Journal of Advanced Artificial Intelligence
Volume 1 – No.4, January 2025

Road Traffic Congestion Prediction using AI/ML and Spatiotemporal Data: Literature Review

Mohammad Alam
University of the Cumberlands
Williamsburg, Kentucky, USA

ABSTRACT
Road traffic congestion is a critical issue that impacts urban mobility, environmental sustainability, and economic productivity. The advent of Artificial Intelligence (AI) and Machine Learning (ML) technologies, combined with spatiotemporal data, offers promising solutions for predicting and managing traffic congestion more effectively. This literature review explores the current state of research on AI/ML models for traffic congestion prediction, focusing on integrating spatiotemporal data, including traffic flow, weather conditions, road networks, and temporal patterns. It examines various predictive modeling techniques, such as supervised, deep, and reinforcement learning. The review also highlights the challenges, such as data quality, model generalization, and computational efficiency, while discussing the potential of hybrid approaches that combine multiple modeling strategies. Furthermore, it presents a summary of key findings, trends, and future directions for the development of intelligent traffic management systems.

Keywords
Traffic Congestion Prediction, Artificial Intelligence (AI), Machine Learning (ML), Spatiotemporal Data, Predictive Analytics.

1. INTRODUCTION
The exponential growth of urbanization and the corresponding surge in vehicles have led to severe traffic congestion in cities worldwide. This congestion results in prolonged travel times and increased fuel consumption and contributes significantly to air pollution and economic inefficiencies. Traditional traffic management approaches, such as expanding road infrastructure and adjusting traffic signal timings, have proven inadequate in addressing the complexities of modern traffic systems. Consequently, there is a growing need for advanced, technology-driven solutions to manage and mitigate traffic congestion effectively.

AI/ML represents cutting-edge technologies that can potentially transform traffic management. AI involves the creation of intelligent systems capable of performing tasks that typically require human intelligence, such as decision-making and pattern recognition. ML, a subset of AI, focuses on developing algorithms that allow systems to learn from data and improve their performance over time. These technologies are particularly well-suited for traffic management, where the ability to analyze large datasets and make accurate predictions is crucial.

Recently, AI and ML have been increasingly applied to traffic congestion prediction. These technologies can process and analyze spatiotemporal data, including spatial and temporal dimensions, to identify patterns and trends in traffic flow. By utilizing AI and ML, traffic management systems can predict congestion before it occurs, enabling proactive measures to prevent or mitigate its impact. This predictive capability is essential for optimizing traffic flow, reducing delays, and enhancing the overall efficiency of urban transportation networks.

Spatiotemporal data captures traffic flow's spatial and temporal dimensions, providing detailed insights into traffic patterns. Sources of spatiotemporal data include GPS devices, traffic sensors, mobile phone data, and social media feeds. Integrating this data allows for a comprehensive understanding of how traffic evolves over time and space, which is crucial for accurate congestion prediction. Integrating and analyzing spatiotemporal data poses several challenges, including data heterogeneity, high dimensionality, and the need for real-time processing. These challenges require advanced modeling techniques and computational resources to ensure accurate and efficient traffic analysis.

This review examines the application of AI and ML techniques to predict road traffic congestion using spatiotemporal data. The objectives of this review are as follows: (1) to explore the current state-of-the-art methodologies employed in traffic congestion management using AI and ML, (2) to assess the effectiveness and challenges associated with these approaches, and (3) to identify gaps in existing research and suggest potential directions for future studies. By synthesizing findings from a broad range of studies, this review seeks to offer valuable insights into the role of AI and ML in enhancing traffic management and reducing congestion.

2. LITERATURE REVIEW
2.1 Historical Perspective on Traffic Congestion Research Using AI Models
AI in traffic congestion research represents a recent but rapidly evolving field. This historical perspective aims to trace the trajectory of AI-based approaches in understanding and mitigating traffic congestion, highlighting key developments and contributions. Traffic congestion prediction has been a critical research area for several decades. These areas have seen significant advancements with the advent of AI. AI models have revolutionized traffic management systems by enabling more accurate and real-time predictions.

