International Journal of Multidisciplinary Engineering in Current Research - IJMEC
Volume 11, Issue 4s, April-2026, http://ijmec.com/, ISSN: 2456-4265

Full Length Article

Time Series Traffic Prediction With Vehicle-Type Suggestions

Akber Mohammed Arshad[1], Mohammed Saifullah Hussain Farooqui[2], Mohammed Shareeful Hassan[3], Ms. Sumrana Tabassum[4]
[1,2,3]B.E Students; Department of CSE ISL Engineering College Hyderabad India
[4]Assistant Professor; Department of CSE ISL Engineering College Hyderabad India
Emails:Akberarshad2@gmail.com,160522733025@islec.edu.in,160522733053@islec.edu.in
Accepted 23-04-2026

Abstract

Urban traffic congestion is a major challenge in modern cities, leading to increased travel times, fuel consumption, and air pollution. To address this issue, Deep Traffic-VTS presents an intelligent hybrid system that integrates Long Short-Term Memory (LSTM) networks for time series forecasting with YOLO (You Only Look Once) for vehicle detection. The LSTM model analyzes historical traffic data—such as vehicle count, average speed, and congestion levels—to predict traffic conditions over upcoming time intervals. Simultaneously, YOLO processes live video feeds to detect and classify vehicle types on the road, including two-wheelers, cars, buses, and emergency vehicles. Based on both predicted and real-time traffic conditions, the system provides adaptive suggestions on the most suitable vehicle types for efficient navigation—for example, recommending two-wheelers in high-congestion zones due to their maneuverability, while advising larger vehicles to reroute or delay travel. This combined approach enables more effective traffic management, emergency response optimization, and smart urban mobility planning.

Based on both predicted and real-time traffic conditions, the system provides adaptive suggestions on the most suitable vehicle types for efficient navigation. Specifically, when congestion levels are high, the system recommends small vehicles such as two-wheelers due to their maneuverability; for medium congestion, it suggests medium-sized vehicles like cars; and for low congestion, it supports the use of larger vehicles such as buses and trucks for efficient mass transportation. In addition, emergency vehicles like ambulances and fire trucks can be given priority-based navigation routes, reducing response times in critical situations.

Keywords— *Traffic Prediction, LSTM, YOLOv8, Smart Cities, AI, Computer Vision.*

Introduction:

Urban traffic congestion has become one of the most pressing challenges in modern cities, contributing to longer travel times, increased fuel consumption, environmental pollution, and reduced quality of life. Traditional traffic management systems often struggle to handle the dynamic and complex nature of urban traffic, as they typically rely on static rules and limited real-time data. To address these limitations, the integration of advanced machine learning techniques and computer vision offers a promising solution. Deep Traffic-VTS is a hybrid intelligent system designed to improve urban traffic efficiency by combining predictive and real-time analysis. It employs Long Short-Term Memory (LSTM) networks to forecast traffic conditions based on historical data such as vehicle counts, average speeds, and congestion trends. Simultaneously, the system uses YOLO (You Only Look Once) to detect and classify vehicles from live video feeds, including cars, buses, two-wheelers, and emergency vehicles. By merging these insights, Deep Traffic-VTS can provide adaptive recommendations for optimal vehicle movement, helping to alleviate congestion, optimize travel routes, support emergency responses, and enable smarter urban mobility planning. This approach demonstrates the potential of combining time series forecasting and real-time detection to create a proactive, data-driven traffic management system capable of enhancing the safety, efficiency, and sustainability of urban transportation networks. Based on both **predicted and real-time traffic conditions**, the system provides **adaptive suggestions** on the most suitable vehicle types for efficient navigation. Specifically, when congestion levels are **high**, the system recommends **small vehicles such as two-wheelers** due to their maneuverability; for **medium congestion**, it suggests **medium-sized vehicles like cars**; and for **low congestion**, it supports the use of **larger vehicles such as buses and trucks** for efficient mass transportation. In addition, emergency vehicles like ambulances and fire trucks can be given **priority-based navigation routes**, reducing response times in critical situations.

