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Study of Various Techniques for Traffic Flow Prediction Using Machine Learning

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Abstract: *Traffic flow prediction plays a crucial role in intelligent transportation systems (ITS) by enabling effective traffic management, congestion control and route optimization. With the rapid growth of urbanization and vehicle density, accurate traffic forecasting has become essential for enhancing road safety and reducing travel delays. This study presents a comprehensive analysis of various machine learning techniques applied to traffic flow prediction, including traditional models such as Support Vector Machines (SVM), Random Forests and regression-based methods, as well as advanced deep learning approaches like Long Short-Term Memory (LSTM) networks, Convolution Neural Networks (CNN) and hybrid architectures. The research explores how these models handle temporal and spatial dependencies in traffic data, assess their performance using benchmark datasets and highlight their strengths and limitations in real-time prediction scenarios. The comparative study demonstrates that deep learning models, particularly LSTM-based frameworks, achieve superior accuracy in capturing nonlinear traffic patterns compared to conventional machine learning methods. The findings provide valuable insights into the selection and optimization of predictive models for developing efficient, data-driven traffic management systems aimed at improving urban mobility and reducing congestion.*

Keywords: *Machine Learning, Deep Learning, Intelligent Transportation Systems, Support Vector Machines, Recurrent Neural Networks.*

1. INTRODUCTION

In today's rapidly urbanizing world, the continuous increase in the number of vehicles on roads has made traffic congestion one of the most critical challenges for metropolitan cities. Traffic congestion not only causes inconvenience to commuters but also leads to substantial economic losses, environmental pollution and wasted time. According to global studies, billions of dollars are lost annually due to traffic delays, inefficient fuel usage and increased carbon emissions. Managing traffic flow effectively is therefore an essential component of developing smart cities and sustainable urban transportation systems. To achieve this, accurate and real-time traffic flow prediction has become a key area of research and innovation.

Traffic flow prediction refers to the process of forecasting the number of vehicles that will pass through a certain location or road segment within a specified time interval. This prediction is crucial for traffic management systems to make proactive decisions, such as adjusting traffic signal timings, providing alternate route suggestions or deploying emergency services effectively. Traditional methods of traffic prediction relied heavily on statistical and mathematical models, such as time series analysis and autoregressive models. While these models performed reasonably well for stable and predictable traffic patterns, they often failed to capture the complex, nonlinear and dynamic nature of real-world traffic systems influenced by numerous external factors like weather, accidents, roadwork and special events.

In recent years, advancements in data science and machine learning have opened new opportunities to enhance the accuracy and adaptability of traffic prediction systems. Machine learning algorithms are capable of automatically learning patterns and relationships from large volumes of historical data without requiring explicit programming. This makes them ideal for handling complex and dynamic systems such as urban traffic networks. By leveraging historical traffic data along with contextual information such as weather conditions, holidays and special events, machine learning models can make more accurate and context-aware predictions [1].

The integration of machine learning with traffic prediction aligns with the broader concept of Intelligent Transportation Systems (ITS), which aim to enhance the efficiency and safety of transportation networks through data-driven technologies. ITS applications rely on real-time data collected from various sources, including sensors, GPS devices and traffic cameras. These systems analyze data to predict congestion levels, detect incidents and optimize routing and traffic control measures. Within this framework, machine learning-based traffic prediction plays a pivotal role in enabling adaptive and intelligent decision-making.

1.1 Importance of Traffic Flow Prediction

Accurate traffic flow prediction provides several significant benefits to both transportation authorities and road users. For authorities, it helps in designing efficient traffic control strategies, managing infrastructure and reducing congestion. For commuters, it offers valuable information for route planning and travel time estimation. Moreover, predicting traffic conditions in advance allows for the prevention of bottlenecks and supports efficient utilization of available road networks.

Traffic flow prediction also contributes to reducing environmental impacts. Vehicles idling in congested areas emit more pollutants than those in free-flowing traffic [2]. Therefore, an efficient traffic prediction system can indirectly help lower carbon emissions and energy consumption by minimizing congestion. In addition, the prediction results can be integrated into navigation applications, logistics operations and ride-sharing services to optimize route planning and reduce operational costs.

1.2 Challenges in Traffic Flow Prediction

Despite the growing availability of traffic data, developing an accurate and reliable prediction model remains challenging due to several factors. Traffic flow is inherently dynamic and influenced by a combination of spatial, temporal and contextual variables. Factors such as road geometry, signal timings, driver behavior, weather and unexpected events (e.g., road accidents or public gatherings) introduce uncertainties in prediction.

