decision-making, including route optimization and speed modulation, to enhance traffic flow and alleviate congestion. Autonomous systems may enhance transportation efficiency, improve road safety, and elevate overall travel experiences by forecasting traffic conditions (Mauri et al., 2021).

The foundation of a deep learning-based framework for smart mobility is the use of deep learning algorithms to analyze various data sources and make informed decisions to optimize travel and improve mobility. Below is a compilation of the components

[1]*Associate Professor, Department of Computer Science and Engineering, International School of Technology and Sciences for Women*

[2]*Assistant Professor, Department of Computer Science and Engineering International School of Technology and Sciences for Women*

that may constitute such a framework: Data must first be collected from several sources, including traffic sensors, GPS data from vehicles, meteorological information, social media feeds, and other relevant data streams. The information provides a comprehensive overview of current traffic conditions and the factors influencing mobility. The obtained data must undergo preprocessing to reduce noise, address missing values, and standardize the format for analysis. Preprocessing raw data to extract valuable information may include data cleaning, normalization, and feature engineering. Convolutional neural networks (CNNs), recurrent neural networks (RNNs), and transformers are examples of deep learning models used to identify complex patterns and relationships in data (Wang et al., 2019).

The models can process many data types, including time series, text, and image data, and extract valuable insights. Deep learning models may be trained to predict journey durations, traffic trends, and levels of congestion. The models may provide accurate predictions of future traffic conditions by analyzing historical traffic data, real-time sensor data, and other relevant factors (Razali et al., 2021). This information may facilitate route planning, traffic flow management, and congestion alleviation. Route optimization algorithms may incorporate deep learning models to suggest the most efficient routes based on projected traffic conditions. These algorithms can dynamically adjust routes to circumvent congestion and reduce travel time by considering both historical patterns and real-time traffic information. Utilizing deep learning models for real-time decision-making is an alternative. Autonomous vehicles may use deep reinforcement learning algorithms to ascertain optimal practices based on environmental conditions and prevailing traffic scenarios (Nama et al., 2021). Utilizing the models, vehicles may navigate complex traffic scenarios safely and effectively. The framework may include techniques for continuous learning, allowing deep learning models to evolve and improve over time. The system can adjust to evolving traffic patterns and fluctuating mobility requirements by continuously collecting new data and updating the models. An intelligent mobility framework may facilitate informed decision-making for many stakeholders, including autonomous vehicles, traffic management systems, and transportation planners, by using deep learning to provide real-time traffic predictions, optimize routes, and provide services. A framework of this kind may enhance productivity, reduce traffic, improve safety, and provide superior mobility solutions (Nacef et al., 2022).

