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# DEMAND FORECASTING IN TRANSPORTATION NETWORKS USING DEEP LEARNING

**Umer Ahmad Kithran[1], Arfaa Khanam[2], Sana Ilyas[3], Reehan Yaqoob[*4], Muhammad Hannan[5]**

[1]*University of Texas at Arlington, Department of Civil Engineering, Major in Transportation Engineering*
[2]*Lecturer, Department of Computer Science, National University of Modern Languages (NUML), Faisalabad*
[3]*Department: Computer Science, Lecturer School of Computing Sciences, NFC Institute of Engineering and Fertilizer Research, Faisalabad. Pakistan, PhD scholars from National Textile university Faisalabad*
[*4,5]*Department of Computer Science, The University of Faisalabad, Punjab, Pakistan*

[1]umerahmad01@gmail.com, [2]arfaa.khanam@numl.edu.pk, [3]sana.ilyas@iefr.edu.pk, [*4]reehan.yaqoob@gmail.com, [5]a.hannan17008@gmail.com

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**Corresponding Author:** *
**Reehan Yaqoob**

**Abstract**

*Accurate demand forecasting in transportation networks is essential for efficient resource allocation, effective traffic management, and sustainable urban planning. With the continuous growth of urban populations and increasing vehicle usage, transportation systems generate vast amounts of complex and dynamic data. Traditional statistical models, such as linear regression and ARIMA, often struggle to capture nonlinear relationships and sudden fluctuations in traffic flow and passenger demand. These limitations reduce their effectiveness in real-time forecasting, especially in large-scale metropolitan networks where demand patterns are highly variable and influenced by multiple interacting factors. To overcome these challenges, this study proposes a deep learning-based framework for transportation demand prediction. Specifically, Long Short-Term Memory (LSTM) networks are employed to capture temporal dependencies in sequential traffic data, as they are capable of learning long-term patterns and handling time-series dynamics effectively. In addition, Convolutional Neural Networks (CNNs) are utilized to extract spatial features from geographically distributed traffic and GPS data. By integrating both temporal and spatial learning mechanisms, the proposed model can better understand complex traffic behaviors and passenger movement trends across different regions of the network. Experimental results indicate that deep learning models significantly outperform conventional time-series approaches in both short-term and long-term forecasting tasks. The hybrid CNN-LSTM architecture demonstrates improved predictive accuracy, lower error rates, and greater robustness in handling peak-hour demand variations. These findings highlight the practical value of deep learning in intelligent transportation systems, enabling transit authorities to optimize routes, reduce congestion, improve service reliability, and enhance overall commuter satisfaction.*

## 1. INTRODUCTION

Urban transportation networks are increasingly challenged by rapid population growth, urbanization, and the continuous rise in private vehicle ownership. Expanding metropolitan areas experience higher travel demand, leading to congestion, delays, fuel wastage, and environmental pollution. As cities evolve into smart urban ecosystems, transportation systems must operate efficiently to ensure economic productivity and quality of life. In this context, accurate forecasting of traffic demand and passenger flow has become a fundamental requirement for effective mobility management and sustainable development. Reliable demand prediction enables transportation authorities to make informed decisions regarding fleet allocation, route scheduling, signal timing optimization, and infrastructure expansion. Short-term forecasts assist in managing peak-hour congestion and real-time operational adjustments, while long-term forecasts support strategic planning and investment decisions. Without accurate predictive mechanisms, transportation systems risk inefficiencies such as overcrowded public transit, underutilized routes, and increased operational costs. Therefore, advanced forecasting techniques are essential for maintaining system resilience and adaptability.