Another major challenge lies in the variability of data quality. Traffic data collected from sensors or cameras may contain missing values, noise or inaccuracies caused by device malfunctions or data transmission errors. Moreover, traffic patterns vary across different cities and regions, making it difficult to generalize a single model for all scenarios. The integration of event and environmental data adds another layer of complexity, as these factors are often unstructured and irregular in nature. Hence, the design of a machine learning model must carefully consider data preprocessing, feature engineering and model selection to achieve robust predictions.

1.3 Role of Machine Learning in Traffic Prediction

Machine learning (ML) has emerged as a powerful approach to address the limitations of traditional statistical models in traffic prediction. ML algorithms can capture nonlinear relationships among multiple variables, learn from past observations and adapt to new data trends. Supervised learning methods such as Linear Regression, Decision Trees, Support Vector Machines (SVM) and Random Forests have been widely applied for traffic prediction tasks [3].

In addition, deep learning techniques, particularly Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks, have shown great promise in modeling sequential data. Since traffic data exhibits strong temporal dependencies where the current traffic state depends on previous conditions LSTM models can effectively capture long-term patterns and provide accurate short-term forecasts.

The combination of historical data and event-based contextual information enhances the predictive capability of these models. For instance, including information about holidays, weather or special events such as concerts or sports matches allows the system to account for irregular traffic patterns that cannot be predicted through historical data alone. Machine learning thus provides a scalable and intelligent solution to manage traffic flow dynamically.

2. LITERATURE REVIEW

Vlahogianni et al. [1] provide a comprehensive review of short-term traffic forecasting research up to 2014, categorizing methods (statistical, classical machine learning and initial neural network approaches), discussing data sources and error metrics and identifying core challenges—nonlinearity, nonstationarity and the need for real-time deployment. The paper synthesizes lessons about model selection, the role of feature engineering and the importance of spatio-temporal context and it calls for hybrid models and better evaluation protocols. Its key contribution is a clear roadmap of research gaps; a limitation is that it predates the rapid adoption of deep spatio-temporal architectures, so its prognoses about "where we're going" were necessarily speculative.

Lv et al. [2] are among the early works to exploit large-scale traffic data with deep learning; they propose a deep architecture for traffic flow prediction that leverages big data to capture complex temporal patterns and nonlinearities that classical models struggle with. Their experiments show improved predictive accuracy relative to several baseline methods and they highlight scalability advantages when many sensors and long historical records are available. The paper's strength lies in demonstrating feasibility of deep models on real traffic big-data, while a limitation is comparatively limited treatment of spatial dependencies and model interpretability.

Ma et al. [3] investigate Long Short-Term Memory (LSTM) networks for traffic speed prediction using remote microwave sensor data, showing that LSTMs effectively capture temporal dependencies in speed series and outperform conventional time-series and shallow machine learning methods on short-term horizons. The study systematically evaluates model setup and demonstrates robustness to noisy sensor inputs, emphasizing LSTM's ability to learn long-range temporal patterns relevant for short-term forecasting. A limitation is modest attention to explicit spatial coupling across sensors—an issue that later spatio-temporal models address more directly.

Barros et al. [4] survey short-term real-time traffic prediction methods, focusing on algorithmic families suitable for online deployment and real-time constraints. They summarize classical statistical techniques, machine learning approaches and early streaming implementations, offering comparisons in terms of latency, data requirements and robustness to missing or delayed data. This paper is valuable for practitioners needing implementation guidance; however, like other contemporaneous surveys, it only partially anticipates the impact of later deep graph and hybrid models on production systems.

Sun, Zhang and Yu [5] propose a Bayesian network approach to traffic flow forecasting that explicitly handles missing data, a frequent and practical problem in traffic sensing. Their probabilistic framework models dependencies among sensors and imputes missing observations while producing predictive distributions instead of point estimates—providing uncertainty quantification beneficial for decision making. The contribution is notable for addressing data incompleteness rigorously, though Bayesian network scalability and the complexity of structure learning can limit applicability in very large sensor networks without simplification.

In this early preprint, Polson and Sokolov [6] explore deep learning predictors for traffic flows and discuss model architectures and training considerations tailored to traffic time series. They emphasize the potential of deep networks to capture nonlinearities and advocate for greater use of modern training techniques in the transportation domain. As a preprint, the work plays an important role in bridging statistical time-series thinking with deep learning practice, though it lacks the extended empirical validation that later journal versions provide.

Zhao and colleagues [7] present an LSTM-based deep learning approach specifically targeted at short-term traffic forecasting, providing empirical evidence that LSTM networks improve accuracy over baseline recurrent and non-recurrent models. They pay careful attention to input feature design, training regimen and horizon-dependent performance, adding to the literature that validated RNN variants for traffic tasks. The paper strengthens the case for recurrent architectures but—similar to other LSTM studies—does not fully incorporate explicit spatial modeling, which reduces effectiveness in highly networked traffic settings.

