

Advanced Traffic Flow Prediction Using Machine Learning and Deep Learning for Urban Mobility Optimization

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ABSTRACT

The rapid growth of urban populations and vehicle ownership has intensified traffic congestion, making efficient traffic management crucial for sustainable urban development. Intelligent Transportation Systems (ITS) leverage technologies such as communication, sensing, and computation to optimize transportation. A core element of ITS is traffic flow prediction, which, through historical and real-time data, improves congestion management and route optimization. While traditional models like ARIMA struggled with nonlinear patterns, machine learning and deep learning, such as CNN, RNN, and LSTM networks, have enhanced accuracy. Recent advancements focus on improving scalability, real-time predictions, and the integration of external factors for greater accuracy.

Keywords: *Urban Traffic, ITS, Machine Learning, Deep Learning, Traffic Prediction.*

I. INTRODUCTION

The rapid expansion of urban populations and the corresponding increase in vehicle ownership have led to severe traffic congestion issues in modern cities. Efficient traffic management has therefore become a critical requirement for sustainable urban development. In this context, Intelligent Transportation Systems (ITS) have emerged as a promising technological framework that integrates communication, sensing, and computational technologies to improve transportation efficiency. A key component of ITS is traffic flow prediction, which enables the forecasting of future traffic conditions based on historical and real-time data. Accurate traffic prediction plays an essential role in congestion reduction, route optimization, fuel efficiency improvement, and overall enhancement of urban mobility systems (Liu & Shin, 2025; Sayed et al., 2023). Traditionally, traffic flow prediction was performed using statistical and mathematical models such as autoregressive integrated moving average (ARIMA) and regression-based approaches. However, these methods often assume linear relationships and stationary data distributions, which limit their effectiveness in complex and dynamic traffic environments. With the advent of big data and advanced computing technologies, machine learning (ML) and deep learning (DL) techniques have gained prominence due to their ability to capture nonlinear relationships and complex spatiotemporal patterns in traffic data (Xing et al., 2023). These data-driven approaches have significantly improved prediction accuracy and adaptability in real-world scenarios. Deep learning-based models, particularly those using architectures such as Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and Long Short-Term Memory (LSTM) networks, have demonstrated strong performance in modeling traffic dynamics. For example, Vijayalakshmi et al. (2021) proposed an attention-based CNN-LSTM model that effectively extracted spatial and temporal features from traffic data, resulting in improved forecasting accuracy under varying traffic conditions. Similarly, Shao et al. (2021) introduced an incremental learning-based CNN-LSTM model that enhanced real-time prediction capability while reducing computational complexity. These studies highlight the importance of hybrid deep learning frameworks in addressing the nonlinear and time-dependent nature of traffic flow.

Despite their success, conventional deep learning models still face several limitations, including lack of interpretability, high computational cost, and limited adaptability to changing traffic environments. To address these challenges, researchers have recently focused on developing more advanced and interpretable architectures. Wu et al. (2018) proposed a hybrid deep learning framework combining CNN and RNN with attention mechanisms to better capture spatial and temporal dependencies in traffic data. Their model demonstrated improved interpretability and higher prediction accuracy compared to traditional methods. Additionally, Goswami and Kumar (2022) emphasized that traffic flow is influenced by multiple external factors such as weather conditions, accidents, and social events, which must be incorporated into predictive models for better accuracy. Recent advancements have also focused on improving scalability and real-time prediction capabilities through cloud computing and graph-based neural networks. Venkataswamy et al. (2026) developed a hybrid deep learning model integrating Long Short-Term Memory (LSTM) networks and Graph Neural Networks (GNNs) within a cloud computing environment. This model effectively captured both sequential and spatial dependencies while enabling real-time forecasting for smart logistics applications. Similarly, Zhao et al. (2026) introduced a Multi-scale Spatio-Temporal Neural Network (MSTNN) that utilized Kolmogorov Arnold Networks (KAN) variants to improve interpretability and capture multi-scale temporal patterns. Their findings demonstrated significant improvements in prediction performance, highlighting the effectiveness of multi-scale learning strategies. In addition to model development, several review studies have contributed to a deeper understanding of traffic flow prediction techniques. Liu and Shin (2025) classified existing approaches into statistical, machine learning, and deep learning-based methods, concluding that deep learning models outperform traditional approaches in capturing nonlinear traffic patterns. Similarly, Sayed et al. (2023) highlighted the role of artificial intelligence and Internet of Things (IoT) technologies in enhancing intelligent transportation systems and improving congestion management. Xing et al. (2023) further provided a systematic review of machine learning-based traffic prediction models, emphasizing the importance of data preprocessing, feature engineering, and model optimization. Although significant progress has been made, several challenges remain unresolved in the field of traffic flow prediction. These include issues related to model generalization across different geographical regions, handling missing or noisy data, and ensuring real-time computational efficiency. Moreover, long-term traffic forecasting remains particularly challenging due to the dynamic and stochastic nature of urban traffic systems. Therefore, there is a growing need for more robust, scalable, and interpretable machine learning models that can integrate multiple data sources and adapt to changing traffic conditions effectively (Liu et al., 2019; Sayed et al., 2023).