Traditional forecasting methods, including the Autoregressive Integrated Moving Average (ARIMA) model, have historically been applied to traffic prediction problems. While these statistical approaches are effective for linear and stationary time-series data, they often struggle to capture nonlinear relationships, sudden demand fluctuations, and complex spatial-temporal dependencies inherent in modern transportation datasets. Urban traffic patterns are influenced by numerous dynamic factors such as weather conditions, social events, accidents, road construction, and human behavioral variability, which conventional models cannot fully represent. With the rapid advancement of machine learning, data-driven models have emerged as powerful tools for transportation analytics. Deep learning, in particular, has demonstrated exceptional performance in handling large-scale, high-dimensional data. Long Short-Term Memory (LSTM) networks are specifically designed to learn sequential and temporal dependencies, making them highly suitable for traffic flow prediction. Their ability to retain information over extended time intervals allows them to model daily, weekly, and seasonal demand variations effectively.

In addition to temporal dynamics, transportation demand exhibits strong spatial correlations across interconnected road networks and transit corridors. Convolutional Neural Networks (CNNs), widely known for their success in image and pattern recognition tasks, can be adapted to extract spatial features from grid-based traffic data and sensor networks. By identifying regional traffic density patterns and spatial interactions between adjacent zones, CNN models enhance predictive performance when integrated with temporal learning architectures. This study explores the combined application of LSTM and CNN models for forecasting demand in urban transportation networks. The proposed framework utilizes real-time data collected from GPS sensors embedded in vehicles, traffic surveillance cameras, and historical ridership records from public transit systems. Data preprocessing techniques, including normalization, feature extraction, and time-window segmentation, are applied to ensure robust model training. By integrating multiple heterogeneous data sources, the system captures both short-term fluctuations and long-term demand trends.

Furthermore, the integration of deep learning models into intelligent transportation systems supports the broader vision of smart cities. By leveraging real-time analytics and predictive modeling, transportation authorities can shift from reactive traffic control to proactive demand management. For example, predicted surges in passenger demand can trigger adaptive signal control, dynamic pricing strategies, or temporary deployment of additional transit vehicles. Such predictive capabilities not only improve operational efficiency but also enhance passenger experience by reducing waiting times and travel uncertainty. Over time, consistent demand forecasting can contribute to lower emissions, improved fuel efficiency, and better utilization of infrastructure resources. In addition, the scalability and adaptability of deep learning models make them suitable for diverse urban contexts, ranging from densely populated megacities to developing metropolitan regions. As transportation data continues to grow in volume and complexity through the expansion of Internet of Things (IoT) devices and smart sensors, advanced neural network architectures can continuously learn and update from new data streams. This adaptability ensures that forecasting models remain robust under changing traffic conditions, seasonal variations, and unexpected disruptions. Consequently, deep learning-based demand forecasting represents a transformative approach toward building resilient, data-driven, and sustainable transportation networks for the future.

## 1. Related work

Prior research on traffic demand prediction has evolved significantly over the past few decades, reflecting advancements in data availability and computational techniques [1]. Early studies primarily relied on traditional statistical approaches, focusing on time-series analysis methods that assumed linearity and stationarity in traffic data [2]. These models were suitable for small-scale datasets and short-term forecasting but lacked the flexibility to handle complex, real-world transportation dynamics. Among the earliest and most widely adopted techniques was the Autoregressive Integrated Moving Average model. ARIMA and its seasonal variants were commonly used for traffic flow and passenger demand forecasting due to their structured mathematical framework and interpretability [3]. Similarly, exponential smoothing methods, including Holt–Winters models, were applied to capture trend and seasonal patterns in transportation data [4]. While these approaches provided reasonable accuracy under stable conditions, they often failed to model nonlinear interactions and abrupt changes caused by incidents, weather variations, or special events [5].

As transportation datasets grew in size and complexity, researchers began exploring machine learning techniques to overcome the limitations of purely statistical models [6]. Algorithms such as Random Forests, Support Vector Machines (SVM), and k-Nearest Neighbors (k-NN) were introduced for traffic prediction tasks [7]. These models improved forecasting accuracy by capturing nonlinear relationships between variables such as traffic volume, time of day, and road characteristics. However, despite their advantages, traditional machine learning methods generally required extensive feature engineering and were not inherently designed to model sequential dependencies in time-series data [8]. Artificial Neural Networks (ANNs) marked a transitional phase between classical machine learning and deep learning approaches [9]. Feedforward neural networks demonstrated better performance compared to linear models in several traffic prediction studies. Nonetheless, their inability to effectively retain past information limited their capacity to model long-term temporal patterns [10]. This shortcoming motivated the exploration of recurrent neural networks (RNNs), which were specifically developed to process sequential data [11].

