DEEP LEARNING–BASED COMPARATIVE TRAFFIC FLOW FORECASTING FOR WESTERN HIGHWAYS IN BANGLADESH

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ABSTRACT

Traffic flow prediction is a key component of Intelligent Transportation Systems (ITS) for enabling efficient traffic management, congestion mitigation and data-driven decision-making for road infrastructure planning. Despite the country's rapid urbanization and growing reliance on road transport, very few studies in Bangladesh have conducted traffic forecasting utilizing the advanced machine learning techniques. This study aims to address this gap by developing traffic flow prediction models for the N5 and N8 highways using Long Short-Term Memory (LSTM) networks and Facebook's Prophet model. A three-year dataset of toll booth traffic volume, from 01 July, 2022 to 30 June, 2025 were collected and analyzed. The dataset was divided into training (first two years) and testing (final year) subsets, and model performance was assessed using Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and Mean Absolute Error (MAE). The study indicates that although FB-Prophet can effectively capture seasonal trend, its performance is limited when handling traffic variations influenced with external factors. In contrast, LSTM which is capable of learning complex temporal dependencies has demonstrated higher predictive accuracy on the forecasting metrics. The LSTM model outperformed the Prophet in capturing both long-term trends and short-term fluctuations. As a result, it generated more reliable predictions of the real condition of highway traffic. This work is the first of its kind in Bangladesh to apply machine learning based neural regression models to traffic forecasting on highways. The findings hold significant implications for future ITS development and offers practical insights for highway authorities, policymakers and engineers in designing congestion control strategies and optimizing toll operations. By demonstrating the effectiveness of LSTM over Prophet in the Bangladeshi context, this study also lays the foundation for future work that could integrate real-time traffic feeds, multimodal data sources, and external variables to improve predictive performance for events like holidays and extreme weather evacuation.

Keywords: *LSTM, Prophet, freeway, network models, deep learning*

1. INTRODUCTION

The increasing rate of motor conveyance in recent years in Bangladesh is causing congestion on the national highways, particularly at the strategic river-crossing points like Padma Multipurpose Bridge (N8) and Jamuna Multipurpose Bridge (N5) corridors. The bridges act as arterial routes to facilitate connections to Dhaka and the southwestern and northern parts of the country. The proposed roadways carry large volumes of traffic every year. In such high-usage scenarios, there is potential for Intelligent Transportation Systems (ITS) to bring innovation to traffic management. A basic aspect of implementing the Intelligent Transportation Systems is the availability of short-term to medium-term traffic volume forecasts to facilitate congestion control.

Traffic modeling and forecasting have increasingly gained global focus with the improved accuracy of both traditional statistical models and deep learning methods. Models such as ARIMA Models, Support Vector Regression models, as well as neural network models, have been increasingly used to model traffic flows in road corridors and multilane highways in developed countries like those in Europe and America, as well as in Asia. At the same time, the arrival of Facebook's Prophet-toolkit with its capability to automatically determine trend seasonality patterns and holiday patterns with relatively fewer tuning parameters is noteworthy. As such, there have been instances when the model proved inefficient in dynamic traffic patterns like those during peak events or weather-related traffic congestion patterns. By contrast, Long Short-Term Memory (LSTM) neural networks with their nonlinear predictive modeling have proved efficacious (Yongxue Tian & Li Pan, 2015).

Despite such achievements, there have been very few studies assessing the effectiveness of Prophet and LSTM on real toll booth data available on highways in South Asia. Currently, traffic related literature in Bangladeshi publications is centered on predictive modeling of traffic streams on highways for longer periods of time. Also, real granular data available for highways and their incorporation within modeling frameworks have been relatively untouched in such publications. Not to mention the lack of deep learning-based modeling on the Padma and Jamuna bridges, which are among the country's leading bridges. This is in stark contrast to publications related to other parts of the world such as the Netherlands. A recent publication there comparatively analyzed the effectiveness of LSTM and Prophet on short-term traffic patterns in high density inductive loop detector data available in the roads of Den Haag (Ziyar Uzel, 2023). While it concluded that Prophet had little effectiveness in modeling traffic patterns to their short-term anomalies on such roads, it again confirmed the role of context-dependent validation. This is comparable to another recent publication titled "Identification of peak hours of Turkish cities with the usage of Prophet model," wherein Saracoglu et al. confirmed the effectiveness of the Prophet model in describing peak traffic patterns in Turkish cities with incorporation of their corresponding trend changes (Saracoglu et al., 2021). These confirm two takeaways. First, the Prophet model is efficient in accurately modeling traffic patterns within their seasonal variability at a large-scale like cities. Secondly, neural models have to be developed to accurately model traffic patterns at short-term periods.