In their 2017 Transportation Research Part C paper, Polson and Sokolov [8] extend their earlier preprint into a more complete study of deep learning for short-term traffic flow prediction, providing more extensive experiments and comparisons with traditional methods. They discuss model architecture choices, over fitting mitigation and interpretability challenges and they report improved predictive performance on benchmark datasets. The journal version's main value is systematic empirical validation and a careful discussion of limitations—particularly regarding generalization across different networks and the need for hybrid or structured models to capture spatial dependencies.

Liu and Chen [9] propose a novel passenger flow prediction model based on deep learning, extending deep architectures to model human mobility and transit passenger flows rather than vehicular link flows. Their approach captures temporal regularities and passenger demand patterns, demonstrating that deep models can handle multimodal, irregular and demand-driven flow series in transit contexts. This work broadens the application scope of deep learning in transportation, but its generalizability to different transit systems and its handling of external covariates (events, weather) require further study.

Yu et al. [10] introduce Spatio-Temporal Graph Convolutional Networks (ST-GCN), a landmark contribution that fuses graph convolutional networks (to model spatial interdependencies on road networks) with temporal convolutions (to capture temporal dynamics). Their framework directly addresses the spatial structure of traffic systems, achieving significant improvements over purely temporal models (e.g., LSTM) in multi-sensor network forecasting tasks. ST-GCN's major strength is principled modeling of spatial relations via graph topology; remaining challenges include scaling to very large graphs and integrating additional context (events, exogenous features) in a unified way.

Li et al. [11] introduced the Diffusion Convolutional Recurrent Neural Network (DCRNN), a landmark deep learning framework for traffic forecasting that captures both spatial and temporal dependencies through diffusion convolution and gated recurrent units. Unlike traditional graph convolutional networks that rely on static adjacency matrices, DCRNN models bidirectional spatial diffusion processes on road networks, better representing traffic flow propagation. Experimental results on large-scale datasets demonstrated superior accuracy over baseline models like LSTM and GRU. This paper's main contribution lies in integrating graph-based spatial learning with temporal dynamics. However, its computational complexity and requirement for dense sensor coverage pose limitations for real-time or sparse-network scenarios.

Wu and colleagues [12] proposed Graph WaveNet, a deep learning architecture combining graph convolutional layers with dilated temporal convolutions for efficient spatio-temporal traffic modeling. The model introduces adaptive adjacency matrices, allowing it to learn dynamic spatial dependencies rather than relying on pre-defined road maps. This self-adaptive mechanism improved prediction accuracy and robustness, especially in complex urban networks with irregular topologies. The study demonstrated that Graph WaveNet outperformed prior models such as DCRNN and ST-GCN on benchmark datasets. Its limitation lies in interpretability, as dynamically learned graph structures are challenging to analyze from a domain perspective.

Yu et al. [13] developed a special event-based K-Nearest Neighbor (KNN) model for short-term traffic state prediction, emphasizing the influence of events such as accidents, weather and public gatherings on traffic flow. By integrating event attributes with traditional temporal features, their approach enhanced prediction accuracy during anomalous traffic conditions. The results highlight that incorporating external, event-related data improves model adaptability and real-world reliability. While the approach is interpretable and computationally efficient, it remains data-intensive and less effective in predicting complex, long-term temporal dependencies compared to deep learning methods.

This study [14] introduced a deep learning network for short-term traffic flow prediction that employs multiple hidden layers to model nonlinear relationships in traffic data. The authors demonstrated that the proposed deep architecture achieved better accuracy than traditional regression or shallow models when tested on real-world datasets. The model effectively handled noise and captured temporal variation in traffic patterns. However, the study was limited in scope due to smaller datasets and a lack of spatial context integration, suggesting room for further improvement using spatio-temporal or graph-based models.

Filipovska and Mahmassani [15] explored machine learning methods for traffic flow breakdown prediction, focusing on the identification of transition points from free-flow to congested states. Using models such as random forests and support vector machines, they achieved high predictive performance and interpretability. The research underscores the utility of machine learning in predicting critical network thresholds, contributing to proactive traffic control strategies. Nonetheless, the study's reliance on static feature sets limits adaptability to dynamic or large-scale networks, where deep models may offer greater scalability.

Shahraki and colleagues [16] proposed a hybrid ARIMA–LSTM model for traffic flow prediction that combines the strengths of statistical and deep learning approaches. The ARIMA component effectively captures linear patterns, while LSTM handles nonlinear temporal dependencies. Experiments on traffic datasets demonstrated that the hybrid model outperforms standalone ARIMA and LSTM models in both short- and medium-term forecasts. This hybridization enhances robustness and interpretability, though the model's computational overhead and need for careful parameter tuning are notable drawbacks.