Recurrent Neural Networks introduced the concept of memory into predictive modeling, allowing information from previous time steps to influence future predictions [12]. However, traditional RNNs suffered from the vanishing and exploding gradient problems, which hindered their performance when dealing with long sequences. To address this issue, Long Short-Term Memory (LSTM) networks were proposed. LSTMs incorporate gating mechanisms that regulate information flow, enabling them to capture long-term dependencies in traffic demand data [13]. Numerous studies have demonstrated that LSTM models significantly outperform ARIMA and conventional machine learning models in both short-term and multi-step forecasting scenarios [14].

In addition to temporal modeling, researchers recognized the importance of spatial relationships within transportation networks. Traffic conditions at one location are often influenced by adjacent roads or connected transit routes [15]. Convolutional Neural Networks (CNNs), originally developed for image processing, were adapted to capture spatial correlations in grid-based traffic representations [16]. By applying convolutional filters, CNNs can automatically extract spatial features such as congestion clusters and regional demand patterns, enhancing forecasting performance. Further recent research has focused on hybrid and integrated deep learning architectures that combine spatial and temporal modeling capabilities. CNN-LSTM models, for instance, use convolutional layers to learn spatial dependencies and LSTM layers to model temporal sequences [17]. Other advanced approaches include Graph Neural Networks, which explicitly represent transportation networks as graphs and capture complex topological relationships. These hybrid frameworks have shown superior predictive accuracy in large-scale urban environments where both spatial and temporal factors strongly interact [18].

Overall, the progression from statistical models to deep learning architectures reflects the growing need for robust, scalable, and data-driven forecasting methods in intelligent transportation systems [19]. While traditional approaches laid the foundation for traffic demand prediction, modern deep learning models provide greater flexibility, adaptability, and accuracy. The integration of spatial-temporal learning techniques continues to be a promising research direction, offering more reliable forecasts for complex and dynamic urban transportation networks [20]. Recent advancements in deep learning have further accelerated the evolution of traffic demand forecasting by introducing more sophisticated architectures capable of handling large-scale, heterogeneous transportation data [21]. One notable direction involves the application of attention mechanisms within sequence modeling frameworks. Attention-based models, particularly those integrated with LSTM or Transformer architectures, allow the model to selectively focus on the most relevant time steps and features when making predictions. This significantly enhances forecasting accuracy, especially in scenarios involving irregular traffic patterns and long-term dependencies [22]. Studies have demonstrated that attention-enhanced LSTM models outperform conventional LSTM approaches by dynamically weighting historical observations rather than treating all past data equally [23].

Building upon attention mechanisms, the introduction of Transformer-based models has marked a paradigm shift in time-series forecasting. Originally developed for natural language processing, Transformers rely entirely on self-attention mechanisms and eliminate the need for recurrent structures [24]. In the context of transportation networks, Transformer models have shown strong potential in capturing both short-term fluctuations and long-range dependencies in traffic demand. Their parallel processing capability also enables efficient training on large datasets, making them suitable for real-time intelligent transportation systems [25]. Variants such as Temporal Fusion Transformers have been successfully applied to multi-horizon demand forecasting, incorporating static, known, and observed inputs in a unified framework [26]. Another important development is the integration of Graph Neural Networks with temporal models to better represent the topological structure of transportation systems [27]. Unlike grid-based CNN approaches, GNNs model road networks as nodes and edges, preserving their inherent connectivity. Techniques such as Graph Convolutional Networks and Graph Attention Networks have been employed to capture spatial dependencies more accurately [28]. When combined with temporal models like LSTM or gated recurrent units, these architectures often referred to as Spatio-Temporal Graph Neural Networks (ST-GNNs) have demonstrated state-of-the-art performance in traffic flow and demand prediction tasks [29]. These models are particularly effective in urban environments where complex road interactions and dynamic traffic flows are prevalent [30].