LITERATURE SURVEY:

Yang *et al.* (2022) proposed a multi-task deep learning framework for predicting multiple levels of traffic accident severity while providing interpretable explanations. The framework simultaneously predicts various severity categories using shared feature representations, thereby improving prediction efficiency and accuracy. The authors integrated explainable artificial intelligence techniques to identify the most influential factors contributing to accident severity. Their approach was validated using large-scale accident datasets and demonstrated superior performance compared to conventional single-task prediction models. The study contributes significantly to intelligent transportation systems by enhancing both predictive capability and interpretability in accident analysis.

Champahom *et al.* (2022) investigated the factors affecting the severity of motorcycle accidents on Thailand's arterial roads using multiple correspondence analysis and ordered logistic regression methods. The study analyzed variables such as rider behavior, road conditions, environmental factors, and traffic characteristics to determine their impact on crash severity. The findings revealed that poor road infrastructure, unsafe riding practices, and unfavorable weather conditions were major contributors to severe motorcycle accidents. The authors emphasized the importance of infrastructure development, stricter traffic law enforcement, and public awareness campaigns for improving road safety and reducing accident severity.

Guido *et al.* (2022) evaluated the contributing factors influencing the number of vehicles involved in crashes on rural roads in Cosenza, Italy, through the application of machine learning techniques. The research utilized datasets containing traffic indicators, road geometry information, and crash statistics to identify significant crash-related patterns. The machine learning models achieved higher predictive accuracy than traditional statistical approaches and highlighted factors such as road curvature, speed limits, and traffic flow as major contributors to crash severity. The study demonstrated the effectiveness of machine learning in traffic safety analysis and provided valuable insights for developing targeted accident prevention strategies.

Elvik (2024) critically examined the role of risk factors as causes of traffic accidents by focusing on the logical structure of causality and the completeness of accident explanations. The study proposed a comprehensive framework for linking accident occurrence to specific causal factors and emphasized the need for accurate and complete datasets in accident research. The author argued that understanding causal relationships is essential for designing effective road safety policies and preventive measures. The research contributes to the theoretical foundation of traffic accident analysis by improving the interpretation and classification of accident causation factors.

Shinar and Hauer (2024) discussed the relationship between crash causation, countermeasures, and policy implications in road safety research. The editorial highlighted the importance of translating scientific findings into practical safety interventions, including infrastructure modifications, traffic enforcement strategies, and driver education programs. The authors stressed the significance of interdisciplinary collaboration among researchers, policymakers, and transportation authorities to address the complex nature of road safety challenges. Their work provides a policy-oriented perspective on reducing traffic accidents and improving overall transportation safety systems.

Jung *et al.* (2020) proposed a lightweight lane detection approach by optimizing spatial embedding techniques to improve computational efficiency while maintaining high detection accuracy. The study focused on reducing the processing complexity of lane detection algorithms for real-time applications in autonomous driving and advanced driver assistance systems. Experimental evaluations demonstrated that the optimized spatial embedding method effectively balanced accuracy and computational performance, making it suitable for practical deployment in intelligent transportation environments. The research contributes to the development of efficient vision-based lane detection systems for modern traffic management and autonomous vehicle technologies.

Methodologies:

Modules Name:

1. Data Collection Module
2. Traffic Prediction Module (LSTM-based)
3. Vehicle Detection Module (YOLO-based)
4. Data Integration and Analysis Module
5. Adaptive Recommendation Module
6. System Evaluation Module

MODULES EXPLANATION:

A. Data Collection

The proposed intelligent traffic management system begins with the collection of both historical and real-time traffic data. Historical traffic information such as vehicle counts, average vehicle speed, congestion levels, traffic density, and time-of-day patterns is gathered from various sources including traffic sensors, CCTV cameras, smart road infrastructure, and government traffic databases. This data helps in understanding long-term traffic behavior and identifying recurring congestion trends in urban environments. In addition to historical records, live video feeds from urban roads and intersections are continuously captured using CCTV surveillance cameras. These real-time video streams provide up-to-date information about ongoing traffic movement and road conditions, enabling dynamic traffic monitoring and immediate analysis.