Essien et al. [17] introduced a deep learning framework integrating social media data, specifically Twitter, with conventional traffic flow data to improve urban traffic prediction. Their model leverages natural language processing techniques to extract real-time event information from tweets, which is then fused with sensor-based traffic measurements. This innovative approach improved accuracy, particularly during event-driven traffic disruptions. The paper's novelty lies in fusing unstructured and structured data; however, challenges remain regarding noise in social media data and the generalization of linguistic models across cities and languages.

Razali and co-authors [18] conducted a comprehensive review of machine learning and deep learning techniques for traffic flow prediction, identifying research gaps, evaluation metrics and methodological trends. The study categorizes existing models into traditional ML, deep temporal and spatio-temporal frameworks, emphasizing the progression toward graph-based and hybrid models. The authors highlight the need for standardized datasets and metrics for fair comparison. This review serves as a valuable resource for researchers but notes that interpretability, scalability and real-time deployment remain open challenges.

Zhu and colleagues [19] developed a hybrid deep learning model combining Long Short-Term Memory (LSTM) and Multilayer Perceptron (MLP) networks for predicting traffic incident duration on urban expressways. The model integrates temporal traffic data with contextual factors such as incident type, location and time of occurrence. Results demonstrated that the LSTM-MLP architecture effectively captured complex dependencies, achieving higher accuracy than traditional regression methods. The study expands deep learning applications beyond flow prediction to incident management, though it depends heavily on the quality of incident reporting data.

Yin and co-authors [20] presented a comprehensive analysis of deep learning methods for traffic prediction, discussing model architectures, data characteristics and performance comparisons. Their work systematically categorizes models into convolution-based, recurrent-based and graph-based frameworks, providing insights into their relative strengths and limitations. The study also outlines future research directions such as explainable AI, transfer learning and multi-source data fusion. This paper is significant for offering both theoretical synthesis and practical guidance, though its broad focus means limited empirical experimentation.

Chiabaut and Faitout [21] proposed a travel time and congestion prediction method that leverages historical congestion maps and identifies “consensual days”—days with similar traffic patterns—to enhance predictive reliability. By clustering days with similar congestion profiles, their model captures periodic trends and recurring congestion phenomena without relying solely on time-series forecasting. The study demonstrates that this historical-pattern-based method provides robust travel time estimation in urban environments. Its advantage lies in interpretability and computational simplicity, while limitations include reduced adaptability to unexpected traffic events or structural changes in the network.

Chen and colleagues [22] presented a comprehensive survey on machine learning-based traffic prediction, reviewing traditional and deep learning models, hybrid frameworks and ensemble techniques. The authors categorized models according to their capacity to handle spatial-temporal dependencies and summarized key datasets and evaluation metrics. Their findings indicate a transition from regression-based approaches to deep architectures such as CNNs, RNNs and GNNs, driven by the increasing availability of large-scale data. The study’s strength is its broad coverage and identification of open research problems, including real-time scalability, model interpretability and the need for explainable AI in transportation systems.

Cai and collaborators [23] introduced the Traffic Transformer model, which applies transformer architecture to traffic flow prediction by capturing both temporal continuity and periodicity. Unlike recurrent neural networks, transformers can learn long-range dependencies without sequential bottlenecks. Their approach integrates positional encoding for daily and weekly cycles, achieving superior accuracy on benchmark datasets. The model effectively captures complex periodic behaviors in urban traffic, showing transformer-based architectures’ potential. However, high computational cost and data requirements remain practical limitations for large-scale deployment.

Song and colleagues [24] developed a Spatial-Temporal Synchronous Graph Transformer (STSGT) for traffic flow prediction. This model integrates graph convolutional networks and transformer layers to capture spatial correlations among nodes (e.g., sensors) and long-term temporal dependencies simultaneously. Unlike traditional sequential models, STSGT models spatial and temporal relationships synchronously, leading to significant accuracy gains on standard datasets. The framework outperforms earlier GCN- and RNN-based approaches, though its complexity and need for powerful hardware make real-time inference challenging in large transportation networks.

Ma and co-authors [25] conducted a comprehensive review of short-term traffic flow prediction methods, summarizing statistical, machine learning and deep learning approaches. The review provides detailed comparisons in terms of accuracy, data dependency, interpretability and computational requirements. It highlights the growing dominance of deep learning techniques—particularly graph-based and transformer-based architectures—due to their ability to model nonlinearity and spatial dependencies. The authors also discuss future research needs, such as hybrid models and multi-source data integration. This review serves as a valuable synthesis of post-2018 traffic prediction developments.

Bilotta et al. [26] proposed a convolutional deep learning model for short-term city traffic flow prediction, focusing on spatial feature extraction from traffic sensor grids. The model employs convolutional neural networks (CNNs) to learn spatial correlations and temporal trends from historical traffic maps. Experimental results demonstrate that CNN-based models achieve high prediction accuracy and computational efficiency, making them suitable for real-time systems. However, the absence of temporal modeling components like LSTM or attention mechanisms limits their performance in capturing long-term dependencies.