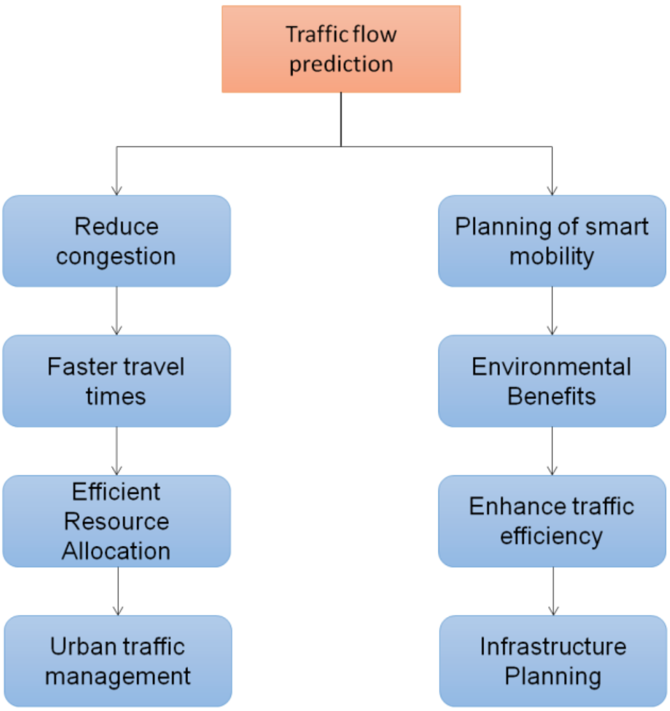

Figure 1. Benefits of Traffic flow prediction

Forecasting traffic flow has several benefits, as seen in (Figure 1), for enhancing overall mobility and fortifying transportation networks. Presented here are many notable advantages: Real-time selection of the most efficient routes and guidance systems is facilitated by precise traffic flow estimations. Optimal route selection and avoidance of congested areas may significantly reduce travel times, leading to less time spent in traffic and enhanced overall efficiency. Transportation authorities and traffic management systems use traffic flow prediction to proactively identify and address congested regions. By pinpointing locations anticipated to encounter congestion, preemptive measures may be implemented to mitigate it. Traffic signal timings may be adjusted, dynamic lane management implemented, and alternative routes proposed to distribute traffic more evenly (Kim et al., 2022). Traffic flow prediction enhances safety by allowing autonomous systems to anticipate potential traffic congestion and hazardous situations. Utilizing this information, appropriate measures may be implemented and styles adjusted as needed, therefore reducing the probability of accidents and enhancing overall road safety. Traffic flow prediction enhances the scheduling and planning of public transportation systems. Public transit agencies may improve routes and timetables by anticipating traffic conditions to ensure that buses, trains, and other forms of public transportation align with predicted traffic patterns (Zhang et al., 2022). Traffic flow prediction reduces emissions and fuel consumption by optimizing traffic and alleviating congestion. An environmentally friendly and sustainable transportation system may be established via efficient route planning that minimizes idle time. The steps may lead to a reduction in carbon dioxide emissions and an improvement in air quality. Traffic flow prediction facilitates the more efficient and swift navigation of emergency response services through traffic (Tang et al., 2021). An emergency may be sent via the most efficient routes by accurately predicting traffic conditions, facilitating rapid assistance in critical situations. The forecasting of traffic flows generates valuable data applicable to transportation planning. Urban planners and lawmakers may make informed decisions on infrastructure development, road expansion, traffic signal optimization, and enhancements to public transport by using historical traffic flow data and forecasts. Traffic flow prediction enhances travel efficiency, alleviates congestion, increases safety, mitigates environmental effects, and informs data-driven transportation planning, therefore benefiting individuals, communities, and transportation authorities. Transportation systems may enhance their effectiveness, sustainability, and responsiveness to the needs of commuters and visitors via accurate traffic flow forecasts (Lilhore et al., 2022). The Improved Spider Monkey Swarm Optimized Generative Adversarial Network (ISMSO-GAN) architecture offers a robust combination of deep learning, optimization, and generative modeling techniques for autonomous traffic prediction in smart mobility. Consequently, more precise, effective, and flexible traffic forecasts are generated, ultimately leading to more intelligent and efficient transportation systems.

Principal Contributions:

The ISMSO-GAN-based autonomous traffic prediction system might significantly enhance smart transportation. The following notable contributions are enumerated:

• To facilitate accurate traffic forecasting, real-time observation, adaptive traffic management, and autonomous traffic prediction aimed at enhancing user experiences and safety. • Traffic integration enhances the efficiency of transportation systems, mitigates congestion, and improves overall mobility for individuals and communities through the application of advanced machine learning techniques such as ISMSO-GAN.

The subsequent sections of the paper are organized as follows: Segment 2 delineates the prior study and highlights any flaws or contradictions regarding the research goals or objectives. Segment 3 delineates the study methods and procedures used for data collection and analysis, along with suggestions for future research derived from the results. Prior to succinctly and systematically presenting the research findings, we will first examine and elucidate them in relation to the study's goals or objectives, as outlined in Segment 4's Discussion and Results. Segment 5 offers a summary of the study's principal components, along with its significance and contributions, possible implications for practice or policy, and prospective avenues for future research.