The lack of comparative assessment in the context of Bangladesh is important given the individual temporal patterns at work in influencing traffic patterns, particularly the Eid festival peak patterns, weekly patterns observable within Dhaka commuter traffic patterns (Hamid-uz-Zaman, 2006). Although able to model regional holiday patterns natively, the reproducibility of erratic peaks in traffic patterns is not established with toll data.

This paper fills this information gap by designing and assessing the performance of two machine learning-based time series modeling tools: Facebook Prophet and LSTM models on the total vehicle count data at four large monitoring points on the N5 & N8 roads for three years. This data is taken from July 2022 to June 2025 and includes data on both weekdays and weekend days as well as general and Eid holidays and a prolonged curfew situation between July 20, 2024, and June 30, 2025. The purpose of this paper includes assessing the performance of both tools in terms of directional flows and analyzing how external temporal classifications have affected the results. While the performance of Prophet is expected to include regular patterns related to dates (El Motaki et al., 2025), the accuracy of the LSTM model is expected to be superior because it can accurately detect non-linear patterns related to Eid and emergency situations (Shohan et al., 2022).

The originality of this paper is threefold. First, to the best of our knowledge, it is the first paper to explore machine learning-based highway traffic forecasting in Bangladesh. Secondly, it compares influences of temporal context such as traveling during Eid and Curfew. Thirdly, it provides insight that LSTM is vastly superior to Prophet for learning short-term variations in traffic patterns. This is proved to be the first stepping stone towards the deployment of Intelligent Transport Systems for congestion control on National Highways.
Beyond algorithmic comparison, this study offers practical novelty by using audited national toll-booth data collected during rare socio-temporal conditions, such as Eid-related mass migration and extended curfew periods. These extreme demand variations are rarely captured in traffic forecasting studies, especially in developing countries. Therefore, the findings provide not only methodological insights but also policy-relevant evidence to support sustainable highway management in South Asia.

2. METHODOLOGY

This section discusses the study area, data information, data preprocessing, feature engineering, model training, and results evaluation. Figure 1 demonstrates the overall procedure adopted in the training and validation phase for modelling.