In addition to architectural innovations, recent research has emphasized the incorporation of external and contextual data sources to improve prediction accuracy. Factors such as weather conditions, public events, holidays, road incidents, and socio-economic indicators have been integrated into deep learning frameworks [31]. Multimodal learning approaches allow

models to process heterogeneous data streams simultaneously, providing a more comprehensive understanding of demand fluctuations [32]. For instance, studies have shown that incorporating weather data and event schedules can significantly reduce forecasting errors in ride-hailing and public transportation demand prediction [33]. Another emerging trend is the use of reinforcement learning in conjunction with demand forecasting models. While deep learning models focus on predicting future demand, RL-based systems utilize these predictions to optimize decision-making processes such as dynamic pricing, fleet management, and route planning [34]. Deep Reinforcement Learning frameworks have been applied to real-time traffic control and adaptive transportation systems, enabling continuous learning and system optimization based on changing demand patterns. This integration highlights a shift from purely predictive models toward intelligent, decision-support systems [35].
Furthermore, the growing availability of large-scale transportation datasets has encouraged the use of transfer learning and domain adaptation techniques [36]. These methods aim to leverage knowledge learned from one city or region and apply it to another with limited data availability [37]. Transfer learning reduces the need for extensive training data and computational resources, making deep learning models more scalable and applicable across different geographical contexts [38]. Recent studies have demonstrated that pre-trained models can be fine-tuned for new environments while maintaining high prediction accuracy [39]. Despite these advancements, several challenges remain in the field of traffic demand forecasting. One major issue is data sparsity and missing values, which can significantly affect model performance [40]. Although deep learning models are robust, they still require high-quality data for optimal results. Techniques such as data imputation, augmentation, and robust training strategies have been proposed to address these issues [41]. Additionally, the interpretability of deep learning models remains a concern, as many models operate as black boxes, making it difficult for transportation planners to understand the underlying decision-making process [42].
Scalability and computational efficiency also pose challenges, particularly for real-time applications in large metropolitan areas. While models such as Transformers and GNNs offer high accuracy, they often require substantial computational resources [43]. Researchers are increasingly focusing on developing lightweight and efficient architectures that can be deployed in edge computing environments for real-time traffic monitoring and prediction [44]. Finally, recent studies have explored the role of federated learning in transportation systems, where models are trained across decentralized data sources without sharing raw data. This approach addresses privacy concerns while enabling collaborative learning across multiple regions or organizations. Federated deep learning has shown promising results in traffic demand forecasting by leveraging distributed data while preserving data confidentiality [45]. In summary, the field of traffic demand forecasting has progressed from traditional statistical models to highly advanced deep learning frameworks incorporating attention mechanisms, graph-based modeling, and multimodal data integration [46]. Emerging technologies such as reinforcement learning, transfer learning, and federated learning are further expanding the capabilities of intelligent transportation systems. These developments highlight a clear trend toward more adaptive, scalable, and context-aware forecasting models, paving the way for smarter and more efficient transportation networks [47].

## 2. Methodology

The proposed methodology is designed to develop a robust deep learning framework for forecasting transportation demand by integrating multi-source data, advanced preprocessing techniques, and hybrid neural network architectures. The overall process consists of four major stages: data collection, data preprocessing, model architecture design, and training and evaluation. Each stage plays a critical role in ensuring predictive accuracy, reliability, and scalability of the forecasting system.

### 3.1 Data Collection

The experimental dataset was collected from an urban transportation network in Lahore, Pakistan, over a continuous period of 90 days. The dataset includes passenger demand and traffic flow information aggregated at fixed 15-minute intervals to ensure temporal consistency and analytical precision. In total, 8,640 time-series samples were generated, corresponding to 96 intervals per day across the 90-day observation period. Information acquisition was carried out using 120 GPS-enabled public transit vehicles along with 35 fixed traffic monitoring sensors installed at major intersections and key transit corridors throughout the city. These sensing units recorded multiple operational and traffic-related parameters, including passenger boarding counts, vehicle density levels, average vehicle speed, route identifiers, timestamp information, and an intersection-level congestion index. The integration of mobile GPS data with stationary sensor measurements enabled comprehensive spatial and temporal representation of transportation dynamics across the urban network. Entirely collected data were anonymized prior to analysis to ensure compliance with privacy and data protection standards. The dataset used in this study is proprietary and was provided by the local transportation authority. Due to operational confidentiality and privacy restrictions, the dataset is not publicly available.