RELATED WORKS

Miglani and Kumar (2019) examined autonomous vehicles' route planning and adaptive decision-making about their environment, emphasizing the importance of traffic flow prediction. Nonetheless, because to the intricate non-linear interactions between the spatial and temporal data obtained from the environment during the previously stated adaptive traffic prediction decisions, contemporary machine learning techniques may not be directly applicable in this context. Shao and Sun (2020) proposed a method for a connected and autonomous vehicle to navigate intersections that minimizes fuel usage. It is developed as a control system that integrates speed optimization with connectivity-enhanced traffic forecasting. The traffic prediction relies on a traffic flow model and is adjustable for mixed traffic scenarios, including both connected and disconnected vehicles on the route. A 'partial' evaluation of traffic conditions is facilitated by real-time data from interconnected vehicles and traffic signals. Lee et al. (2020) created a machine learning-driven traffic management system and a routing methodology that dynamically selects autonomous vehicle routes with reduced congestion levels. The research predicted congestion at critical bottleneck locations and used these predictions to adaptively manage the paths of all vehicles to avert congestion. The research conducted an experimental analysis to evaluate the anticipated efficacy of four prominent algorithms. A simulation study using data from semiconductor manufacturers was conducted to demonstrate the efficacy and superiority of the proposed technique. Shah et al. (2021) examined the Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), and hybrid CNN-LSTM models used to address the difficulty. The study revealed that our deep learning models outperformed the traditional linear regression method after six months of training on actual traffic flow data provided by the California Department of Transportation (Caltrans). An architecture examination of deep learning models is also performed for the traffic flow prediction problem. Mall et al. (2023) noted that the number of cars on the road in smart cities has significantly expanded over time, resulting in critical issues such as traffic congestion, accidents, and many other difficulties. The sophisticated traffic control system now implemented is based on image processing technology.

(Prarthana et al., 2022) aimed to compare various vehicle identification and classification strategies while presenting the reader with contemporary AI-based classification algorithms. The current categorization algorithms may be categorized into two types based on the kind of input, such as images or videos. The Intelligent Transportation System (ITS) integrates technology such as artificial intelligence, image processing, data mining, and sensors to monitor road conditions, initiate autonomous identification, and efficiently regulate traffic flow.

Yu et al. (2020) analyzed the characteristics, projected vehicular edge processing capabilities, and evaluated the Wireless Access in Vehicular Environment (WAVE) architecture inside a simulation of Harbin city. The Study also assessed a traffic efficiency application designed to reduce waiting times and fuel consumption, using the proposed architecture. The simulation results illustrated the proposed framework's capacity to provide dynamic integration between ITS Edge computing technologies for future urban models. Jaffry and Hasan (2020) investigated models for autonomous cellular traffic prediction using deep learning techniques such as recurrent neural networks and long short-term memory. Alghmgham et al. (2019) assessed the development of an autonomous system for traffic and road sign recognition and identification with Deep Convolutional Neural Networks. The proposed technology identifies and recognizes traffic sign pictures instantaneously. The supplementary article also has a newly established collection of 24 unique traffic signs collected from various sites in Saudi Arabia. The images were taken under diverse conditions and from several viewpoints. Li et al. (2022) proposed a vehicle trajectory prediction method using the Clustering Convolution-Long Short-Term Memory (CC-LSTM) model. Nearby autos with analogous paths are categorized by the fuzzy clustering method to derive their temporal characteristics. Density clustering is used to classify the attributes of the historical trajectory, identifying commonalities across segments that serve as spatial elements of the target vehicle's trajectory. The Las Vegas Wrapper (LVW) method integrates filtered spatio-temporal features to provide novel input data for the Convolution-LSTM network to produce predictions.

EXPERIMENTAL PROCEDURE

This section delineates the methodology used in model construction, outlines the principal phases undertaken in its development, and provides a comprehensive description of the actions involved in the proposed model seen in Figure 2. This conversation has four components: The first phase focuses on data collection. In the subsequent section, we will discuss the procedure, feature selection and extraction techniques, as well as other data pre-processing approaches. The third section, detailing the efforts undertaken to develop the proposed model and compile essential experiences, presents the most significant information. In the fourth step, the efficacy of each existing and new model is assessed by comparing the relevant parameters.