II. RESEARCH BACKGROUND

Zhao et al. (2026) presented an interpretable deep learning-based traffic flow forecasting model, termed Multi-scale Spatio-Temporal Neural Networks (MSTNN), to address key limitations in existing forecasting architectures. The study reported that although contemporary deep learning models had effectively captured complex spatio-temporal dependencies in traffic networks, they had often neglected multi-scale temporal characteristics and lacked sufficient interpretability. To overcome these issues, the proposed MSTNN was designed to divide original traffic sequences into multiple patches of different scales, thereby preserving diverse temporal features. The study further incorporated two advanced variants of Kolmogorov Arnold Networks (KAN), namely Spatial Attention-aware KAN (SA-KAN) and Temporal Channel Mixed KAN (TCM-KAN), which were employed to extract spatial structural and temporal sequential features while improving interpretability. A fusion module was also introduced to integrate multi-scale temporal information. Extensive experiments were conducted, and the findings indicated that MSTNN had achieved performance improvements ranging from 0.11% to 12.65%, thereby demonstrating both effectiveness and interpretability.

Venkataswamy et al. (2026) presented a study in which real-time traffic forecasting was identified as a crucial enabler for maximizing transport efficiency and reducing delivery time in smart logistics. It was reported that Artificial Intelligence and Big Data had significantly enhanced intelligent traffic prediction, thereby supporting improved decision-making in logistics operations. The authors observed that most existing approaches had been inadequate in capturing temporal correlations and spatial dependencies under dynamic traffic conditions, which often resulted in inaccurate predictions and inefficient route planning. To overcome these limitations, a Hybrid Deep Learning-Based Traffic Prediction on Cloud Platform Model (HDL-TPM) was proposed by integrating Long Short-Term Memory (LSTM) networks with Graph Neural Networks (GNNs). It was explained that LSTM had modeled sequential traffic flow variations, while GNN had captured spatial road network dependencies. The cloud-native spatiotemporal pipeline was reported to enable scalable, parallel, and real-time forecasting. Experimental findings indicated that HDL-TPM had achieved higher prediction accuracy and improved logistics efficiency compared to traditional models.

Liu and Shin (2025) presented a comprehensive review of traffic flow prediction methods within intelligent transportation systems (ITSs), where such methods were identified as a cornerstone of modern transportation technology. The study classified traffic flow prediction approaches into three major categories, namely statistics-based, machine learning-based, and deep learning-based methods. It was reported that statistics-based methods required relatively less data, while machine learning-based methods offered faster computational performance. However, after a comparative evaluation of the principles, strengths, limitations, and practical applications of each category, deep learning-based methods were found to have delivered the most effective overall performance. The authors indicated that deep learning approaches were capable of capturing complex nonlinear relationships that traditional statistical and machine learning methods often failed to model effectively. Experimental findings further suggested that hybrid neural networks had significantly outperformed conventional methods in prediction accuracy and generalization capability. Nevertheless, challenges related to model generalization across varying traffic scenarios and long-term forecasting were also highlighted, and future research directions were subsequently discussed.