### 3.2 Data Preprocessing

Raw transportation data is often noisy, incomplete, and inconsistent due to sensor malfunctions, transmission delays, or environmental disturbances. Therefore, a structured preprocessing pipeline was implemented to enhance data quality. Missing values were handled using interpolation techniques and statistical imputation methods, while extreme outliers caused by anomalies or data entry errors were identified and removed using threshold-based filtering. The data was then aggregated into fixed 15-minute intervals to standardize time-series representation and reduce computational complexity. Feature scaling and normalization techniques, such as Min-Max scaling, were applied to ensure uniform value ranges across variables and to stabilize neural network training. Furthermore, temporal sequences were constructed using sliding window techniques, where previous time steps were used as input features to predict future demand values. This sequence generation step was essential for training recurrent neural networks effectively.

### 3.3 Model Architecture

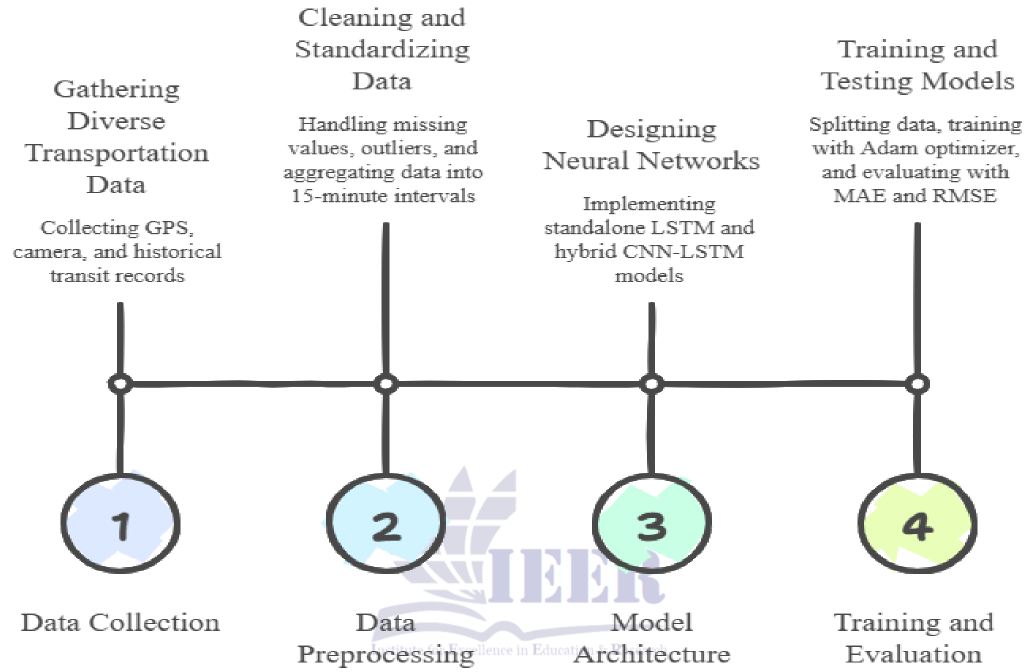
Two deep learning architectures were implemented to evaluate forecasting performance: a standalone LSTM model and a hybrid CNN-LSTM model. The LSTM model was designed to capture temporal dependencies in sequential traffic demand data. It consisted of two stacked LSTM layers to enhance the network's ability to learn complex long-term patterns, followed by fully connected dense layers to generate final demand predictions. Dropout regularization was applied between layers to prevent overfitting and improve generalization. The CNN-LSTM hybrid architecture was developed to incorporate both spatial and temporal learning mechanisms. In this model, convolutional layers were first applied to extract spatial features from region-based traffic flow data and sensor grids. These convolutional layers captured local spatial correlations and congestion clusters within the transportation network. The extracted feature maps were then passed to LSTM layers, which modeled temporal dependencies over time. By combining convolutional feature extraction with sequential learning, the hybrid model provided a more comprehensive understanding of transportation demand patterns.