B. Traffic Prediction Using LSTM

To predict future traffic conditions, the system employs Long Short-Term Memory (LSTM) networks, a specialized type of recurrent neural

https://doi.org/10.63665/IJMEC.1104s.02
ISSN: 2456-4265
IJMEC 2026

network designed for time-series forecasting. The LSTM model is trained using historical traffic datasets so that it can learn temporal traffic patterns, daily fluctuations, peak-hour trends, and congestion behavior over time. By analyzing sequential traffic data, the model can accurately forecast upcoming traffic conditions for future time intervals. The predictions include expected congestion levels, traffic density, average vehicle speed, and possible traffic bottlenecks. These forecasts assist traffic authorities and navigation systems in taking preventive actions before severe congestion occurs.

C. Vehicle Detection Using YOLO

For real-time traffic monitoring, the system integrates the YOLO (You Only Look Once) object detection algorithm. YOLO processes live video feeds from CCTV cameras and detects vehicles with high speed and accuracy. The model identifies and classifies different categories of vehicles such as two-wheelers, cars, buses, trucks, and emergency vehicles. Along with classification, YOLO also provides information regarding the number of vehicles, their movement, and their location within the road network. The real-time detection capability enables the system to continuously monitor traffic flow and detect unusual traffic situations instantly.

D. Integration and Analysis

The outputs generated from the LSTM traffic prediction model and the YOLO vehicle detection model are integrated to create a comprehensive traffic analysis framework. The predicted traffic conditions are combined with real-time vehicle detection data to obtain a complete understanding of current and future road situations. The system analyzes traffic density, vehicle distribution, and congestion-prone areas to determine the most suitable routes for different vehicle categories. This integration enables intelligent decision-making by identifying heavily congested roads and suggesting alternate navigation strategies for efficient traffic management.

E. Adaptive Recommendations

Based on the integrated traffic insights, the system provides adaptive route recommendations for different types of vehicles. Two-wheelers are recommended for highly congested routes because of their ability to maneuver through narrow spaces and dense traffic conditions more efficiently. Larger vehicles such as buses and trucks are advised to use alternate routes or postpone travel during peak congestion periods to reduce traffic pressure on busy roads. Emergency vehicles including ambulances, fire trucks, and police vehicles are given the highest priority, and the system identifies the fastest and least congested routes to ensure rapid emergency response. These adaptive recommendations help improve overall traffic flow, reduce travel delays, and enhance road safety.

F. System Evaluation

The effectiveness of the proposed intelligent traffic management system is evaluated using multiple performance metrics. The LSTM model is assessed based on traffic prediction accuracy and forecasting reliability, while the YOLO model is evaluated using vehicle detection accuracy and classification performance. Additional evaluation parameters include congestion reduction efficiency, travel time optimization, traffic flow improvement, and emergency vehicle response time. The system's ability to provide accurate predictions and intelligent routing recommendations demonstrates its potential for enhancing smart city traffic management.

G. Implementation

The proposed system is implemented in a web-based environment using Jupyter Notebook software. The server acts as the intelligence processing unit where machine learning and deep learning models are trained and executed. The implementation platform uses Windows 10 Professional operating system for development and deployment purposes. The user interface is developed within the Jupyter Notebook environment, providing an interactive platform for traffic analysis, visualization, prediction results, and route recommendation outputs. This implementation setup ensures flexibility, ease of experimentation, and efficient integration of multiple AI-based traffic management modules.

Algorithm used:

In the DeepTraffic-VTS system, YOLOv8 (You Only Look Once version 8) is employed as a state-of-the-art real-time object detection model to identify and classify various vehicle types from live video feeds. YOLOv8 offers significant improvements in speed and accuracy over previous versions, making it ideal for urban traffic environments where rapid and reliable detection is crucial. It can accurately recognize two-wheelers, cars, buses, and emergency vehicles in diverse traffic scenarios, even under challenging conditions such as occlusions and varying lighting. By integrating YOLOv8, the system gains the ability to monitor real-time traffic flow, assess current congestion levels, and feed dynamic vehicle data into the recommendation engine, enabling context-aware suggestions for efficient mobility and smarter routing decisions.