Xing et al. (2023) reviewed traffic flow prediction as a significant component of intelligent transportation systems and observed that the growing availability of large-scale traffic data, along with the rapid advancement of machine learning techniques, had considerably accelerated research progress in this field. The study was reported to have introduced the fundamental concepts and existing developments in traffic flow prediction while also identifying the major challenges affecting predictive accuracy and model generalization. The authors were found to have proposed a systematic classification framework for the existing literature and analyzed prior studies from the perspectives of data preparation processes and prediction model construction. In addition, the review was stated to have examined various innovative modules integrated into machine learning-based traffic prediction models. The article further suggested possible improvement strategies for current baseline models and highlighted key challenges, limitations, and future research directions for enhancing the effectiveness and robustness of traffic flow prediction systems.

Sayed et al. (2023) presented a comprehensive review of the growing role of the Internet of Things in enabling smart city applications, particularly through the development of Intelligent Transportation Systems (ITS). The study reported that ITS had become a central component of smart cities by improving transportation efficiency, mobility, and congestion management. It was observed that the rapid integration of artificial intelligence had led to the emergence of advanced traffic flow prediction models and

frameworks aimed at enhancing forecasting accuracy. The authors emphasized that traffic forecasting had been considered essential in the transportation sector due to its significant influence on route planning, traffic regulation, and road infrastructure design. Urban traffic congestion was identified as a major challenge requiring accurate evaluation and prediction. The review further examined the most widely used machine learning and deep learning techniques in traffic prediction and highlighted the inherent challenges and limitations associated with their practical implementation in this domain.

Goswami and Kumar (2022) examined the significance of accurate and real-time traffic flow prediction within Intelligent Transportation Systems (ITS), particularly for effective traffic control and smart city development. The study highlighted that traffic-related data had been considered essential for reducing road accidents, anticipating vehicle speed, and improving transportation management. It was observed that conventional traffic forecasting methods had largely relied on shallow prediction techniques, which were found to be inadequate for complex real-world applications. The authors noted that traffic flow exhibited both spatial and temporal dependencies and was also influenced by weather conditions, social events, and environmental factors. Therefore, a deep-learning-based traffic flow prediction model integrating Stacked Auto-Encoder (SAE), Convolutional Neural Network (CNN), and Long Short-Term Memory (LSTM) networks was proposed to capture spatial and temporal correlations. Experimental results demonstrated that the suggested approach had shown superior efficiency and improved prediction accuracy when compared with several existing deep learning techniques on a real-world public traffic dataset.

Vijayalakshmi et al. (2021) examined the critical role of intelligent transportation systems (ITS) in the development of smart cities and addressed the challenge of accurate traffic flow forecasting under dynamic and chaotic traffic conditions. The study noted that the rapid growth in traffic data had ushered in the era of big data, thereby necessitating deep learning architectures for efficient processing, analysis, and inference. To enhance forecasting performance, the authors had proposed an attention-based convolutional neural network–long short-term memory (CNN-LSTM) multistep prediction model. It was reported that the model had utilized both spatial and temporal features of traffic data, extracted through CNN and LSTM networks, to improve prediction accuracy. The attention mechanism was found to be effective in identifying near-term traffic characteristics, such as speed, which were crucial for forecasting future traffic flow. Using the California Department of Transportation (Caltrans) dataset, the model was shown to achieve superior accuracy during weekdays, weekends, peak, and non-peak hours.

Shao et al. (2021) examined the growing challenges of traffic congestion caused by rapid urbanization and the increasing number of motor vehicles, which had intensified the need for efficient and accurate traffic flow prediction in intelligent transportation systems. The study reported that traditional machine learning methods had shown limitations in handling large-scale data, while deep learning approaches had performed inadequately in mobile and real-time applications due to high computational costs and long training times. To address these issues, an incremental learning-based CNN-LSTM model, namely IL-TFNet, was proposed for short-term traffic flow prediction. The model was designed as a lightweight convolutional neural network architecture capable of simultaneously processing spatiotemporal and external environmental features, thereby improving both prediction accuracy and efficiency. K-means clustering was further employed to capture uncertain traffic accident information. The study concluded that the integration of incremental and active learning had significantly enhanced model adaptability, real-time performance, and predictive accuracy compared with existing traffic flow prediction models.