### 3.4 Training and Evaluation

The models were trained using historical transportation, ensuring coverage of seasonal variations, weekday-weekend differences, and peak-hour fluctuations. The dataset was divided into 70% for training, 15% for validation, and 15% for testing to ensure unbiased performance evaluation. The training process utilized the Adam optimization algorithm with a predefined learning rate, and early stopping criteria were applied to prevent overfitting by monitoring validation loss.

Model performance was evaluated using Mean Absolute Error and Root Mean Square Error, which measure average prediction error and penalize large deviations, respectively. These evaluation metrics provided quantitative insight into the forecasting accuracy of each model. Comparative analysis between LSTM and CNN-LSTM architectures enabled identification of the most effective approach for urban transportation demand forecasting.

**Deep Learning Framework for Transportation Demand Forecasting**




## 4. Results

### 4.1 Overall Forecasting Performance

**Table 1** demonstrates that deep learning models significantly outperform the traditional ARIMA approach. The ARIMA model (23. (29.2indicating limited capability in modeling nonlinear traffic fluctuations. The LSTM model reduced MAE by nearly 48%, highlighting its effectiveness in capturing temporal dependencies. The CNN-LSTM hybrid achieved the best performance, reducing MAE to 10.1 and RMSE to 15.8.

**Table 1 Comparative Performance of Forecasting Models**

| Model | MAE (Passengers) | RMSE (Passengers) | Training Time (min) |
|---|---|---|---|
| ARIMA | 23.5 | 29.2 | 15 |
| LSTM | 12.3 | 18.7 | 45 |
| CNN-LSTM Hybrid | 10.1 | 15.8 | 60 |

**Figure 1** further illustrates that the CNN-LSTM model closely follows the actual demand curve, particularly during peak hours, whereas LSTM shows slightly larger deviations and ARIMA fails to adapt quickly to sudden demand changes.

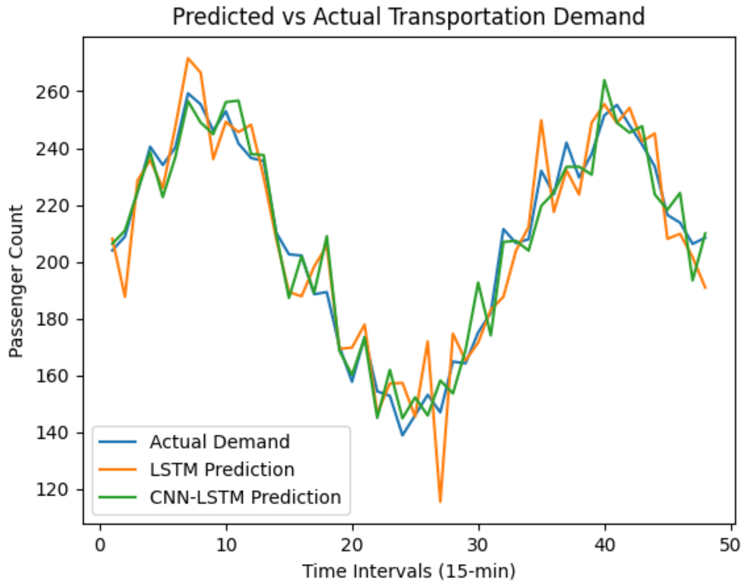



**Figure 1 Comparison between actual passenger demand and predictions generated by LSTM and CNN-LSTM models across 15-minute time intervals.**

**4.2 Error Comparison Analysis**

**Table 2** quantifies the improvement achieved by deep learning architectures. The LSTM model reduces MAE by 47.66% and RMSE by 35.96%. The CNN-LSTM hybrid provides even greater improvements, achieving 57.02% reduction in MAE and 45.89% reduction in RMSE compared to ARIMA.