The origins of AI-based traffic congestion research can be traced back to the late 20th century, coinciding with the emergence of neural networks and machine learning techniques like decision trees. Early endeavors focused on historical data, data analysis algorithms, and a time-series model to predict traffic flow and identify congestion patterns [1]. These initial efforts laid the groundwork for subsequent advancements in the field.

Neural networks, one of the earliest AI approaches used in traffic congestion research, demonstrated the ability to learn from data and identify patterns that traditional models could not. These models were particularly effective in handling non-linear relationships in traffic data. Decision trees provided a straightforward method for traffic congestion prediction by breaking down data into smaller subsets based on specific criteria. This approach was advantageous due to its interpretability and ease of implementation. Still, it was often less accurate than more complex models where the congestion level must be known [2].

In the early 21st century, the proliferation of data collection technologies, such as GPS and traffic sensors, fueled the growth of AI-driven traffic management systems. Researchers began leveraging AI algorithms, including deep learning (DL) and reinforcement learning (RL), to optimize traffic signal control (TSC) and mitigate congestion within urban areas [3]. The mid-2010s witnessed a paradigm shift with the advent of big data analytics and cloud computing, enabling researchers to process vast amounts of traffic data in real time. AI models were deployed to predict traffic congestion in multi-intersection, detect incidents, and recommend adaptive traffic control [4]. Integrating AI with transportation infrastructure marked a significant milestone in traffic congestion research. Smart city initiatives leveraged AI-powered traffic management systems to enhance mobility, reduce travel times, and minimize environmental impacts [5].

DL models have gained prominence in traffic congestion research. These models, particularly Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), have significantly improved accuracy and processing capabilities. CNNs have been widely used for processing traffic cameras and sensor spatial data. They extract features from images and video data, making them ideal for detecting traffic congestion from inspection footage [6]. Recent studies have shown that CNNs can accurately predict congestion levels by analyzing traffic density and flow patterns. RNNs are particularly effective in analyzing temporal traffic data, making them suitable for predicting future traffic conditions based on historical patterns. Long Short-Term Memory (LSTM) networks, a type of RNN, have been extensively used to model traffic flow and congestion over time. These models can capture long-term dependencies in traffic data, leading to more accurate predictions. Combining CNNs and RNNs has resulted in hybrid models that leverage the strengths of both architectures. These models simultaneously process spatial and temporal data, offering superior performance in traffic congestion prediction. For instance, a hybrid CNN-RNN model developed by [7] demonstrated significant improvements in accuracy and speed compared to traditional models.

RL has emerged as a powerful tool for dynamic traffic management. RL algorithms learn optimal traffic signal control strategies by interacting with the traffic environment, leading to substantial reductions in congestion. Multi-agent reinforcement learning (MARL) has effectively coordinated traffic signals across large urban networks. Single-agent RL approaches involve a single agent learning to control traffic signals at an intersection. These models have shown promise in optimizing traffic flow and reducing waiting times. However, their effectiveness is limited when applied to larger, more complex traffic networks. MARL extends single-agent RL by involving multiple agents coordinating their actions to optimize traffic flow across intersections. This approach has proven highly effective in managing urban traffic systems.

Research on autonomous vehicles and their potential to mitigate traffic congestion has surged recently. AI has profoundly transformed the transportation sector with a wide range of innovations. These advancements encompass autonomous vehicles, efficient traffic management systems, optimized routing, and enhanced logistics, thus providing the safety of drivers and vehicles [8]. Contemporary AI-based traffic congestion research is interdisciplinary, drawing insights from computer science, transportation engineering, and urban planning. By integrating AI technologies, encouraging collaboration (government, academy, and industry), and customizing solutions to meet local needs, urban areas can develop sustainable and efficient transportation systems that significantly improve the quality of life for their residents [9].

2.2 Review of Traditional Methods for Congestion Prediction

Traditional methods for predicting congestion have evolved significantly with AI and ML techniques. Effective congestion prediction is crucial for managing and alleviating traffic issues. Traditional congestion prediction methods have been extensively researched, relying on a combination of data collection techniques, statistical models, and algorithmic approaches. This section explores recent advances in these traditional methods, focusing on integrating AI/ML models.