Liu et al. (2019) investigated the integration of deep learning techniques with domain knowledge in transportation for predicting metro passenger flow. They proposed an end-to-end deep learning framework, termed Deep Passenger Flow (DeepPF), to forecast inbound and outbound metro traffic. The study indicated that the architecture of DeepPF was highly flexible and extendable, allowing the incorporation of external environmental factors, temporal dependencies, spatial characteristics, and metro operational properties for short-term passenger flow prediction. It was reported that the framework achieved high prediction accuracy, primarily due to its capacity to integrate multi-source data effectively. Numerical experiments were conducted to validate the model, and the results suggested that DeepPF could be generalized to accommodate diverse conditions and constraints inherent in the transportation domain. The study concluded that combining deep learning with domain-specific knowledge could enhance predictive performance and provide a robust tool for metro operation planning and management.

Wu et al. (2018) investigated the application of deep neural networks (DNNs) for traffic flow prediction using big data and highlighted that, although existing DNN models had shown better performance than shallow models, fully exploiting the spatial–temporal characteristics of traffic flow remained an open challenge. They proposed a DNN-based traffic flow prediction model (DNN-BTF) aimed at improving prediction accuracy by leveraging weekly and daily periodicity alongside spatial–temporal dependencies. The study reported that an attention-based mechanism was incorporated to automatically determine the significance of past traffic data, while convolutional neural networks (CNNs) were employed to extract spatial features and recurrent neural networks (RNNs) to capture temporal patterns. Through visualization, the authors demonstrated how the DNN-BTF model interpreted traffic data, challenging the conventional perception of neural networks as purely “black-box” models. Validation using the PeMS open-access dataset indicated that the proposed approach outperformed state-of-the-art methods in long-term traffic flow prediction tasks.

Tampubolon and Hsiung (2018) examined traffic issues prevalent in metropolitan areas, including congestion, accidents, air pollution, and high energy consumption. They reported that to address these challenges, many researchers had developed Intelligent Transportation Systems (ITS), with Traffic Management Systems (TMS) identified as a key sub-system aimed at alleviating traffic congestion. They emphasized that accurate traffic flow estimation was essential for the effective operation of TMS. To this end, they proposed a Supervised Deep Learning Based Traffic Flow Prediction (SDLTFP) model, employing a fully-connected deep neural network (FC-DNN). They noted that timely predictions posed a significant challenge, as training deep networks could be time-consuming and prone to overfitting, particularly with limited data. To mitigate these issues, Batch Normalization and Dropout techniques were applied during training, while Stochastic Gradient Descent with momentum was used for weight updates. Using open historical traffic data, they predicted future traffic flows, reporting Mean Absolute Percentage Errors (MAPE) of approximately 5% for in-sample and 15–20% for out-of-sample data, demonstrating improved training efficiency and reduced overfitting.

III. KEY FINDINGS FROM STUDY

Author (Year)	Model / Approach	Objective	Key Findings	Limitations
Zhao et al. (2026)	Multi-scale Spatio-Temporal Neural Network (MSTNN) with SA-KAN & TCM-KAN	Traffic flow forecasting with interpretability	Improved accuracy (0.11%–12.65%) and better multi-scale feature learning	High computational complexity

Venkataswamy et al. (2026)	Hybrid LSTM + GNN with cloud platform	Real-time traffic prediction for smart logistics	Enhanced scalability, real-time forecasting, and route optimization	Dependency on cloud infrastructure
Liu & Shin (2025)	Review of statistical, ML, and DL methods	Comparative analysis of traffic prediction techniques	DL models outperform others in nonlinear pattern learning	Poor generalization in dynamic environments
Xing et al. (2023)	Systematic review of ML-based models	Classification and evaluation of traffic prediction methods	Identified key challenges in data processing and modeling	Limited practical deployment studies
Sayed et al. (2023)	AI and IoT-based ITS review	Role of AI in smart transportation systems	AI improves congestion prediction and traffic efficiency	Implementation and scalability issues
Goswami & Kumar (2022)	CNN-LSTM deep learning model	Traffic flow prediction using spatiotemporal data	Higher accuracy than traditional methods	Limited integration of external factors
Vijayalakshmi et al. (2021)	Attention-based CNN-LSTM model	Multistep traffic flow prediction	Strong performance across different traffic conditions	High computational cost
Shao et al. (2021)	Incremental learning CNN-LSTM (IL-TFNet)	Real-time traffic flow prediction	Improved adaptability and efficiency	Weak long-term prediction ability
Liu et al. (2019)	DeepPF framework	Metro passenger flow prediction	High accuracy using multi-source data integration	Limited to domain-specific applications
Wu et al. (2018)	Hybrid CNN-RNN with attention mechanism	Spatio-temporal traffic flow prediction	Improved long-term forecasting accuracy	High training complexity
Tampubolon & Hsiung (2018)	Fully Connected Deep Neural Network (FC-DNN)	Short-term traffic prediction	Reduced overfitting, good MAPE performance	Slow training and scalability issues