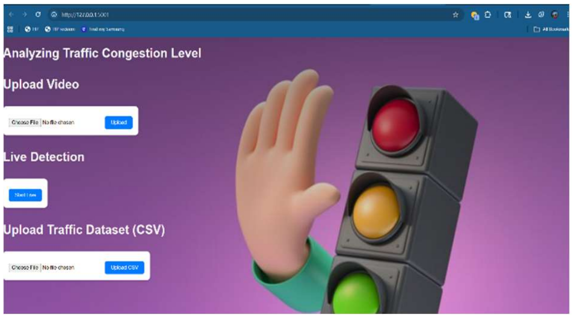
The Long Short-Term Memory (LSTM) neural network is utilized in DeepTraffic-VTS for predicting future traffic conditions based on historical time series data. LSTM is particularly well-suited for modeling sequential patterns and long-term dependencies in traffic data, such as vehicle counts, average speed, and congestion levels recorded over time. By learning these temporal patterns, the LSTM model can forecast short- to medium-term traffic trends with high accuracy. These predictions are essential for anticipating congestion before it occurs, allowing the system to generate proactive recommendations on optimal vehicle usage. For instance, if high congestion is predicted, the system may recommend two-wheelers or emergency vehicles for quicker transit, while advising larger vehicles to delay or reroute. The

https://doi.org/10.63665/IJMEC.1104s.02
ISSN: 2456-4265
IJMEC 2026

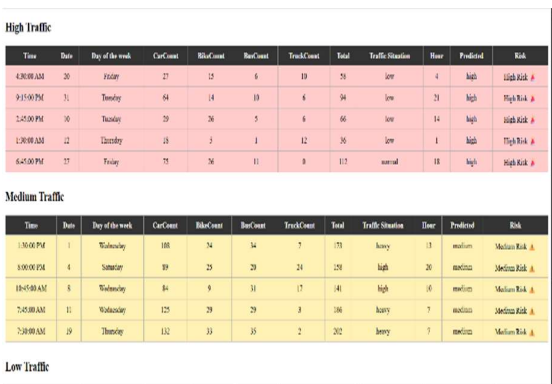
International Journal of Multidisciplinary Engineering in Current Research - IJMEC
Volume 11, Issue 4s, April-2026, http://ijmec.com/, ISSN: 2456-4265

integration of LSTM thus adds a predictive intelligence layer to the system, enhancing its ability to support real-time decisions with future-aware insights.

Results (screenshots):



(i)



High Traffic

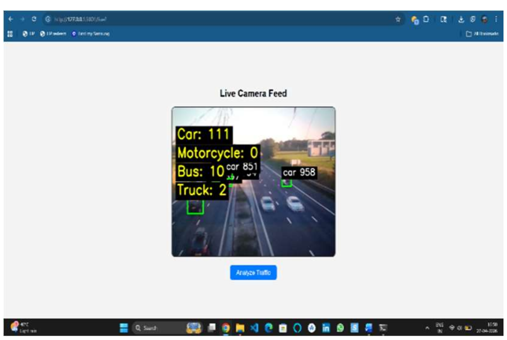
Time	Date	Day of the week	CarCount	BikeCount	BusCount	TruckCount	Total	Traffic Situation	Hour	Predicted	Risk
4:30:00 AM	20	Friday	27	15	6	10	58	low	4	high	High Risk
9:15:00 PM	31	Tuesday	64	14	10	6	94	low	21	high	High Risk
2:45:00 PM	10	Tuesday	29	26	5	6	66	low	14	high	High Risk
1:30:00 AM	12	Thursday	18	5	1	12	36	low	1	high	High Risk
6:45:00 PM	27	Friday	75	26	11	0	112	normal	18	high	High Risk

Medium Traffic

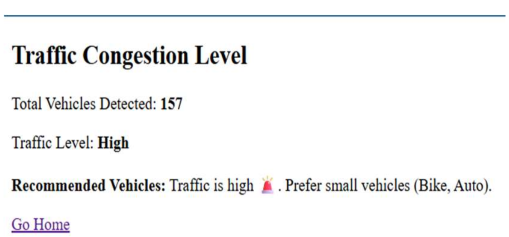
Time	Date	Day of the week	CarCount	BikeCount	BusCount	TruckCount	Total	Traffic Situation	Hour	Predicted	Risk
1:30:00 PM	1	Wednesday	108	24	34	7	173	heavy	13	medium	Medium Risk
8:00:00 PM	4	Saturday	89	25	20	24	158	high	20	medium	Medium Risk
10:45:00 AM	8	Wednesday	84	9	31	17	141	high	10	medium	Medium Risk
7:45:00 AM	11	Wednesday	125	29	29	3	186	heavy	7	medium	Medium Risk
7:30:00 AM	19	Thursday	132	33	35	2	202	heavy	7	medium	Medium Risk