Statistical models, such as regression analysis and time series forecasting, have been traditionally used for traffic congestion prediction. These models analyze historical traffic data to identify patterns and trends, which are then used to forecast future traffic conditions. Regression models can account for various factors influencing traffic flow, including time of day, day of the week, and weather conditions. A study by Ranjan et al. [10] applied time series analysis to predict traffic congestion on city-wide road networks, demonstrating their utility in anticipating congestion trends.

Although ML is often associated with more advanced approaches, traditional algorithms like linear regression and decision trees have been extensively used for congestion prediction. A recent study by Kang et al. [11] employed decision tree algorithms to assess traffic capacity and evaluate the efficiency of various road sections in alleviating traffic flow during a specific period. Their results highlighted the efficiency of these algorithms in making accurate predictions. Supervised learning models, such as support vector machines (SVM), decision trees, and random forests, have been widely applied in traffic congestion studies. These models can classify traffic states and predict congestion by learning from labeled historical traffic data [12]. Queuing theory models traffic flow as a queuing system, where vehicles are considered customers in a queue. Queuing theory has been used to predict congestion by analyzing traffic demand and service rates. [13] utilized queuing models to assess congestion at toll plazas, establishing the lane work-schedule model.

These traditional methods continue to evolve, incorporating new technologies and analytical techniques to address the growing challenges of urban traffic congestion. Integrating AI/ML techniques has significantly enhanced traditional congestion prediction methods. These advancements have led to more accurate, real-time, and scalable solutions for managing urban traffic congestion. Ongoing research and development in this field promise further improvements, contributing to more efficient and sustainable urban transportation systems.

Table 1. Strengths and Weaknesses of Traditional Congestion Prediction Methods

Method	Strengths	Weaknesses
Historical Trend Analysis	Simple to implement and interpret. Utilizes readily available past traffic data.	Fails to adapt to real-time conditions. Inaccurate for predicting unusual or unexpected events like accidents or weather disruptions.
Time Series Analysis (e.g., ARIMA)	Captures periodic traffic patterns. Models seasonality and trends effectively.	Requires stationary data and extensive preprocessing. Poor at handling abrupt changes or outliers.
Regression Analysis	Can quantify the influence of specific factors (e.g., weather, time of day). Easy to interpret.	Assume linear relationships, which may not always hold. Struggles with complex, non-linear relationships in large datasets.
Queuing Theory	Effective for analyzing bottlenecks and capacity. Useful in controlled traffic systems.	Simplifies real-world traffic dynamics. Limited applicability in real-time, large-scale, or dynamic environments.
Support Vector Machines (SVM)	Handles high-dimensional data effectively. Works well with non-linear traffic patterns through kernel functions.	Computationally intensive, especially for large datasets. Requires parameter tuning, which can be complex.
Decision Tree Models	Easy to understand and interpret. Handles non-linear data well.	Prone to overfitting with complex datasets. Performance can degrade if not optimized (e.g., through pruning).
Random Forest Models	Reduces overfitting by averaging multiple decision trees. Handles missing and noisy data effectively.	Computationally expensive for large datasets. Results can be difficult to interpret due to the ensemble nature of the model.

3. CRITICAL ANALYSIS OF EXISTING STUDIES ON AI-BASED ROAD CONGESTION PREDICTION

A critical analysis of existing AI-based road congestion prediction studies reveals a landscape marked by remarkable advancements and persistent challenges. Many researchers have successfully applied ML techniques, such as neural networks, support vector machines, and ensemble methods, to achieve notable accuracy in predicting traffic congestion. However, many of these studies often focus on controlled environments or small-scale datasets, limiting their findings' generalizability and real-world applicability. Additionally, while some research incorporates spatiotemporal data effectively, there is often a lack of comprehensive evaluation across diverse urban settings and conditions. Moreover, issues related to data quality, including noise and incompleteness, as well as computational limitations, continue to hamper the efficacy of these AI models. A thorough critique of these studies highlights the need for more robust, scalable, and adaptable AI solutions, alongside improved data integration techniques, to better address the complexities of real-world traffic systems.