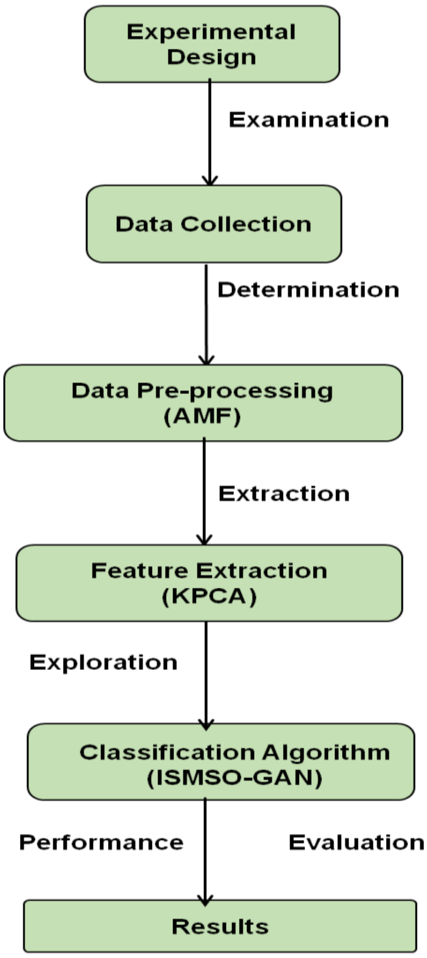

Figure 2. Experimental design of Autonomous traffic prediction for smart mobility

Dataset

The training set comprises data from January 12, 2018, to June 11, 2018, while the test set consists of data from June 17, 2018, to January 12, 2019. The primary objective of our study in data mining is to analyze data patterns from 6:00 to 21:00, the peak hours of the day (Hou et al., 2021).

RESULTS AND DISCUSSION

Deep learning frameworks have shown encouraging outcomes in several traffic prediction applications, particularly in traffic flow forecasting. Deep learning algorithms can comprehend intricate patterns and connections to provide accurate predictions about traffic conditions by using extensive amounts of historical and real-time traffic data.

a) Accuracy

The ISMSO-GAN framework can proficiently identify the fundamental patterns and dynamics of traffic behavior, resulting in accurate forecasts, as seen in Formula (14). The enhanced precision in traffic forecasting indicates that this is true. The intricate and dynamic characteristics of transportation networks hinder the attainment of high accuracy in traffic forecasting, with inherent uncertainties and unpredictability affecting predictive precision.

Accuracy = (TP + TN) / (TP + TN + FP + FN) (14)

Table 2. Quantitative results of the precision for current and planned methodologies. Figure 3 illustrates the comparative accuracy of the proposed and current methodologies. Accuracy levels are often expressed as a percentage of the aggregate. Both the current approach and the proposed method are susceptible to generating erroneous estimations. The proposed method, ISMSO-GAN, achieves an accuracy rate of 92%, while RNN, DCNN, and CC-LSTM exhibit accuracy rates of 42%, 58%, and 76%, respectively. The suggested method thus exhibits the highest accuracy rate.

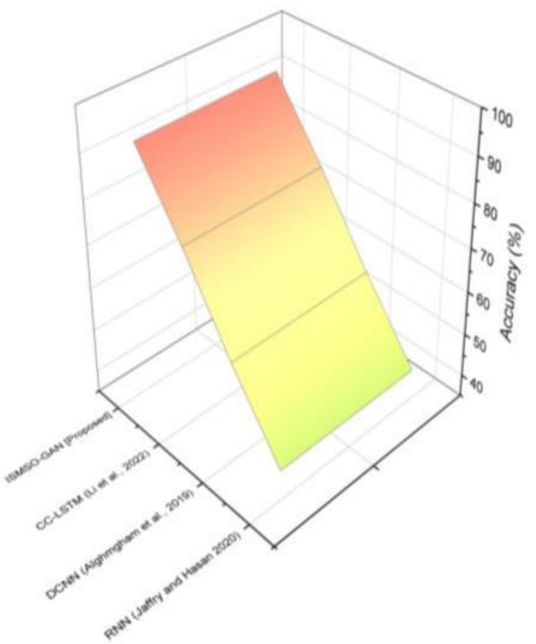

Figure 3. Comparison of accuracy for existing and proposed methods

Mean Absolute Error (MAE)

The Mean Absolute Error (MAE) quantifies the average absolute deviation between anticipated and actual values in traffic prediction. In the autonomous forecasting of traffic variables such as traffic flow, congestion levels, or trip durations, Mean Absolute Error (MAE) quantifies the average size of errors. To compute the Mean Absolute Error (MAE) for traffic prediction, the projected values, including predicted traffic flow, are juxtaposed with the corresponding actual values (ground truth). The absolute discrepancies between each predicted value and its corresponding actual value are calculated, summed, and divided by the total number of samples.