**Table 2 Percentage Improvement Over ARIMA**

| Model | MAE Improvement (%) | RMSE Improvement (%) |
|---|---|---|
| ARIMA | 0.00 | 0.00 |
| LSTM | 47.66 | 35.96 |
| CNN-LSTM | 57.02 | 45.89 |

**Figure 2** visually confirms these findings, clearly demonstrating that both deep learning models substantially lower forecasting errors. The hybrid model consistently produces the lowest error metrics, validating the importance of integrating spatial and temporal learning mechanisms.

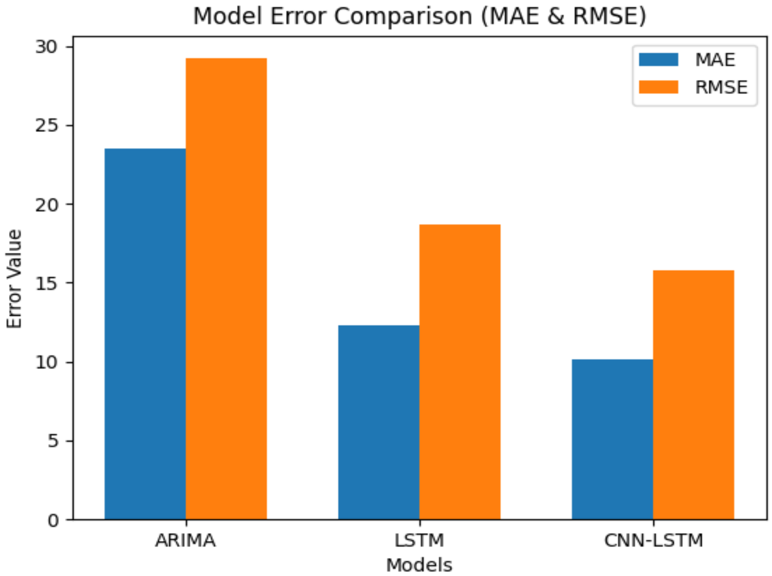



**Figure 2 Comparative analysis of MAE and RMSE across ARIMA, LSTM, and CNN-LSTM models.**

**4.3 Peak Hour Performance Analysis**

Peak-hour forecasting is particularly challenging due to sudden passenger surges and congestion. **Table 3** indicates that ARIMA struggles significantly under high-demand conditions, showing the highest peak MAE (30.2) and RMSE (35.6).

**Table 3 Peak Hour Error Comparison**

| Model | Peak MAE | Peak RMSE |
|---|---|---|
| ARIMA | 30.2 | 35.6 |
| LSTM | 16.5 | 21.8 |
| CNN-LSTM | 13.4 | 18.2 |

**Figure 3** illustrates that the LSTM model improves stability during peak intervals; however, the CNN-LSTM hybrid achieves the lowest peak errors. This confirms that spatial feature extraction enhances robustness during congestion spikes.