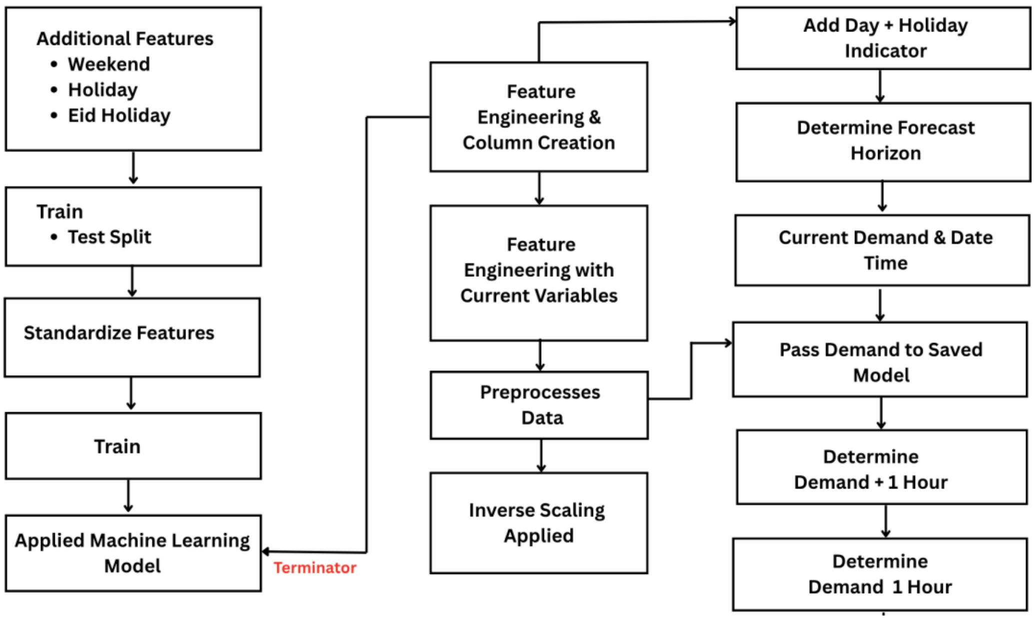

Figure 1 : Overall Process Flow of Training Validation

2.1 Study Area and Data Description

The data includes aggregate toll booth vehicle counts at four highway monitoring points, accounting for both inbound and outbound vehicle traffic on two large national corridor bridges. For the N8 (Padma) corridor, the monitoring points measured the outbound counts at Mawa and inbound at Jajira. For the N5 (Jamuna) corridor, it measured the outbound counts at Jamuna East and inbound at Jamuna West. These bridges serve as crucial transportation gateways between Dhaka's metropolitan area and the northern and southwestern districts.

Table 1: Summary of Toll-Booth Observation Sites and Traffic Flow Direction

Corridor	Station Name	Direction	Description

N8	Mawa	Outbound	Dhaka → Southwest
N8	Jajira	Inbound	Southwest → Dhaka
Corridor	**Station Name**	**Direction**	**Description**
N5	Jamuna East	Outbound	Dhaka → North
N5	Jamuna West	Inbound	North → Dhaka

Table 1 summarizes the four toll-booth stations included in the analysis.

Data on daily vehicle flows is collected from July 1, 2022 to June 30, 2025. All analyses and forecasts are conducted at a daily temporal resolution. Accordingly, the forecasting horizon in this study is one-day-ahead, consistent with the aggregation level of the toll-booth dataset. The original time series data provides about 1,095 data points per toll booth location. Each day is classified according to four categories: work day, weekend day, general public holiday, and Eid public holiday. Moreover, a curfew is identified to span July 20, 2024 to June 30, 2025. This provides a context to validate the effectiveness of time series models under both regular and disturbed demand conditions.

Table 2: Temporal Classifications Used for Feature Encoding

Category	Definition	Number of Days
Workday	Sunday–Thursday	719
Weekend	Friday–Saturday	263
General Holiday	National non-Eid holiday	70
Eid Holiday	Eid-ul-Fitr / Eid-ul-Adha (travel surge)	44
Curfew	July 20, 2024 – June 30, 2025 (mobility restriction)	11

As shown in Table 2, categorical labels were incorporated to encode socio-temporal dynamics.

2.2 Data Pre-processing

The toll booth data had very little data cleaning to perform because it came from an automated source; although checks had to be done to eliminate missing and repeated dates. Daily aggregation allowed it to have homogeneous temporal resolution suitable for medium-term forecasting. Scale operations were necessary for training the LSTM model; Min-max normalization was done on each site's data. The Prophet model took raw data volumes and dummy variables for holiday types.

2.3 Feature Engineering

To model country-specific behavior patterns, the features to identify weekend days, public holidays, Eid holidays, and curfew days affected were included. These features include binary or multiple features to capture systematic temporal anomalies. In Prophet modeling, additive regressors were used to include effects of public holidays to allow seasonality adjustments during Eid. These features were combined with the sequence windows to form a multiple-feature input in the LSTM model.