Çiftçi and Kazan [27] introduced a machine learning model for traffic event analysis using social media data, particularly Twitter. Their approach applies natural language processing (NLP) techniques to detect traffic-related incidents and model their impact on flow conditions. By combining event-driven insights with traditional traffic data, the model provides enhanced situational awareness and predictive capability during unplanned disruptions. This work highlights the growing trend of heterogeneous data fusion in intelligent transportation but faces challenges related to data noise, event verification and linguistic diversity.

Qi and colleagues [28] proposed a multifactor fusion spatio-temporal graph convolutional network (ST-GCN) for long-term traffic prediction. The model integrates diverse data sources—such as weather, events and temporal indices—into a unified deep learning framework. The multifactor fusion approach enables the model to handle complex long-term dependencies, improving forecasting performance beyond short-term horizons. Experimental validation shows the proposed model outperforms traditional ST-GCN and LSTM methods. Its main limitation is increased computational demand and the difficulty of feature engineering for heterogeneous data sources.

Wang et al. [29] introduced an event-driven urban traffic prediction model that fuses heterogeneous information—traffic sensor data, event logs and contextual metadata—using deep neural networks. Their framework captures both regular traffic flow patterns and irregular disturbances caused by accidents or weather events. The study emphasizes the benefits of event-driven learning for adaptive prediction in dynamic urban systems. The model demonstrated superior performance on real-world datasets, yet challenges remain in handling real-time event detection and the integration of unstructured event data.

Aljuaydi and co-authors [30] developed multivariate machine learning prediction models for freeway traffic flow under non-recurrent events, focusing on conditions such as accidents or road closures. Using ensemble techniques including random forest and gradient boosting, their study achieved reliable predictions under abnormal traffic situations. The results show that multivariate learning enhances resilience to data variation and improves prediction robustness. However, the approach depends heavily on the availability and accuracy of event-related variables and it lacks the automatic feature learning capability of deep models.

Sayed et al. [31] presented a comprehensive review of artificial intelligence (AI)-based traffic flow prediction methods, covering classical machine learning algorithms, deep learning models and hybrid approaches. The authors discussed the evolution of AI techniques in handling nonlinear and spatio-temporal complexities inherent in traffic data. The review categorized existing models based on architecture and application scope while identifying research gaps in interpretability, data heterogeneity and model scalability. Their findings emphasize the growing importance of deep and hybrid learning models in real-world deployment. The study is valuable for its holistic synthesis, though it lacks an empirical comparison of the reviewed algorithms.

Abdullah and colleagues [32] proposed a Soft Gated Recurrent Unit (Soft-GRU) based deep learning framework to enhance congestion prediction in smart cities. The model introduces adaptive gating functions to improve the learning of temporal dependencies and smooth gradient flow during training. Experimental evaluations show that Soft-GRU networks outperform standard GRU and LSTM models in predicting urban congestion levels. This approach optimizes traffic flow management by enabling more accurate short-term forecasts. The paper’s innovation lies in model optimization and real-time applicability, although it requires high-quality, continuous traffic data for best results.

Hussain and colleagues [33] developed an urban traffic flow estimation system using a Gated Recurrent Unit (GRU)-based deep learning model integrated with the Internet of Vehicles (IoV) infrastructure. Their system utilizes vehicular sensor data to predict dynamic traffic flow, contributing to intelligent transportation systems (ITS) for connected vehicles. Results demonstrate significant improvements in prediction accuracy and communication efficiency. The study highlights the importance of combining deep learning with IoV technologies but also notes scalability challenges related to data transmission delays and system interoperability across vehicular networks.

Nigam and Srivastava [34] proposed hybrid deep learning models for predicting traffic stream variables—such as flow, speed and density—under rainfall conditions. Their model integrates convolutional and recurrent neural networks to capture both spatial and temporal dependencies influenced by weather. The results show enhanced prediction accuracy compared to conventional LSTM or CNN models alone. This research is significant in highlighting the role of environmental factors in traffic forecasting, though it focuses on a limited dataset and specific weather conditions, suggesting future work should generalize to other external influences.

Chen and colleagues [35] presented a deep learning model for travel time prediction that incorporates both chronological and retrospective time-order information from large-scale traffic data. By structuring data sequences to include both forward and backward temporal dependencies, their model captures the evolution and recurrence of traffic trends more effectively. The study demonstrates substantial improvements over baseline LSTM and Transformer models. Its novelty lies in the dual time-ordering mechanism, which enhances learning of cyclical traffic patterns. However, the model’s high computational complexity and data preprocessing demands may limit real-time applications.