Low Traffic

(ii)



(iii)



(iv)

Conclusion:

DeepTraffic-VTS showcases an innovative approach to tackling urban traffic congestion by leveraging the strengths of both predictive analytics and real-time computer vision. By employing LSTM networks for accurate traffic forecasting and YOLO for live vehicle detection and classification, the system provides actionable insights that help optimize traffic flow and improve decision-making for commuters and traffic authorities alike. The integration of these two powerful techniques allows the system to dynamically adapt to changing traffic conditions, offering suitable vehicle routing suggestions, minimizing delays, and reducing fuel consumption.

FUTURE SCOPE:

The scope of DeepTraffic-VTS encompasses the development of an intelligent traffic management system that integrates predictive analytics with real-time vehicle detection. The system can forecast traffic conditions using historical data and detect vehicle types from live video feeds, enabling adaptive recommendations for efficient navigation and also we recommend the vehicles based on the congestion levels. It aims to assist in reducing traffic congestion, optimizing travel times, minimizing fuel consumption, and improving emergency vehicle response. Additionally, the project supports smart urban planning by providing actionable insights for traffic flow optimization and resource allocation. While the current implementation focuses on urban road networks and common vehicle types, the framework can be extended to include more complex traffic scenarios, multi-modal transport systems, and integration with city-wide smart infrastructure in the future.

REFERENCES

[1] Z. Yang, W. Zhang, and J. Feng, ‘‘Predicting multiple types of traffic accident severity with explanations: A multi-task deep learning framework,’’ Saf. Sci., vol. 146, Feb. 2022, Art. no. 105522, doi: 10.1016/j.ssci.2021.105522.

[2] F. Zong, X. Chen, J. Tang, P. Yu, and T. Wu, ‘‘Analyzing traffic crash severity with combination of information entropy and Bayesian network,’’ IEEE Access, vol. 7, pp. 63288–63302, 2019, doi: 10.1109/ACCESS.2019.2916691.

[3] Global Status Report on Road Safety 2018, World Health Organization, Geneva, Switzerland, 2018. [Online]. Available: https://apps.who.int/iris/handle/10665/276462

[4] J. Roland, P. D. Way, C. Firat, T.-N. Doan, and M. Sartipi, ‘‘Modeling and predicting vehicle accident occurrence in Chattanooga, Tennessee,’’ Accident

Anal. Prevention, vol. 149, Jan. 2021, Art. no. 105860, doi: 10.1016/j.aap.2020.105860.

[5] R. Elvik, F. Sagberg, and P. A. Langeland, ''An analysis of factors influencing accidents on road bridges in Norway,'' Accident Anal. Prevention, vol. 129, pp. 1–6, Aug. 2019, doi: 10.1016/j.aap.2019.05.002.

[6] L. Eboli, C. Forciniti, and G. Mazzulla, ''Factors influencing accident severity: An analysis by road accident type,'' Transp. Res. Proc., vol. 47, pp. 449–456, Jan. 2020, doi: 10.1016/j.trpro.2020.03.120.

[7] R. L. Rodriguez, J. Tricia, B. Villamaria, and M. I. Noroña, ''Analysis of factors affecting road traffic accidents in the city of makati Philippines,'' Tech. Rep., 2021.

[8] I. Pugachev, Y. Kulikov, G. Markelov, and N. Sheshera, ''Factor analysis of traffic organization and safety systems,'' Transp. Res. Proc., vol. 20, pp. 529–535, Jan. 2017, doi: 10.1016/j.trpro.2017.01.086.

[9] B. Dadashova, B. A. Ramírez, J. M. McWilliams, and F. A. Izquierdo, ''The identification of patterns of interurban road accident frequency and severity using road geometry and traffic indicators,'' Transp. Res. Proc., vol. 14, pp. 4122–4129, Jan. 2016, doi: 10.1016/j.trpro.2016.05.383.