2.4 Modelling Approach: Facebook-Prophet

Time series data is decomposed in Prophet into trend data, seasonality data, and data associated with holidays. Its model architecture is designed to facilitate easy explanation to analysts with less focus on

hyper-parameter adjustment. A logistic growth model was unnecessary given the non-saturation nature of traffic volumes at bridge tolls. A seasonality model with daily seasonality components and regressors for holiday effects is employed. Holiday offsets during the Eid season correspond to trend components with small intervals. Curfew weeks correspond to level shifts. Models for Prophet were developed for each toll site separately.
Prophet models traffic volume $y(t)$as the additive combination of trend, seasonal structure, holiday effects, and noise using equation (1) (Gao et al., 2025).

$$y(t) = g(t) + s(t) + h(t) + \epsilon(t) \tag{1}$$

where
$g(t)$= piecewise-linear trend
$s(t)$= seasonal component (Fourier basis)
$h(t)$= holiday/irregular event effect
$\epsilon(t)$= residual error
Seasonality is modeled as:

$$s(t) = \sum_{n=1}^{N} \left(a_n \cos\left(\frac{2\pi nt}{P}\right) + b_n \sin\left(\frac{2\pi nt}{P}\right) \right)$$

with period $P$and Fourier order N.

2.5 Modelling Approach: Long Short-Term Memory (LSTM)

The LSTM model had a typical stacked architecture well-suited for dealing with long-term dependencies. It took a sliding window of data with exogenous features concatenated. This architecture included two layers with dropout for regularizing overfitting and a dense output layer to finish the model. Backpropagation with the Adam optimizer and mean squared error as the loss function handled training. A training schedule employed data for the first two years (70 percent) to train the model. The third year's data (30 percent) formed the testing sample. A predictive loop allowed autoregressive projections. The overall process involves tasks such as raw counts to normalization to coding to windowing to training to inverse transformation to predictions, as done in Figure 1.
LSTM controls information flow using three gates (Chen et al., 2023):

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f)$$
$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$$
$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C)$$
$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t$$
$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)$$
$$h_t = o_t \odot \tanh(C_t)$$

where
f_t= forget gate
i_t= input gate
o_t= output gate
C_t= cell state
h_t= hidden state
σ= sigmoid; $\odot$= element-wise product

Table 3: Model Configuration Summary

Model	Key Parameters
Prophet	Seasonality: weekly; Changepoint prior: default; Holiday regressors: Eid, general holidays; Growth: linear
LSTM	Window size: 14 days; Layers: 2; Neurons: 64, 32; Dropout: 0.2; Optimizer: Adam; Epochs: 100

The summary of the key parameters and model configuration is shown in Table 3.
Hyperparameters were selected based on commonly adopted configurations in traffic forecasting literature and preliminary convergence testing to ensure stable training and generalization. (Abduljabbar et al., 2021; Muzaffar & Afshari, 2019)

2.6 Evaluation Metrics

Performance metrics include three typical measures: RMSE, MAPE, and MAE. These measures reflect the absolute error, proportional error, and absolute deviation of actual and fitted data. It's easy to calculate and compare results among directional flows and sub-periods using equations 2 and 3. The model's forecasting accuracy is tested with the final year data (Muzaffar & Afshari, 2019).

$$MAE = \frac{1}{n}\sum_{t=1}^{n} |\hat{y}_t - y_t| \tag{2}$$

$$MAPE = \frac{100}{n}\sum_{t=1}^{n} \left|\frac{\hat{y}_t - y_t}{y_t}\right| \tag{3}$$

These equations are referenced in the Results Section to compare forecasting performance.

3. RESULTS

Both the Prophet model and the LSTM model were trained for the four toll-booth sites. From the results obtained, there is a consistent trend that showed the superiority of the results obtained by the LSTM model over the Prophet model for all the directional flows.