Bhartiya et al. [36] explored a machine learning framework for predictive analysis of traffic flow using regression and ensemble algorithms such as Random Forest and Gradient Boosting. The study focuses on improving model accuracy through feature engineering and parameter tuning. Results show effective short-term prediction performance with relatively low computational overhead. This research contributes to the practical understanding of ML-driven traffic forecasting but lacks comparison with deep learning or hybrid architectures, which currently dominate the field.

Berlotti and colleagues [37] proposed a machine learning approach for traffic flow prediction employing supervised learning algorithms including Support Vector Machines (SVM), Decision Trees and Gradient Boosting. Their model was tested on real-world urban data, showing strong generalization ability and robustness against noise. The study emphasizes simplicity and interpretability, providing valuable insights for smaller-scale or resource-constrained environments. However, its reliance on static feature sets limits adaptability to dynamic, spatio-temporal changes in complex traffic systems.

Ulu and co-authors [38] developed a geohash-based machine learning model for predicting traffic incident locations. The model encodes spatial regions using geohash grids and applies algorithms such as Random Forest and XGBoost to estimate likely incident hotspots. This approach enables efficient spatial indexing and faster location-based predictions. Experimental results validate its utility in proactive traffic management and emergency response. The method’s primary limitation is its dependence on accurate spatial labeling and sufficient historical incident data to train the model effectively.

Zhang and Zhao [39] explored the application of Large Language Models (LLMs) in traffic flow prediction, representing a novel paradigm that integrates natural language understanding with spatio-temporal analytics. Their study reviews how transformer-based architectures, originally designed for text data, can be fine-tuned to model traffic sequences and generate explainable predictions. The authors also discuss the future potential of integrating multimodal data—such as text-based traffic reports, GPS trajectories and sensor readings—into unified LLM frameworks. While largely conceptual, this work marks a significant step toward next-generation intelligent mobility systems.

Abdul Jabbar and colleagues [40] reviewed machine learning-based traffic flow prediction models within the context of smart and sustainable traffic management. Their paper examines recent developments in AI-driven approaches, highlighting how models contribute to reducing congestion, fuel consumption and emissions. They stress the role of interpretability, data ethics and green computing in future ITS designs. The review consolidates the intersection of sustainability and machine learning but remains high-level, with limited empirical benchmarking of specific model performances.

Fadel and Abuhamoud [41] proposed a machine learning-based traffic flow prediction framework for urban traffic management, combining regression and neural network models. Their study demonstrates how integrating multiple learning algorithms can enhance short-term forecasting accuracy and system responsiveness. The model was validated on regional datasets, showing practical applicability for adaptive traffic control. The work contributes to operational aspects of traffic management but could be extended by including spatio-temporal or event-based variables for greater robustness.

Xu and colleagues [42] analyzed the performance of deep learning algorithms based on LSTM for traffic flow prediction and proposed several improvements, including attention mechanisms and optimized training strategies. Their experiments demonstrated significant accuracy gains and reduced overfitting on large traffic datasets. The paper provides both theoretical and experimental insight into refining recurrent neural models for predictive efficiency. However, the model’s high resource demands and limited interpretability remain areas for future improvement.

3. CONCLUSION

This review paper comprehensively analyzed various machine learning and deep learning techniques employed for traffic flow prediction, highlighting the evolution from traditional statistical methods to advanced AI-driven models. Early approaches primarily relied on regression and time-series analysis, offering limited adaptability to nonlinear and dynamic traffic patterns. With the advent of deep learning, architectures such as CNN, RNN, LSTM, GRU and their hybrid or transformer-based variants have significantly enhanced the accuracy and robustness of traffic forecasting by capturing complex spatio-temporal dependencies. Recent developments, including Soft-GRU, attention mechanisms and graph-based models, demonstrate the growing emphasis on real-time adaptability and contextual awareness, particularly under diverse conditions such as weather, incidents and special events.

Furthermore, the integration of Internet of Vehicles (IoV), sensor networks and big data analytics has expanded the predictive capacity of intelligent transportation systems. Studies also underline the importance of sustainability and interpretability, ensuring that AI-driven systems contribute to smart, energy-efficient urban mobility. Emerging research using large language models (LLMs) and multimodal fusion indicates a paradigm shift toward more holistic and explainable traffic prediction frameworks.

While current models achieve remarkable accuracy, challenges remain in terms of scalability, data quality and transferability across different cities. Future research should focus on developing lightweight, interpretable and adaptive models that can generalize across diverse environments. The synergy between AI, IoT and smart city infrastructures will play a pivotal role in achieving efficient, sustainable and intelligent traffic management systems.

REFERENCES

[1] M. Vlahogianni, M. Karlaftis and J. Golias, “Short-term traffic forecasting: Where we are and where we’re going,” Transportation Research Part C, vol. 43, pp. 3–19, 2014.