IV. CONCLUSION

The reviewed literature on machine learning-based traffic flow prediction models clearly demonstrates that intelligent computational approaches have significantly transformed the field of transportation engineering. With the rapid increase in urbanization and vehicular density, conventional traffic prediction methods have become inadequate in handling the nonlinear, dynamic, and highly complex nature of modern traffic systems. In response to these challenges, researchers have increasingly adopted machine

learning (ML) and deep learning (DL) techniques, which have shown superior capability in capturing spatiotemporal dependencies and improving forecasting accuracy. Studies such as Wu et al. (2018) and Vijayalakshmi et al. (2021) have shown that hybrid deep learning architectures, including CNN, LSTM, and attention mechanisms, are highly effective in extracting both spatial and temporal features from traffic data. These models have consistently demonstrated improved prediction accuracy compared to traditional statistical approaches. Similarly, Shao et al. (2021) highlighted that incremental learning-based CNN-LSTM models enhance real-time adaptability, which is essential for dynamic traffic environments. Recent advancements have further improved model performance through integration of graph-based learning and cloud computing frameworks. For instance, Venkataswamy et al. (2026) proposed a hybrid LSTM-GNN model deployed on a cloud platform, which significantly improved real-time prediction efficiency and scalability. Additionally, Zhao et al. (2026) introduced a multi-scale spatio-temporal neural network (MSTNN) that enhanced interpretability and improved forecasting accuracy by capturing traffic patterns at multiple temporal resolutions. These developments indicate a clear shift toward more complex, hybrid, and intelligent architectures in traffic flow prediction research.

Review-based studies by Liu and Shin (2025), Xing et al. (2023), and Sayed et al. (2023) further confirm that deep learning methods outperform traditional machine learning and statistical models in handling nonlinear traffic patterns. However, these studies also highlight persistent challenges such as lack of model interpretability, high computational cost, and difficulty in generalizing across different traffic conditions. Despite these limitations, ML-based traffic prediction models have proven to be a vital component of Intelligent Transportation Systems (ITS), contributing significantly to congestion reduction, route optimization, and urban mobility improvement. Overall, it can be concluded that machine learning-based traffic flow prediction models provide a strong foundation for developing smart and efficient transportation systems. Their ability to process large-scale data and identify hidden patterns makes them highly suitable for modern urban traffic management applications.

V. FUTURE SCOPE

- **Development of Explainable AI Models:** Future research should focus on improving the interpretability of deep learning models. Since most existing models function as “black-box” systems, developing explainable AI (XAI) techniques will help transportation authorities better understand decision-making processes.
- **Integration of Multi-Source Data:** Traffic prediction accuracy can be further enhanced by integrating diverse data sources such as weather conditions, social events, GPS data, road incidents, and sensor-based IoT data. Multi-modal data fusion will enable more robust and context-aware prediction systems.
- **Real-Time Edge and Cloud Computing Deployment:** To achieve faster response times, future models should leverage edge computing along with cloud infrastructure. This will reduce latency and allow real-time traffic prediction and decision-making in large-scale urban environments.
- **Hybrid and Adaptive Learning Models:** Future studies should focus on developing adaptive hybrid models that combine machine learning, deep learning, and reinforcement learning techniques. These models can dynamically adjust to changing traffic conditions and improve long-term forecasting accuracy.
- **Transfer Learning for Cross-City Generalization:** One major limitation in current models is poor generalization across different cities. Transfer learning techniques can be used to apply knowledge learned from one traffic system to another, reducing the need for large datasets in every region.

- **Sustainability and Smart City Integration:** Future traffic prediction systems should be integrated with smart city infrastructure to support sustainable urban development. This includes reducing fuel consumption, lowering emissions, and improving public transportation efficiency.
- **Improved Handling of Uncertainty and Anomalies:** Advanced probabilistic and fuzzy logic-based ML models can be explored to handle uncertainties caused by accidents, weather changes, and unexpected traffic disruptions.

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