3.1 Figures and Graphs

While the Prophet model accurately showed the weekly cycles and medium-scale variations, it tended to underestimate the spike patterns during Eid and the dwindled curfew schedules. The patterns shown by the traffic identified through the FB Prophet and LSTM models were interpreted from the model generated trend graphs.
Figure 2 illustrates the future outbound traffic trend at the Mawa point interpreted from Prophet model

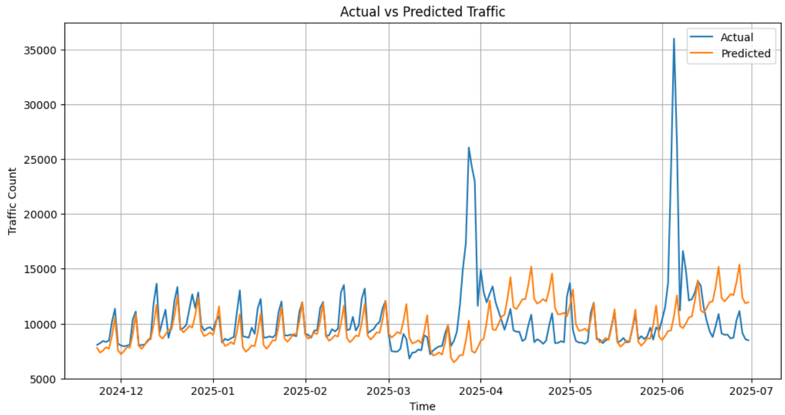

Figure 2: Mawa Point FB Model Result

Figure 3 illustrates the future inbound traffic trend at the Jajira point interpreted from Prophet model.

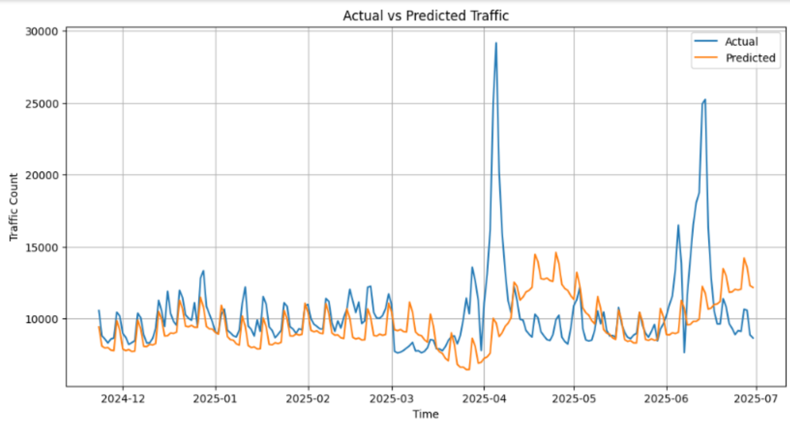

Figure 3: Jajira Point FB Model Result

Figure 4 illustrates the future inbound traffic trend at the Jamuna East point interpreted from Prophet model.

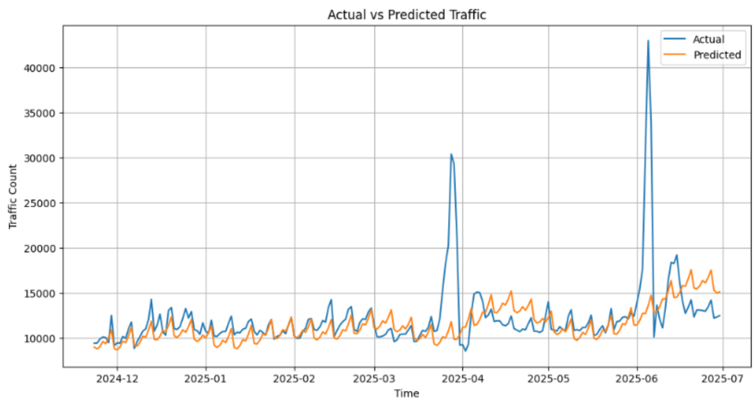

Figure 4: Jamuna East Point FB Model Result

Figure 5 illustrates the future inbound traffic trend at the Jamuna East point interpreted from Prophet model.