ML techniques, including supervised and unsupervised learning, have been widely used to analyze traffic data for congestion prediction. ML models, such as decision trees, support vector machines, and ensemble methods, have effectively handled large and diverse datasets, enabling accurate short-term congestion forecasts. For instance, [14] demonstrated that gradient-boosting decision tree techniques could significantly enhance the accuracy of traffic flow predictions by leveraging historical data. Despite their effectiveness, ML models often struggle with capturing the dynamic and complex nature of traffic patterns. These models typically require extensive feature engineering and are sensitive to the quality of input data. Medina-Salgado et al. [15] noted that ML models could be limited by their inability to handle traffic data from complex road topology effectively.

DL models, particularly those involving CNNs and RNNs, have been employed to analyze high-dimensional and sequential traffic data for more nuanced congestion prediction. DL techniques excel in capturing complex spatial and temporal relationships within traffic data. For example, Christalin et al. [16] utilized LSTM networks to successfully model and predict traffic congestion, demonstrating their capacity to handle time-series data. DL models require substantial computational resources and large datasets for training, which may not always be feasible. They also act as "black boxes," providing limited interpretability. Akhtar and Moridpour [2] highlighted the challenge of interpreting DL models', which can hinder their practical application in traffic management systems.

RL techniques have been applied to develop adaptive systems for real-time traffic control and route optimization, learning optimal strategies to mitigate congestion. RL is particularly effective in dynamic environments where it can learn and adapt to changing traffic conditions. Bouktif et al. [3] showcased an RL-based traffic signal control system that significantly improved traffic flow by dynamically adjusting signal timings in response to real-time traffic data. RL models often require extensive training periods and vast amounts of interaction data, which can be challenging in real-world settings. Furthermore, Mushtaq et al. [17] pointed out the potential complexity of RL models, as they can produce suboptimal policies if the learning environment changes significantly.

Anomaly detection involves identifying unusual patterns in traffic data that may indicate congestion or disruptions. These methods effectively flag unexpected changes in traffic conditions, providing early warnings of potential congestion. Priyadharsini and Chitra [18] presented a kernel support vector machine-based anomaly detection using spatiotemporal motion pattern models in extremely congested scenes. Anomaly detection systems can suffer from high false positive rates, mistaking normal traffic variations for anomalies. This can lead to unnecessary interventions and resource wastage. Furthermore, these systems often struggle to adapt to evolving traffic patterns, long-term periodicity across time, and strong short-term temporal correlations [19].

Short-term forecasting models aim to predict traffic conditions shortly, typically within the next few minutes to hours. These models provide actionable insights that can help mitigate immediate congestion. Liu et al. [20] showcased how DL-based models could accurately predict short-term traffic congestion, allowing for proactive traffic management. Short-term models often assume that future traffic patterns will resemble past trends, which may not hold in rapidly changing conditions. They may also struggle with rare or unexpected events that significantly disrupt traffic flow. Wang et al. [21] noted the challenge of incorporating diverse and real-time data sources to improve the robustness of these predictions.

Long-term analysis focuses on predicting traffic trends over extended periods, providing insights for strategic planning and infrastructure development. Long-term predictions help urban planners and policymakers design better road networks and implement effective congestion mitigation strategies. Li et al. [22] used hybrid DL to forecast long-term traffic trends. These models are often less accurate due to the complexity and variability of long-term traffic dynamics. They may also struggle to account for external factors such as changes in population, economic activities, or transportation policies. Dadashova et al. [23] emphasized the need for integrating broader socioeconomic data to improve the accuracy and relevance of long-term traffic forecasts

Table 2. Comparative Analysis of Traditional and Hybrid Models

Aspect	Traditional AI/ML Models	Hybrid AI/ML Models
Model Type	Single technique (e.g., Decision Trees, SVM, Linear Regression)	Combination of multiple models (e.g., ML + Deep Learning, Evolutionary Algorithms + ML)
Data Requirements	Relatively smaller datasets, simpler feature sets	Large and complex datasets with multimodal data (e.g., historical, real-time, weather)
Accuracy	Moderate accuracy (depends on model choice and feature engineering)	Higher accuracy, as the hybrid approach can leverage the strengths of multiple models
Complexity	Simpler models, easier to implement and understand	More complex models that require careful tuning and integration of different algorithms
Scalability	Limited scalability to handle real-time large-scale data	High scalability, especially when using deep learning or ensemble models
Feature Handling	Struggles with high-dimensional or unstructured data (e.g., images, sensor data)	Better at handling complex and high-dimensional data due to multiple algorithms working together
Training Time	Shorter training time (simple models require fewer resources)	Longer training time due to multiple models and data fusion techniques
Interpretability	Easier to interpret, especially for simpler models (e.g., decision trees)	Less interpretable due to the combination of models (e.g., deep learning + traditional ML)
Adaptability to Dynamic Changes	Lower adaptability to dynamic traffic patterns and real-time events	Higher adaptability, as hybrid models can incorporate real-time data sources and adjust over time
Generalization	May struggle with generalization for unseen or complex traffic scenarios	Better generalization, particularly with ensemble learning or deep learning components
Performance with Noisy Data	Performance may degrade with noisy or incomplete data	Robustness to noisy data due to advanced techniques like ensemble learning or deep neural networks