[2] Lv, Yisheng, Yanjie Duan, Wenwen Kang, Zhengxi Li and Fei-Yue Wang. "Traffic flow prediction with big data: A deep learning approach." Ieee transactions on intelligent transportation systems 16, no. 2 (2014): 865-873.

[3] Y. Ma, Z. Tao, Y. Wang, H. Yu and Y. Wang, “Long short-term memory neural network for traffic speed prediction using remote microwave sensor data,” Transportation Research Part C, vol. 54, pp. 187–197, 2015.

[4] Barros, Joaquim, Miguel Araujo and Rosaldo JF Rossetti. "Short-term real-time traffic prediction methods: A survey." In 2015 international conference on models and technologies for intelligent transportation systems (MT-ITS), pp. 132-139. IEEE, 2015.

[5] S. Sun, C. Zhang and G. Yu, “A Bayesian network approach to traffic flow forecasting under missing data,” Transportation Research Part C, vol. 12, no. 4, pp. 221–240, 2016.

[6] Polson, Nicholas and Vadim Sokolov. "Deep learning predictors for traffic flows." arXiv preprint arXiv: 1604.04527 (2016).

[7] Z. Zhao et al., “LSTM network: A deep learning approach for short-term traffic forecast,” IET Intelligent Transport Systems, vol. 11, no. 2, pp. 68–75, 2017.

[8] Polson, Nicholas G. and Vadim O. Sokolov. "Deep learning for short-term traffic flow prediction." Transportation Research Part C: Emerging Technologies 79 (2017): 1-17.

[9] Liu, Lijuan and Rung-Ching Chen. "A novel passenger flow prediction model using deep learning methods." Transportation Research Part C: Emerging Technologies 84 (2017): 74-91.

[10] B. Yu, H. Yin and Z. Zhu, “Spatio-temporal graph convolutional networks: A deep learning framework for traffic forecasting,” Proceedings of IJCAI, pp. 3634–3640, 2018.

[11] Y. Li, R. Yu, C. Shahabi and Y. Liu, “Diffusion convolutional recurrent neural network: Data-driven traffic forecasting,” ICLR Conference Proceedings, 2018.

[12] H. Wu et al., “Graph WaveNet for deep spatial-temporal graph modeling,” Proceedings of IJCAI, 2019.

[13] Yu, Haiyang, Nan Ji, Yilong Ren and Can Yang. "A special event-based K-nearest neighbor model for short-term traffic state prediction." Ieee Access 7 (2019): 81717-81729.

[14] Yu, Lin, Jiandong Zhao, Yuan Gao and Weijian Lin. "Short-term traffic flow prediction based on deep learning network." In 2019 international conference on robots & intelligent system (ICRIS), pp. 466-469. IEEE, 2019.

[15] Filipovska, Monika and Hani S. Mahmassani. "Traffic flow breakdown prediction using machine learning approaches." Transportation research record 2674, no. 10 (2020): 560-570.

[16] R. A. B. Shahraki et al., “Hybrid ARIMA–LSTM model for traffic flow prediction,” Transportation Research Part C, vol. 128, pp. 103–118, 2021.

[17] Essien, Aniekan, Ilias Petrounias, Pedro Sampaio and Sandra Sampaio. "A deep-learning model for urban traffic flow prediction with traffic events mined from twitter." World Wide Web 24, no. 4 (2021): 1345-1368.

[18] Razali, Noor Afiza Mat, Nuraini Shamsaimon, Khairul Khalil Ishak, Suzaimah Ramli, Mohd Fahmi Mohamad Amran and Sazali Sukardi. "Gap, techniques and evaluation: traffic flow prediction using machine learning and deep learning." Journal of Big Data 8, no. 1 (2021): 152.

[19] Zhu, Weiwei, Jinglin Wu, Ting Fu, Junhua Wang, Jie Zhang and Qiangqiang Shangguan. "Dynamic prediction of traffic incident duration on urban expressways: A deep learning approach based on LSTM and MLP." Journal of intelligent and connected vehicles 4, no. 2 (2021): 80-91.

[20] Yin, Xueyan, Genze Wu, Jinze Wei, Yanming Shen, Heng Qi and Baocai Yin. "Deep learning on traffic prediction: Methods, analysis and future directions." IEEE Transactions on Intelligent Transportation Systems 23, no. 6 (2021): 4927-4943.

[21] Chiabaut, Nicolas and Rémi Faitout. "Traffic congestion and travel time prediction based on historical congestion maps and identification of consensual days." Transportation Research Part C: Emerging Technologies 124 (2021): 102920.

[22] X. Chen et al., “Machine learning-based traffic prediction: A survey,” Applied Sciences, vol. 12, no. 9, pp. 1–20, 2022.