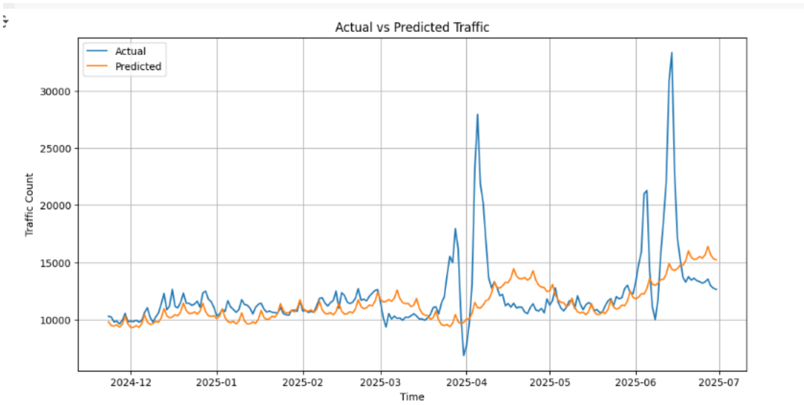

Figure 5 : Jamuna West Point FB Model Result

The results obtained from the LSTM model differ from those of the FB Prophet model which shows improved predictive performance, avoiding the underprediction

Figure 6 highlights the outbound traffic trend at the Mawa point interpreted from LSTM model.

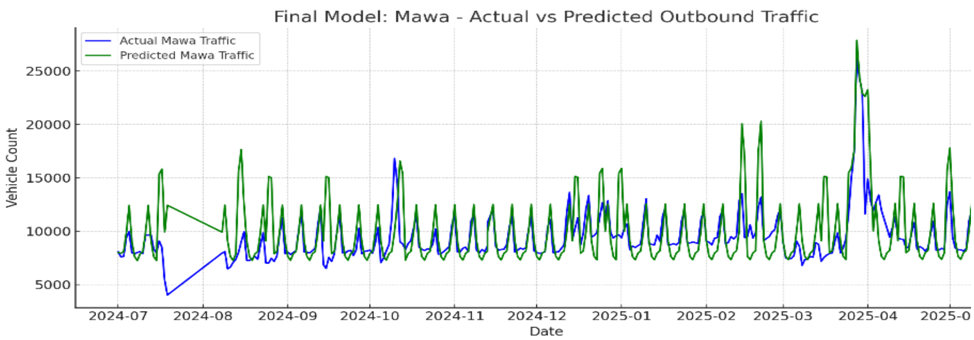

Figure 6 : Mawa Point LSTM Result

Figure 7 highlights the inbound traffic trend at the Jajira point interpreted from LSTM model.

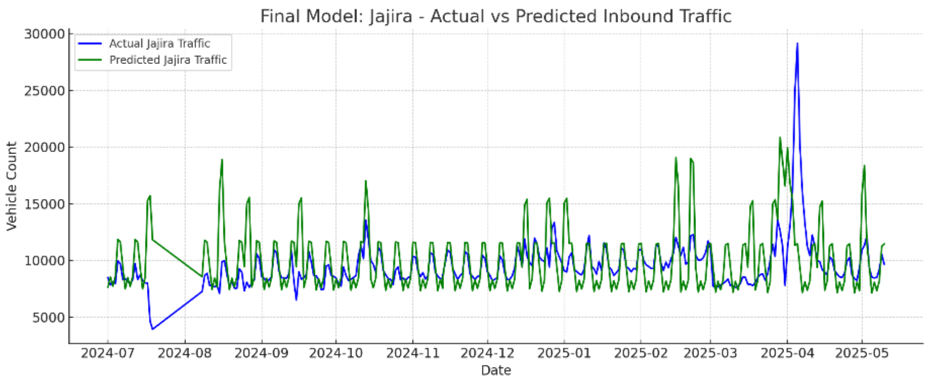

Figure 7 : Jajira Point LSTM Result

Figure 8 highlights the outbound traffic trend at the Jamuna East point interpreted from LSTM model.