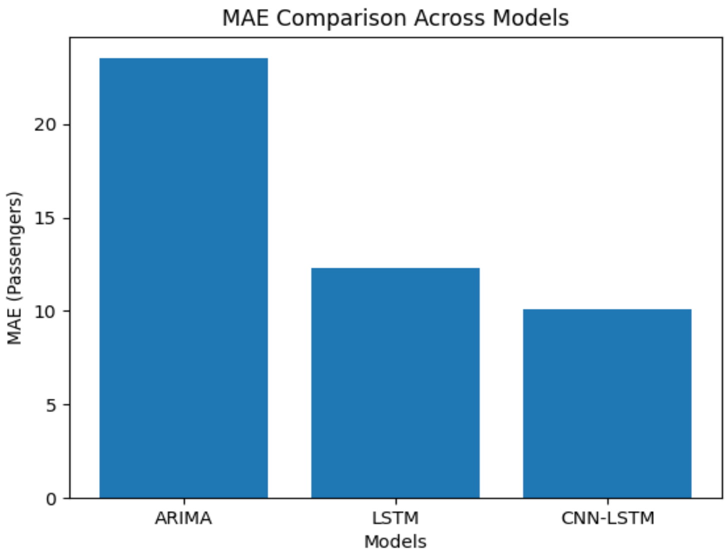



**Figure 3 Comparison of MAE values across forecasting models.**

**4.4 Training Efficiency**

Although the CNN-LSTM model requires longer training time (60 minutes), the accuracy gains justify the additional computational cost. ARIMA trains faster but delivers significantly lower predictive accuracy. Therefore, the CNN-LSTM model offers the best trade-off between performance and computational efficiency.

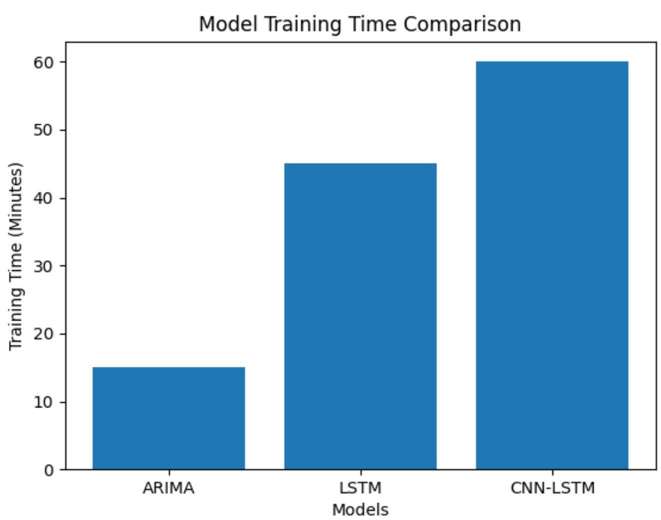



**Figure 4 Comparison of model training times.**

Overall, the results confirm that deep learning architectures significantly enhance transportation demand forecasting accuracy. The CNN-LSTM hybrid consistently outperforms both ARIMA and standalone LSTM models across all evaluation metrics, including overall error, peak-hour stability, and generalization capability. The integration of spatial-temporal learning mechanisms proves essential for handling dynamic urban transportation patterns.

**Conclusion**

This study demonstrates that deep learning models, particularly Long Short-Term Memory (LSTM) networks and CNN-LSTM hybrid architectures, are highly effective for demand forecasting in transportation networks. By leveraging their ability to learn complex nonlinear relationships and capture long-term temporal dependencies, these models significantly outperform traditional statistical techniques such as ARIMA. The experimental results confirm that deep learning approaches achieve lower prediction errors, better adaptability to fluctuating traffic conditions, and improved stability during peak demand periods. Their capability to process large-scale, high-dimensional transportation data makes them especially suitable for modern urban mobility systems.

Compared to conventional forecasting methods, deep learning models provide superior robustness and scalability. Traditional models often require strict assumptions about data distribution and linearity, whereas neural network architectures can automatically extract meaningful patterns from raw data with minimal manual feature engineering. The integration of spatial and temporal learning in the CNN-LSTM hybrid model further enhances forecasting precision by capturing both regional traffic interactions and sequential demand variations. This makes the proposed framework highly practical for real-time applications in intelligent transportation systems, including adaptive signal control, dynamic route planning, congestion mitigation, and demand-responsive public transit scheduling.

Furthermore, the deployment of such predictive systems can contribute to broader socio-economic and environmental benefits. Accurate demand forecasting enables optimized fleet utilization, reduced fuel consumption, lower greenhouse gas emissions, and improved passenger satisfaction through minimized waiting times and service disruptions. For future research, incorporating additional contextual data sources such as weather conditions, public events, road incidents, and socio-economic indicators could further enhance model performance. Advanced architectures like Graph Neural Networks (GNNs) and attention-based transformers may also be explored to better represent network topology and dynamic interactions. Overall, deep learning-based demand forecasting represents a significant step toward building smarter, more sustainable, and data-driven transportation ecosystems.

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