4. SPATIOTEMPORAL DATA AND ITS ROLE IN TRAFFIC CONGESTION PREDICTION

Spatiotemporal data allows models to consider both the spatial distribution and temporal progression of traffic, leading to more accurate predictions. Spatiotemporal data enables a holistic analysis of traffic congestion. This comprehensive view is crucial for identifying congestion hotspots and understanding their underlying causes. Wei et al. [24] utilized spatiotemporal data to analyze congestion patterns across multiple urban areas and big cities, providing insights into regional traffic dynamics and the factors contributing to congestion. Spatiotemporal data supports real-time traffic monitoring and rapid response to emerging congestion issues. This capability is vital for adaptive traffic management systems that must quickly adjust to current conditions. Nie et al. [25] extract spatiotemporal features from traffic speed data and propose a hybrid model, spatial-temporal Gated Graph Attention network (ST-GGAN), following the Graph Attention mechanism (GAT) and Gated Recurrent Unit (GRU). The proposed method has a simpler structure, lower computational costs, and higher predicting accuracy.

Spatiotemporal data is essential for detecting anomalies in traffic flow that could indicate congestion or disruptions. ML models that incorporate spatiotemporal features can identify deviations from normal traffic patterns. Priyadharsini and Chitra [18] used a hybrid model combining spatiotemporal data and ML techniques to detect traffic anomalies, providing early warnings of potential congestion events. Network analysis of spatiotemporal data can reveal congestion propagation across road networks. Wang et al. [26] employed the grid mapping method and proposed an efficient abstraction strategy to simplify the structure of a road network and then to identify urban traffic congestion.

Spatiotemporal data is also valuable for long-term traffic trend analysis and forecasting and is essential for infrastructure planning and policy development. These networks capture traffic data's spatial relationships and temporal dynamics, making them effective for long-term forecasting. Researchers applied spatiotemporal graph networks to predict long-term traffic trends in metropolitan areas, providing insights into future congestion hotspots and potential mitigation strategies. Incorporating spatiotemporal data into scenario-based models helps predict how changes in traffic volume, road infrastructure, or policy measures might impact future congestion.

The effectiveness of spatiotemporal models depends on the quality and availability of data. Inconsistent or sparse data can significantly reduce model performance. Future research should focus on developing methods to handle incomplete or noisy spatiotemporal data. Processing large-scale spatiotemporal data requires substantial computational resources, which can limit the scalability of these models. Efforts should be directed towards optimizing algorithms for better efficiency and scalability, particularly for real-time applications.

5. GAPS IN EXISTING RESEARCH

Despite significant advancements in AI-based traffic congestion prediction using spatiotemporal data, notable gaps remain in existing research that impede the full potential of these technologies. Current models often struggle with scalability, real-time processing, and integrating heterogeneous data sources, leading to suboptimal predictions in dynamic and complex urban environments. Furthermore, many studies lack robustness in dealing with anomalies and rare events, such as sudden road closures or extreme weather conditions. Privacy concerns about using vast amounts of data also present a critical challenge. Addressing these gaps requires developing more sophisticated machine learning algorithms to handle diverse and high-dimensional spatiotemporal data, improve computational efficiencies, and ensure robust data privacy measures. This section comprehensively covers recent advances and identifies critical gaps, challenges, and future directions in AI-based traffic congestion detection and prediction using spatiotemporal data.