[10] A. Montella, L. L. Imbriani, V. Marzano, and F. Mauriello, ''Effects on speed and safety of point-to-point speed enforcement systems: Evaluation on the urban motorway A56 Tangenziale di Napoli,'' Accident Anal. Prevention, vol. 75, pp. 164–178, Feb. 2015, doi: 10.1016/j.aap.2014.11.022.

[11] F. Gross and E. T. Donnell, ''Case–control and cross-sectional methods for estimating crash modification factors: Comparisons from roadway lighting and lane and shoulder width safety effect studies,'' J. Saf. Res., vol. 42, no. 2, pp. 117–129, Apr. 2011, doi: 10.1016/j.jsr.2011.03.003.

[12] H. Martensen, K. Diependaele, S. Daniels, W. Van den Berghe, E. Papadimitriou, G. Yannis, I. Van Schagen, W. Weijermars, W. Wijnen, A. Filtness, R. Talbot, P. Thomas, K. Machata, E. Aigner Breuss, S. Kaiser, T. Hermitte, R. Thomson, and R. Elvik, ''The European road safety decision support system on risks and measures,'' Accident Anal. Prevention, vol. 125, pp. 344–351, Apr. 2019, doi: 10.1016/j.aap.2018.08.005.

[13] R. Sakhapov and R. Nikolaeva, ''Traffic safety system management,'' Transp. Res. Proc., vol. 36, pp. 676–681, Jan. 2018, doi: 10.1016/j.trpro.2018.12.126.

[14] G. Fancello, M. Carta, and P. Fadda, ''A decision support system for road safety analysis,'' Transp. Res. Proc., vol. 5, pp. 201–210, Jan. 2015, doi: 10.1016/j.trpro.2015.01.009.

[15] F. Gargiulo, S. Silvestri, M. Ciampi, and G. De Pietro, ''Deep neural network for hierarchical extreme multi-label text classification,'' Appl. Soft Comput., vol. 79, pp. 125–138, Jun. 2019, doi: 10.1016/j.asoc.2019.03.041.

[16] T. M. Allen, ''A factor analysis of accident records,'' Highway Res. Rec., vol. 79, pp. 17–25, Jan. 1965.

[17] T. Champahom, P. Wisutwattanasak, K. Chanpariyavatevong, N. Laddawan, S. Jomnonkwao, and V. Ratanavaraha, ''Factors affecting severity of motorcycle accidents on Thailand's arterial roads: Multiple correspondence analysis and ordered logistics regression approaches,'' IATSS Res., vol. 46, no. 1, pp. 101–111, Apr. 2022, doi: 10.1016/j.iatssr.2021.10.006.

[18] T. Tsubota, C. Fernando, T. Yoshii, and H. Shirayanagi, ''Effect of road pavement types and ages on traffic accident risks,'' Transp. Res. Proc., vol. 34, pp. 211–218, Jan. 2018, doi: 10.1016/j.trpro.2018.11.034.

[19] L.-Y. Chang, H.-C. Chu, D.-J. Lin, and P. Lui, ''Analysis of freeway accident frequency using multivariate adaptive regression splines,'' Proc. Eng., vol. 45, pp. 824–829, Jan. 2012, doi: 10.1016/j.proeng.2012.08.245.

[20] G. Guido, S. S. Haghshenas, S. S. Haghshenas, A. Vitale, V. Astarita, Y. Park, and Z. W. Geem, ''Evaluation of contributing factors affecting number of vehicles involved in crashes using machine learning techniques in rural roads of Cosenza, Italy,'' Safety, vol. 8, no. 2, p. 28, Apr. 2022, doi: 10.3390/safety8020028.

[21] S. Kumar and D. Toshniwal, ''A data mining framework to analyze road accident data,'' J. Big Data, vol. 2, no. 1, Dec. 2015, doi: 10.1186/s40537- 015-0035-y.

[22] T. Chen, C. Zhang, and L. Xu, ''Factor analysis of fatal road traffic crashes with massive casualties in China,'' Adv. Mech. Eng., vol. 8, no. 4, pp. 1–11, Apr. 2016, doi: 10.1177/1687814016642712.