[23] B. Cai et al., “Traffic transformer: Capturing the continuity and periodicity of traffic flow,” Transportation Research Part C, vol. 140, pp. 103–121, 2022.
[24] H. Song et al., “Spatial-temporal synchronous graph transformer for traffic flow prediction,” AAAI Conference on Artificial Intelligence, 2022.
[25] J. Ma et al., “A review on short-term traffic flow prediction methods,” Journal of Advanced Transportation, vol. 2022, pp. 1–17, 2022.
[26] Bilotta, Stefano, Enrico Collini, Paolo Nesi and Gianni Pantaleo. "Short-term prediction of city traffic flow via convolutional deep learning." IEEE Access 10 (2022): 113086-113099.
[27] Çiftçi, Cihan and Halim Kazan. "Traffic Event Analysis Modeling With Machine Learning Methods Using Social Media Data." International Journal for Traffic & Transport Engineering 12, no. 4 (2022).
[28] Qi, Xiaoyu, Gang Mei, Jingzhi Tu, Ning Xi and Francesco Piccialli. "A deep learning approach for long-term traffic flow prediction with multifactor fusion using spatiotemporal graph convolutional network." IEEE transactions on intelligent transportation systems 24, no. 8 (2022): 8687-8700.
[29] D. Wang, X. Fang and Y. Zhang, “Event-driven urban traffic prediction using heterogeneous information fusion,” *IEEE Transactions on Intelligent Transportation Systems*, vol. 24, no. 3, pp. 2541–2553, 2023.
[30] Aljuaydi, Fahad, Benchawan Wiwatanapataphee and Yong Hong Wu. "Multivariate machine learning-based prediction models of freeway traffic flow under non-recurrent events." Alexandria engineering journal 65 (2023): 151-162.
[31] Sayed, Sayed A., Yasser Abdel-Hamid and Hesham Ahmed Hefny. "Artificial intelligence-based traffic flow prediction: a comprehensive review." Journal of Electrical Systems and Information Technology 10, no. 1 (2023): 13.
[32] Abdullah, Sura Mahmood, Muthusamy Periyasamy, Nafees Ahmed Kamaludeen, S. K. Towfek, Raja Marappan, Sekar Kidambi Raju, Amal H. Alharbi and Doaa Sami Khafaga. "Optimizing traffic flow in smart cities: Soft GRU-based recurrent neural networks for enhanced congestion prediction using deep learning." Sustainability 15, no. 7 (2023): 5949.
[33] Hussain, Abdul Hussain Ali, Montadar Abas Taher, Omar Abdulkareem Mahmood, Yousif I. Hammadi, Reem Alkanhel, Ammar Muthanna and Andrey Koucheryavy. "Urban traffic flow estimation system based on gated recurrent unit deep learning methodology for Internet of Vehicles." IEEE Access 11 (2023): 58516-58531.
[34] Nigam, Archana and Sanjay Srivastava. "Hybrid deep learning models for traffic stream variables prediction during rainfall." Multimodal Transportation 2, no. 1 (2023): 100052.
[35] Chen, Claire YT, Edward W. Sun, Ming-Feng Chang and Yi-Bing Lin. "Enhancing travel time prediction with deep learning on chronological and retrospective time order information of big traffic data." Annals of Operations Research 343, no. 3 (2024): 1095-1128.
[36] Bhartiya, Poonam, Mukta Bhatele and Akhilesh A. Waoo. "A machine learning approach for predictive analysis of traffic flow." ShodhKosh J. Vis. Perform. Arts 5 (2024): 422-430.
[37] Berlotti, Mariaelena, Sarah Di Grande and Salvatore Cavalieri. "Proposal of a machine learning approach for traffic flow prediction." Sensors 24, no. 7 (2024): 2348.
[38] Ulu, Mesut, Erdal Kilic and Yusuf Sait Türkan. "Prediction of traffic incident locations with a geohash-based model using machine learning algorithms." Applied Sciences 14, no. 2 (2024): 725.
[39] Zhang, Muhua and Wenzheng Zhao. "Traffic Flow Prediction Based on Large Language Models and Future Development Directions." In ITM Web of Conferences, vol. 70, p. 01008. EDP Sciences, 2025.
[40] Abduljabbar, Rusul, Hussein Dia and Sohani Liyanage. "Machine Learning Traffic Flow Prediction Models for Smart and Sustainable Traffic Management." Infrastructures 10, no. 7 (2025): 155.
[41] Fadel, Mabrouka and Nassir Abuhamoud. "Machine Learning-Based Traffic Flow Prediction for Enhanced Traffic Management." Wadi Alshatti University Journal of Pure and Applied Sciences (2025): 54-61.
[42] Xu, Wei, Eric Blancaflor and Mideth Abisado. "Performance and improvement of deep learning algorithms based on LSTM in traffic flow prediction." Discover Applied Sciences 7, no. 4 (2025): 278.