5.1 Data Quality and Availity Issues

ML has been extensively employed for traffic congestion prediction. Various algorithms, including SVMs, neural networks, and decision trees, have demonstrated their effectiveness in modeling traffic dynamics. Recent studies have shown that deep learning models, particularly LSTM networks and CNNs, outperform traditional methods in capturing temporal dependencies and spatial correlations. Using spatiotemporal data, which encompasses both spatial and temporal dimensions, is crucial for understanding and predicting traffic patterns. Such data sources include GPS trajectories, traffic sensors, and social media feeds. Integrating these data sources can significantly enhance the accuracy of congestion prediction models. Advanced data fusion techniques have been developed to combine data from heterogeneous sources, yet challenges in data quality and consistency remain.

5.2 Scalability, Interpretability, and Transparency of AI/ML Models for Large-Scale Traffic Management

A significant gap in current research is the scalability of AI models to large-scale urban networks. Many studies focus on specific regions or corridors, limiting the generalizability of their findings to other urban contexts. There is a need for scalable models that can be trained on vast datasets and generalize well across diverse traffic scenarios.

Model interpretability and transparency are crucial for ensuring trust and effective deployment of AI/ML models in traffic congestion detection and prediction. These aspects are particularly important given the high stakes in traffic management systems, where decisions can impact public safety, efficiency, and urban planning. AI models, particularly deep learning approaches, often operate as black boxes, making it challenging to interpret their predictions. This lack of explainability can hinder traffic management authorities' adoption of these models, which require understandable and actionable insights. Developing explainable AI techniques that provide transparency in decision-making is crucial for practical applications.

5.3 Ethical and Privacy Considerations in Using Spatiotemporal Data

The use of spatiotemporal data raises significant privacy and security concerns. The collection and processing of data from individual vehicles and personal devices necessitate robust mechanisms to protect user privacy. Existing research has not sufficiently addressed these issues, leaving a gap in developing secure and privacy-preserving traffic monitoring systems. Integrating AI-based congestion detection systems with existing urban infrastructure remains a challenge. Current research often overlooks the practical aspects of deploying these systems in real-world settings, such as compatibility with legacy traffic management systems and the need for substantial infrastructure investment.

6. FUTURE RESEARCH SCOPE

Most current studies focus on vehicular traffic, neglecting other modes of transportation such as public transit, bicycles, and pedestrians. A comprehensive approach incorporating multimodal traffic analysis is necessary to develop holistic congestion management strategies. Future research could explore the potential of edge computing to address the challenges of real-time data processing and latency in traffic prediction systems. Edge computing brings computational resources closer to data sources, enabling faster data analysis and response times. Combining different AI techniques, such as integrating ML with traditional traffic flow models or leveraging hybrid neural network architectures, can enhance the accuracy and robustness of traffic prediction systems. Research in this direction can bridge the gap between theoretical model development and practical implementation.

Understanding and modeling human behavior in traffic scenarios can significantly improve the prediction of congestion patterns. Future studies should consider behavioral factors, such as driver decision-making processes and public response to traffic advisories, to refine congestion prediction models. There is a growing need to align traffic congestion management with sustainability goals. Future research should focus on developing AI systems that optimize traffic flow while minimizing environmental impacts, such as reducing vehicle emissions and promoting green transportation modes.

As AI technologies become more integrated into traffic management, addressing the ethical implications and policy frameworks governing their use is essential. Research should explore the societal impacts of AI-based traffic systems and develop guidelines to ensure equitable and fair access to these technologies. AI-based traffic congestion prediction systems leveraging spatiotemporal data have shown promising results in addressing urban traffic challenges. However, significant gaps remain in scalability, explainability, data privacy, integration with urban infrastructure, and multimodal analysis. Future research should focus on advancing edge computing, hybrid modeling approaches, understanding human behavior, promoting sustainable transportation, and addressing ethical considerations to develop more effective and comprehensive traffic management solutions.

7. CONCLUSION

One of the most direct economic impacts of AI/ML-based traffic management systems is reduced travel time. By accurately predicting and managing congestion, these systems help decrease delays, allowing commuters and freight to reach their destinations more quickly. This reduction in travel time translates into increased productivity and efficiency for both individuals and businesses.