[23] L. Liu, X. Ye, T. Wang, X. Yan, J. Chen, and B. Ran, ''Key factors analysis of severity of automobile to two-wheeler traffic accidents based on Bayesian network,'' Int. J. Environ. Res. Public Health, vol. 19, no. 10, p. 6013, May 2022, doi: 10.3390/ijerph19106013.

[24] T. Beshah and S. Hill, ''Mining road traffic accident data to improve safety: Role of road-related factors on accident severity in Ethiopia,'' in Proc. AAAI Spring Symp. Ser., Mar. 2010. [25] H. Chen, Y. Zhao, and X. Ma, ''Critical factors analysis of severe traffic accidents based on Bayesian network in China,'' J. Adv. Transp., vol. 2020, pp. 1–14, Nov. 2020, doi: 10.1155/2020/8878265.

[26] E. Sacchi, T. Sayed, and A. Osama, ''Developing crash modification functions for pedestrian signal improvement,'' Accident Anal. Prevention, vol. 83, pp. 47–56, Oct. 2015, doi: 10.1016/j.aap.2015.07.009.

[27] E. Sacchi and T. Sayed, ''Accounting for heterogeneity among treatment sites and time trends in developing crash modification functions,'' Accident Anal. Prevention, vol. 72, pp. 116–126, Nov. 2014, doi: 10.1016/j.aap.2014.06.016.

https://doi.org/10.63665/IJMEC.1104s.02
ISSN: 2456-4265
IJMEC 2026

[28] R. B. Patel, F. M. Council, and M. S. Griffith, ''Estimating safety benefits of shoulder rumble strips on two-lane rural highways in Minnesota: Empirical Bayes observational before-and-after study,'' Transp. Res. Rec., J. Transp. Res. Board, vol. 2019, no. 1, pp. 205–211, Jan. 2007, doi: 10.3141/2019-24.

[29] F. Gross, C. Lyon, B. Persaud, and R. Srinivasan, ''Safety effectiveness of converting signalized intersections to roundabouts,'' Accident Anal. Prevention, vol. 50, pp. 234–241, Jan. 2013, doi: 10.1016/j.aap. 2012.04.012.

[30] M. A. Raihan, P. Alluri, W. Wu, and A. Gan, ''Estimation of bicycle crash modification factors (CMFs) on urban facilities using zero inflated negative binomial models,'' Accident Anal. Prevention, vol. 123, pp. 303–313, Feb. 2019, doi: 10.1016/j.aap.2018.12.009.

[31] A. Osama, T. Sayed, and E. Sacchi, ''Crash modification functions for installation of left-turn lanes at signalized intersection approaches,'' Transp. Res. Rec., J. Transp. Res. Board, vol. 2583, no. 1, pp. 42–49, Jan. 2016, doi: 10.3141/2583-06.

[32] Q. Li, Z. Wang, M. Li, R. Yang, P.-S. Lin, and X. Li, ''Development of crash modification factors for roadway illuminance: A matched case-control study,'' Accident Anal. Prevention, vol. 159, Sep. 2021, Art. no. 106279, doi: 10.1016/j.aap.2021.106279.

[33] F. Gross and P. P. Jovanis, ''Estimation of safety effectiveness of changes in shoulder width with case control and cohort methods,'' Transp. Res. Rec., J. Transp. Res. Board, vol. 2019, no. 1, pp. 237–245, Jan. 2007, doi: 10.3141/2019-28. [34] A. Calvi and C. Petrella, ''An evaluation of the effectiveness of countermeasures for improving the safety of dilemma zones: A driving simulator study,'' Transp. Res. F, Traffic Psychol. Behav., vol. 87, pp. 295–312, May 2022, doi: 10.1016/j.trf.2022.04.013.

[35] Q. Hussain, W. K. M. Alhajyaseen, K. Brijs, A. Pirdavani, and T. Brijs, ''Innovative countermeasures for red light running prevention at signalized intersections: A driving simulator study,'' Accident Anal. Prevention, vol. 134, Jan. 2020, Art. no. 105349, doi: 10.1016/j.aap.2019.105349.