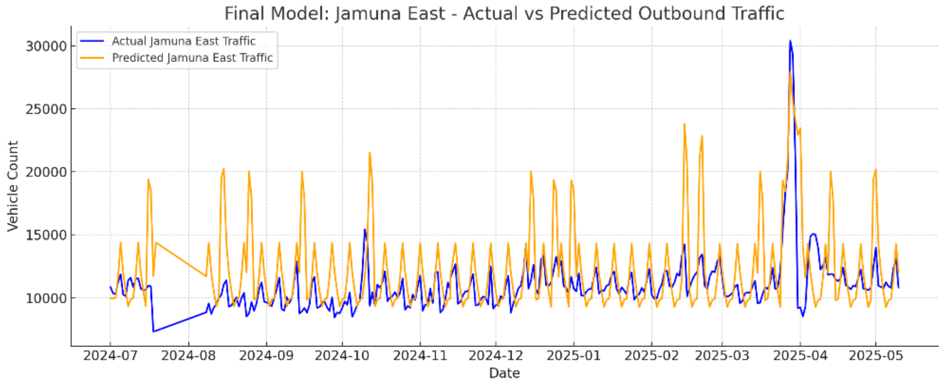

Figure 8 : Jamuna East Point LSTM Result

Figure 9 highlights the inbound traffic trend at the Jamuna West point interpreted from LSTM model.

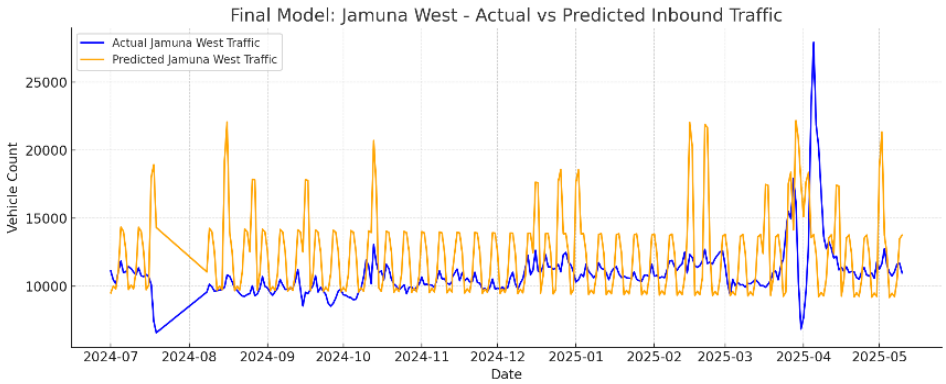

Figure 9 : Jamuna West Point LSTM Result

Table 4 : Model Performance Comparison across Toll-Booth Sites

Station	Model	RMSE	MAE	MAPE (%)
Mawa (Outbound)	LSTM	1486.26	992.38	9.52%
Mawa (Outbound)	Prophet	1980.21	1358.11	15.33%
Jajira (Inbound)	LSTM	1635.22	1033.87	10.31%
Jajira (Inbound)	Prophet	2345.31	1492.22	16.90%
Jamuna East (Outbound)	LSTM	1803.44	1211.56	11.88%
Jamuna East (Outbound)	Prophet	2972.33	1980.22	18.78%
Jamuna West (Inbound)	LSTM	2101.01	1409.20	13.42%
Jamuna West (Inbound)	Prophet	3701.87	2401.15	22.05%
Average	**LSTM**	**-**	**-**	**11.28%**
Average	**Prophet**	**-**	**-**	**18.26%**

Table 4 depicts the model performance observed for each of the sites. For the N8 corridor, both Mawa outgoing and Jajira incoming showed regular weekly cycles with strong peaks during Eid. Prophet

correctly identified peaks as seasonal but showed them to be less intense. Contrast between peaks and troughs improved for both datasets with LSTM, especially Jajira incoming. For Jamuna East outgoing on the N5 corridor, both methods followed congestion recovery post-curfew beginning more accurately with LSTM. For Jamuna West incoming, inter-model differences were largest. Its nocturnal variations were well followed by the LSTM model, with Prophet's cycles amplifying.
In general, numerical measures suggest that there is a marked difference in the model's performance with decreased RMSE and MAE for the LSTM model. The results obtained reveal that the dependency of the Prophet model on trend and season decomposition prevents it from learning exogenous patterns without fine-tuning. Visual comparison of traces suggests that the Prophet model handles weekly seasonality well but fails to cope with steep variations.
To assess overfitting, performance metrics were compared between training and testing periods. The observed differences in RMSE and MAE remained within 8–12% across all sites, indicating stable generalization and no evidence of model overfitting. Dropout regularization in the LSTM further constrained memorization of training data.