CONCLUSION

A deep learning framework for intelligent mobility using ISMSO-GAN introduces an innovative approach for predicting traffic patterns in autonomous traffic systems. The study demonstrates the potential of deep learning techniques to accurately predict future traffic conditions and occurrences. The proposed framework improves the accuracy and reliability of traffic predictions by leveraging the capabilities of ISMSO-GAN, allowing more effective traffic management and optimization of smart mobility systems. Metrics like as accuracy and prediction rate are used to assess the framework's efficacy. The results indicate that the deep learning-based approach yields favorable outcomes, characterized by elevated prediction and accuracy rates. This indicates that the technique may facilitate proactive traffic management decision-making and provide valuable insights into potential traffic patterns. The research underscores the need of accurate traffic forecast for autonomous systems, as it enables optimum resource allocation, traffic management, and enhanced safety measures. The proposed architecture enhances intelligent transportation systems by providing precise and reliable traffic predictions. It is essential to acknowledge some limitations of the framework. The efficacy of the deep learning model may be influenced by factors such as data availability, model intricacy, and computational resources. Further research is required to tackle these difficulties and explore methods to enhance the scalability and generalizability of the system. In conclusion, we favored a deep learning paradigm that has potential for autonomous traffic prediction in intelligent transportation systems. The results indicate that the proposed technique might significantly improve traffic management and optimize resource allocation, paving the way for more efficient and reliable future autonomous transportation systems.

References:

[1] Mall, P. K., Narayan, V., Pramanik, S., Srivastava, S., Faiz, M., Sriramulu, S., & Kumar, M. N. (2023). FuzzyNet-Based Modelling Smart Traffic System in Smart Cities Using Deep Learning Models. In Handbook of Research on Data-Driven Mathematical Modeling in Smart Cities (pp. 76-95). IGI Global. DOI: https://doi.org/10.4018/978-1-6684-6408-3.ch005

[2] Mauri, A., Khemmar, R., Decoux, B., Benmoumen, T., Haddad, M., & Boutteau, R. (2021, July). A Comparative Study of Deep Learning-based Depth Estimation Approaches: Application to Smart Mobility. In 2021 8th International Conference on Smart Computing and Communications (ICSCC) (pp. 80-84). IEEE. DOI: https://doi.org/10.1109/ICSCC51209.2021.9528220

[3] Li, R., Zhong, Z., Chai, J., & Wang, J. (2022). Autonomous Vehicle Trajectory Combined Prediction Model Based on CC-LSTM. International Journal of Fuzzy Systems, 24(8), 3798-3811. DOI: https://doi.org/10.1007/s40815-022-01288-x

[4] Prarthana, V., Hegde, S. N., Sushmitha, T. P., Savithramma, R. M., & Sumathi, R. (2022, December). A Comparative Study of Artificial Intelligence based Vehicle Classification Algorithms used to Provide Smart Mobility. In 2022 4th International Conference on Advances in Computing, Communication Control and Networking (ICAC3N) (pp. 2341-2348). IEEE. DOI: https://doi.org/10.1109/ICAC3N56670.2022.10074282

[5] Razali, N. A. M., Shamsaimon, N., Ishak, K. K., Ramli, S., Amran, M. F. M., & Sukardi, S. (2021). Gap, techniques and evaluation: traffic flow prediction using machine learning and deep learning. Journal of Big Data, 8(1), 1-DOI: https://doi.org/10.1186/s40537-021-00542-7

[6] Shah, S. A. A., Illanko, K., & Fernando, X. (2021, September). Deep learning based traffic flow prediction for autonomous vehicular mobile networks. In 2021 IEEE 94th Vehicular Technology Conference (VTC2021-Fall) (pp.

01-05). IEEE. https://doi.org/10.1109/VTC2021-Fall52928.2021.9625196.