[36] M. Paul, I. Ghosh, and M. M. Haque, ''The effects of green signal countdown timer and retiming of signal intervals on dilemma zone related crash risk at signalized intersections under heterogeneous traffic conditions,'' Saf. Sci., vol. 154, Oct. 2022, Art. no. 105862, doi: 10.1016/j.ssci.2022.105862.

[37] S. Kazemzadehazad, S. Monajjem, G. S. Larue, and M. J. King, ''Evaluating new treatments for improving driver performance on combined horizontal and crest vertical curves on two-lane rural roads: A driving simulator study,'' Transp. Res. F, Traffic Psychol. Behav., vol. 62, pp. 727–739, Apr. 2019, doi: 10.1016/j.trf.2019.03.002.

[38] D. R. Ragland, A. A. Zabyshny, and E. Org. (2003). UC Berkeley Research Reports Title Intersection Decision Support Project: Taxonomy of Crossing-Path Crashes At Intersections Using GES 2000 Data Permalink Https://escholarship.org/uc/item/0201j0v2 Publication Date. [Online]. Available: https://escholarship.org/uc/item/0201j0v2

[39] A. P. Chassiakos, C. Panagolia, and D. D. Theodorakopoulos, ''Development of decision-support system for managing highway safety,'' J. Transp. Eng., vol. 131, no. 5, pp. 364–373, Apr. 2005, doi: 10.1061/(ASCE)0733- 947X(2005)131:5(364).

[40] D. Shinar and E. Hauer, ''Crash causation, countermeasures, and policy– editorial,'' Accident Anal. Prevention, vol. 201, Jun. 2024, Art. no. 107543, doi: 10.1016/j.aap.2024.107543.

[41] R. Elvik, ''Risk factors as causes of accidents: Criterion of causality, logical structure of relationship to accidents and completeness of explanations,'' Accident Anal. Prevention, vol. 197, Mar. 2024, Art. no. 107469, doi: 10.1016/j.aap.2024.107469.

[42] M. Bello, G. Nápoles, R. Sánchez, R. Bello, and K. Vanhoof, ''Deep neural network to extract high-level features and labels in multi-label classification problems,'' Neurocomputing, vol. 413, pp. 259–270, Nov. 2020, doi: 10.1016/j.neucom.2020.06.117.

[43] Y. Xu, Q. Huang, W. Wang, P. Foster, S. Sigtia, P. J. B. Jackson, and M. D. Plumbley, ''Unsupervised feature learning based on deep models for environmental audio tagging,'' IEEE/ACM Trans. Audio, Speech, Language Process., vol. 25, no. 6, pp. 1230–1241, Jun. 2017, doi: 10.1109/TASLP.2017.2690563.

[44] L. Chen, Y. Wang, and H. Li, ''Enhancement of DNN-based multilabel classification by grouping labels based on data imbalance and label correlation,'' Pattern Recognition., vol. 132, Dec. 2022, Art. no. 108964, doi: 10.1016/j.patcog.2022.108964.

[45] A. Maxwell, R. Li, B. Yang, H. Weng, A. Ou, H. Hong, Z. Zhou, P. Gong, and C. Zhang, ''Deep learning architectures for multi-label classification of intelligent health risk prediction,'' BMC Bioinf., vol. 18, no. S14, pp. 121–131, Dec. 2017, doi: 10.1186/s12859-017-1898-z.

[46] H. Liu, X. Li, and S. Zhang, ''Learning instance correlation functions for multilabel classification,'' IEEE Trans. Cybern., vol. 47, no. 2, pp. 499–510, Feb. 2017, doi: 10.1109/TCYB.2016.2519683.

[47] H. H. Mohammed, E. Dogdu, A. K. Gorur, and R. Choupani, ''Multi-label classification of text documents using deep learning,'' in Proc. IEEE Int. Conf. Big Data (Big Data), Dec. 2020, pp. 4681–4689, doi: 10.1109/BigData50022.2020.9378266.

[48] F. Subhan, S. Zhao, E. B. Diop, Y. Ali, and H. Zhou, ''Public intention to pay for road safety improvement: A case study of Pakistan,'' Accident Anal. Prevention, vol. 160, Sep. 2021, Art. no. 106315, doi: 10.1016/j.aap.2021.106315.