With optimized traffic flow and reduced congestion, fuel consumption is significantly lowered. AI/ML systems help minimize stop-and-go traffic and idling, major contributors to fuel wastage. As a result, private and commercial vehicle operators experience substantial savings in fuel costs, contributing to overall economic benefits. AI/ML systems improve the efficiency of public transportation networks by predicting congestion and optimizing routes. This efficiency encourages higher public transport usage, reducing the number of vehicles on the road. Increased use of public transport helps alleviate congestion, further enhancing economic benefits. The long-term economic benefits of AI/ML-based traffic congestion prediction systems include sustained improvements in traffic flow, reduced operational costs, and enhanced overall economic growth. By investing in these technologies, cities can improve their quality of life.

8. REFERENCES

[1] Smith, B. L., & Demetsky, M. J., (1994). Short-term traffic flow prediction: neural network approach. Transportation Research (pp. 98-104). Available online at http://onlinepubs.trb.org/Onlinepubs/trr/1994/1453/1453-011.pdf.

[2] Akhtar, M., & Moridpour, S. (2021). A Review of Traffic Congestion Prediction Using Artificial Intelligence. *Journal of Advanced Transportation*, *2021*(1), 8878011. https://doi.org/10.1155/2021/8878011.

[3] Bouktif, S., Cheniki, A., Ali-Ouni, A., & El-Sayed, H. (2023). Deep reinforcement learning for traffic signal control with consistent state and reward design approach. https://doi.org/10.1016/j.knosys.2023.110440.

[4] Wang, J., Pradhan, M. R., & Gunasekaran, N. (2022). Machine learning-based human-robot interaction in ITS. Information Processing & Management Volume 59, Issue 1, January 2022, 102750. https://doi.org/10.1016/j.ipm.2021.102750.

[5] Joo, H., Ahmed, S. H., & Lim, Y. (2020). Traffic signal control for smart cities using reinforcement learning. Available online at https://doi.org/10.1016/j.comcom.2020.03.005.

[6] Kothai, G., Poovammal, E., Dhiman, G., Ramana, K., Sharma, A., AlZain, M. A., Gaba, G. S., & Masud, M. (2021). A New Hybrid Deep Learning Algorithm for Prediction of Wide Traffic Congestion in Smart Cities. *Wireless Communications and Mobile Computing*, *2021*(1), 5583874. https://doi.org/10.1155/2021/5583874.

[7] Slimani, N., Amghar, M., & Sbiti., N. (2022). Deep learning and time series analysis on traffic flow forecasting. Journal of Theoretical and Applied Information Technology, 100(5). https://www.jatit.org/volumes/Vol100No5/5Vol100No5.pdf.

[8] Iyer, L. S. (2021). AI-enabled applications towards intelligent transportation. Available online at https://doi.org/10.1016/j.treng.2021.100083.

[9] Samaei, S. R., (2024). A Comprehensive Algorithm for AI-Driven Transportation Improvements in Urban Areas. 13th International Conference on Advanced Research in Science, Engineering and Technology, Brussels, Belgium.At: https://civilica.com/doc/1930041/ Volume: 13.

[10] Ranjan, N., Bhandari, S., Zhao, H. P., Kim, H., & Khan, P (2020). City-Wide Traffic Congestion Prediction Based on CNN, LSTM and Transpose CNN, in IEEE *Access*, vol. 8, pp. 81606-81620, 2020, doi: 10.1109/ACCESS.2020.2991462.

[11] Kang, L., Cheng, S., & Lei, B. (2021). Optimization Model and Algorithm of Urban Road Traffic Network Design Based on Decision Tree Quantification. In 2021 International Conference on Aviation Safety and Information Technology (ICASIT 2021). Association for Computing Machinery, New York, NY, USA, 696–699. https://doi.org/10.1145/3510858.3511365.

[12] Bokaba, T., Doorsamy, W., & Paul, B. S. (2022). A Comparative Study of Ensemble Models for Predicting Road Traffic Congestion. Applied Sciences, 12(3), 1337. https://doi.org/10.3390/app12031337.

[13] Wang, P., Zhao, J., Gao, Y., Sotelo, M. A., & Li, Z. (2020) Lane Work-Schedule of Toll Station Based on Queuing Theory and PSO-LSTM Model, in *IEEE Access*, vol. 8, pp. 84434-84443, doi: 10.1109/ACCESS.2020.2992070.