[7] Shakarami, A., Shahidinejad, A., & Ghobaei-Arani, M. (2021). An autonomous computation offloading strategy in Mobile Edge Computing: A deep learning-based hybrid approach. Journal of Network and Computer Applications, 178, 102974. DOI: https://doi.org/10.1016/j.jnca.2021.102974

[8] Shao, Y., & Sun, Z. (2020). Eco-approach with traffic prediction and experimental validation for connected and autonomous vehicles. IEEE Transactions on Intelligent Transportation Systems, 22(3), 1562-1572. DOI: https://doi.org/10.1109/TITS.2020.2972198

[9] Miglani, A., & Kumar, N. (2019). Deep learning models for traffic flow prediction in autonomous vehicles: A review, solutions, and challenges. Vehicular Communications, 20, 100184. DOI: https://doi.org/10.1016/j.vehcom.2019.100184 Nacef, A., Kaci, A., Aklouf, Y., & Dutra, D. L. C. (2022). Machine learning based fast self optimized and life cycle management network. Computer Networks, 209, 108895. DOI: https://doi.org/10.1016/j.comnet.2022.108895

[10] Nama, M., Nath, A., Bechra, N., Bhatia, J., Tanwar, S., Chaturvedi, M., & Sadoun, B. (2021). Machine learning-based traffic scheduling techniques for intelligent transportation system: Opportunities and challenges. International Journal of Communication Systems, 34(9), e4814. DOI: https://doi.org/10.1002/dac.4814

[11] Alghmgham, D. A., Latif, G., Alghazo, J., & Alzubaidi, L. (2019). Autonomous traffic sign (ATSR) detection and recognition using deep CNN. Procedia Computer Science, 163, 266-274.DOI: https://doi.org/10.1016/j.procs.2019.12.108

[12] Hou, Y., Deng, Z., & Cui, H. (2021). Short-term traffic flow prediction with weather conditions: based on deep learning algorithms and data fusion. Complexity, 2021, 1-14. DOI: https://doi.org/10.1155/2021/6662959

[13] Jaffry, S., & Hasan, S. F. (2020, November). Cellular traffic prediction using recurrent neural networks. In 2020 IEEE 5th International Symposium on Telecommunication Technologies (ISTT) (pp. 94-98). IEEE. DOI: https://doi.org/10.1109/ISTT50966.2020.9279373

[14] Kim, C., Cho, J. K., Jung, Y., Seo, S. W., & Kim, S. W. (2022, February). Action-Conditioned Traffic Scene Prediction for Interactive Planning. In 2022 International Conference on Electronics, Information, and Communication (ICEIC) (pp. 1-4). IEEE. DOI: https://doi.org/10.1109/ICEIC54506.2022.9748470

[15] Lee, S., Kim, Y., Kahng, H., Lee, S. K., Chung, S., Cheong, T., ... & Kim, S. B. (2020). Intelligent traffic control for autonomous vehicle systems based on machine learning. Expert Systems with Applications, 144, 113074. DOI: https://doi.org/10.1016/j.eswa.2019.113074

[16] Lilhore, U. K., Imoize, A. L., Li, C. T., Simaiya, S., Pani, S. K., Goyal, N., ... & Lee, C. C. (2022). Design and implementation of an ML and IoT based Adaptive Traffic-management system for smart cities. Sensors, 22(8), 2908. DOI: https://doi.org/10.3390/s22082908

[17] Tang, F., Mao, B., Kawamoto, Y., & Kato, N. (2021). Survey on machine learning for intelligent end-to-end communication toward 6G: From network access, routing to traffic control and streaming adaption. IEEE Communications Surveys & Tutorials, 23(3), 1578-1598. DOI: https://doi.org/10.1109/COMST.2021.3073009

[18] Wang, T., Hussain, A., Bhutta, M. N. M., & Cao, Y. (2019). Enabling bidirectional traffic mobility for ITS simulation in smart city environments. Future Generation Computer Systems, 92, 342-356. https://doi.org/10.1016/j.future.2018.10.015

[19] Yu, K., Lin, L., Alazab, M., Tan, L., & Gu, B. (2020). Deep learning-based traffic safety solution for a mixture of autonomous and manual vehicles in a 5G-enabled intelligent transportation system. IEEE transactions on intelligent transportation systems, 22(7), 4337-4347. DOI: https://doi.org/10.1109/TITS.2020.3042504

[20] Zhang, H., Fu, R., Wang, C., Guo, Y., & Yuan, W. (2022). Turning Maneuver Prediction of Connected Vehicles at Signalized Intersections: A Dictionary Learning-Based Approach. IEEE Internet of Things Journal, 9(22), 23142-23159. DOI: https://doi.org/10.1109/JIOT.2022.3188312