4. DISCUSSIONS

These results confirm that LSTM clearly outpaces the performance of Prophet to accurately model daily traffic data on bridges during both regular and erratic patterns. This is consistent with theoretical discussions in deep learning theory that have noted the superiority of LSTMs at modeling nonlinear patterns because of their sensitivity to external influences and human behavior patterns (Abduljabbar et al., 2021). It is apparent that Prophet is more suited to data with regular weekly patterns; however, their model is less adept at modeling erratic patterns with unknown external influences. This is especially pertinent to Eid rushes in Bangladesh where inter-regional traffic is characterized by sharp peaks during the early instances of the festival (Sarder et al., 2025) (Islam & Hu, 2024). LSTMs partially adjusted to the systematic change during the curfew situation as seen in Table 5.

Table 5 : Post-Event Forecasting Behavior during Eid-Heavy-Traffic Conditions

Station	Condition	Model	Observed Behavior
Mawa	Eid	Prophet	Underestimates peak
Mawa	Eid	LSTM	Tracks surge closely
Jamuna East	Curfew	Prophet	Smoothed decline
Jamuna East	Curfew	LSTM	Captures step-drop

On a standard CPU environment, inference time for daily prediction was below 0.1 seconds for Prophet and approximately 0.3 seconds for LSTM, which is operationally negligible for daily ITS planning applications.
On comparison with similar studies conducted in the European setting, there emerge the differences in context. A similar inductive study conducted in the Netherlands showed Prophet to be weakest among the three models tested, confirming Prophet's ineffectiveness with short-term learning variability (Ziyar Uzel, 2023). In another similar Turkish peak detection model developed, peak detection employed Prophet to detect points of change (Ulu et al., 2024). Forecasting comparison is neither mentioned nor implicated. In the current model as well, the superiority of the LSTM model gets highlighted because of the influence of large national holidays with large transition intervals beyond those encountered in the day-to-day traffic pattern of the European context.
These outcomes have implications for ITS implementation in Bangladesh. First, predictive dashboards utilizing the LSTM model could enable toll-booth employees to forecast congestion points and readjust human and road capacity in advance. Secondly, combining predictive outputs in dynamic route guidance systems could direct traffic to alternative routes in cases where festivals trigger

returning peak flows. Lastly, simulating variations depending on curfew restrictions can validate applying the LSTM method in emergency transportation planning.

5. CONCLUSIONS

This paper proposed and tested LSTM and Prophet models to accurately predict daily traffic volumes at four strategic toll-booth points on the N5 and N8 national highways of Bangladesh. It is evident that LSTM outperforms Prophet at all four toll-booth points on the N5 and N8 national highways. Although Prophet is able to accurately reflect the overall pattern of traffic volumes at toll-booth points on the N5 and N8 national highways of Bangladesh, it fails to accurately reflect peak events. Since Prophet is not able to accurately reflect peak events at toll-booths on the N5 and N8 national highways of Bangladesh, it fails to accurately reflect peak events. This is the first time machine learning-based traffic forecasting is employed at toll-booths on the national highways of a developing nation such as Bangladesh. Despite the efficacy that is proved with this study, there are still limitations to consider. To begin with, the model is based exclusively on toll booth traffic volumes. It would certainly be more precise if it were able to classify vehicles. Additionally, it could improve if it incorporated weather information, traffic incidents, or fuel price data. Finally, it only takes into account four tolls. It would be more valuable if it included other tolls. For future studies, there is a focus on the incorporation of multimodal traffic sensors, real-time feeds, and spatial data through hybrid convolutional or recurrent models. Combination with dynamic tolling or lane control could offer additional operational benefits. A wide range of information such as freight bookings, river crossing capacity for voyages, or holiday bookings could help with strategic planning. Overall, the results show the superiority of LSTM in traffic forecasting in the Bangladeshi scenario especially under behavioral and regulatory changes. This work makes a primary contribution to modeling for applications related to ITS and provides insight to highway authorities.

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