[14] Liu, Y., Zhang, N., Luo, X., & Yang, M. (2021). Traffic Flow Forecasting Analysis based on Two Methods, J. Phys.: Conf. Ser. 1861 012042. doi:10.1088/1742-6596/1861/1/012042.

[15] Medina-Salgado, B., Sanchez-DelaCruz, E., Pozos-Parra, P., & Sierra, J. E. (2022). Urban traffic flow prediction techniques: A review. Sustainable Computing: Informatics and Systems, 35, 100739. https://doi.org/10.1016/j.suscom.2022.100739.

[16] Christalin, N. S., Mandal, T. K., & Prakash, G. L. (2022). A Novel Optimized LSTM Networks for Traffic Prediction in VANET. Journal of System and Management Sciences Vol. 12 No. 1, pp. 461-479 DOI:10.33168/JSMS.2022.0130.

[17] Mushtaq, A., Haq, I. U., Imtiaz, M. U., Khan, A., & Shafiq, O. (2021). Traffic Flow Management of Autonomous Vehicles Using Deep Reinforcement Learning and Smart Rerouting, in IEEE Access, vol. 9, pp. 51005-51019, doi: 10.1109/ACCESS.2021.3063463.

[18] Priyadharsini, N. K., & Chitra, D. (2021). A kernel support vector machine based anomaly detection using spatio-temporal motion pattern models in extremely crowded scenes. J Ambient Intell Human Comput 12, 5225–5234. https://doi.org/10.1007/s12652-020-02000-3.

[19] Sofuoglu, S. E., & Aviyente, S. (2022). GLOSS: Tensor-based anomaly detection in spatiotemporal urban traffic data. *Signal Processing*, *192*, 108370. https://doi.org/10.1016/j.sigpro.2021.108370.

[20] Liu, Y., Wang, X., Hou, W., Liu, H., & Wang, J. (2022). A novel hybrid model combining a fuzzy inference system and a deep learning method for short-term traffic flow prediction. *Knowledge-Based Systems*, *255*, 109760. https://doi.org/10.1016/j.knosys.2022.109760.

[21] Wang, K., Ma, C., Qiao, Y., Lu, X., Hao, W., & Dong, S. (2021). A hybrid deep learning model with 1DCNN-LSTM-Attention networks for short-term traffic flow prediction. *Physica A: Statistical Mechanics and its Applications*, *583*, 126293. https://doi.org/10.1016/j.physa.2021.126293.

[22] Li, Y., Chai, S., Ma, Z., & Wang, G. (2021). A Hybrid Deep Learning Framework for Long-Term Traffic Flow Prediction, in *IEEE Access*, vol. 9, pp. 11264-11271, 2021, doi: 10.1109/ACCESS.2021.3050836.

[23] Dadashova, B., Li, X., Turner, S., & Koeneman, P. (2021). Multivariate time series analysis of traffic congestion measures in urban areas as they relate to socioeconomic indicators. Socioeconomic *Planning Sciences*, *75*, 100877. https://doi.org/10.1016/j.seps.2020.100877.

[24] Wei, X., Ren, Y., Shen, L., & Shu, T. (2022). Exploring the spatiotemporal pattern of traffic congestion performance of large cities in China: A real-time data based investigation. *Environmental Impact Assessment Review*, *95*, 106808. https://doi.org/10.1016/j.eiar.2022.106808.

[25] Nie, X., Peng, J., Wu, Y., Gupta, B., & El-Latif, A. A. A. (2022). Real-Time Traffic Speed Estimation for Smart Cities with Spatial Temporal Data: A Gated Graph Attention Network Approach. *Big Data Research*, *28*, 100313. https://doi.org/10.1016/j.bdr.2022.100313.

[26] Wang, L., Yan, X., Liu, Y., Liu, X., & Chen, D. (2021). Grid Mapping for Road Network Abstraction and Traffic Congestion Identification Based on Probe Vehicle Data, Journal of Transportation Engineering, Part A: Systems, Volume 147 • Issue 5. https://doi.org/10.1061/JTEPBS.0000517.