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Deep learning framework for weather aware spatiotemporal traffic speed forecasting on mountainous tourist roads

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Abstract

Accurate traffic speed prediction plays a crucial role in optimizing traffic management and mitigating incident impacts. However, the presence of complex and dynamic spatiotemporal dependencies, coupled with changes in weather conditions, makes predicting the main components of traffic flow a major challenge. Furthermore, a significant proportion of prior studies either assumed constant weather conditions or completely ignored weather effects altogether, focusing primarily on a limited set of traffic variables. Consequently, neglecting these issues reduces the generalizability and reliability of predictions. In this research, a hybrid traffic speed prediction framework is presented, which concurrently integrates traffic and weather data. Four models were evaluated, including three deep learning approaches LSTM, Conv-LSTM, and Bi-LSTM, and one time-series model (Prophet). Traffic speed data and meteorological parameters were collected and pre-processed for the Chalus Mountain tourist road over a specified time frame. The models' performances were compared based on standard evaluation metrics, including Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Coefficient of Determination (R2). The results indicate that the Conv-LSTM model, with an MAE of 1.69 km/h and higher spatiotemporal correlation compared to the other models, exhibits superior prediction accuracy, and shows fewer oscillatory changes during the study period. The findings suggest that the Wet-Bulb Temperature has the most significant impact on traffic speed on this route. Finally, based on these findings, an intelligent traffic action plan tailored to various weather condition scenarios was developed to assist decision-makers and users in operational planning and mitigating the adverse effects of weather conditions.

Keywords Traffic prediction · Suburban · Weather · Action plan

Introduction

From an operational traffic management perspective, weather conditions exert a substantial influence on roadway capacity and average travel speed, typically inducing congestion and diminishing network efficiency[1]. Despite this, numerous traffic forecasting approaches either assume stable meteorological conditions or disregard weather variables altogether. This omission limits the integration of crucial exogenous factors that could significantly

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improve predictive accuracy and reliability[2]. Consequently, transportation analysts and engineers increasingly seek to incorporate external datasets, particularly meteorological parameters, into planning and operational frameworks. Previous research confirms that integrating weather information as a non-traffic feature can significantly enhance model performance. Leveraging non-traffic data streams through big-data analytics enables deeper insights into the spatiotemporal complexity of traffic flow, especially along corridors exposed to adverse or rapidly changing weather patterns. Scientific and technological advancements, along with the maturation of artificial intelligence (AI) models, have facilitated notable progress in dynamic traffic forecasting across multiple application domains[3].

Over the past three decades, dynamic traffic prediction has served as a core component of intelligent transportation systems, providing a foundation for real-time operational decision-making. Real-time traffic forecasting approaches generally fall into two categories: classical methods, which rely on explicitly formulated mathematical/statistical models, and data-driven methods, which employ contemporary computational techniques, often without an explicit closed-form formulation[4]. Previous studies predominantly utilized traditional statistical models to estimate traffic conditions at specific sites or on linear segmentsMore recently, the focus has shifted toward AI-driven strategies, particularly advanced neural-network architectures, offering diverse algorithmic frameworks for traffic prediction with high adaptability to complex datasets[5,6]. Such models autonomously identify underlying trends, extract key attributes from high-dimensional inputs, and operate effectively under both supervised and unsupervised learning paradigms. Recognizing the existing research gap (Fig. 1), the present study addresses traffic speed forecasting for Chalus Road, a mountainous, weather-sensitive tourist corridor, utilizing weather-event data as the primary exogenous driver. Chalus Road, also referred to as the scenic Kandovan Mountain route, connects Tehran, the capital of Iran, to Chalus city in Mazandaran Province, a small urban center in terms of both geographic extent and population. Dynamic traffic forecasting for this corridor requires coordinated support services to mitigate accident risk, ensure prompt driver alerts, and enhance model prediction accuracy through real-time data assimilation. The inherently dynamic nature of traffic and meteorological datasets, characterized by evolving patterns and trends, necessitates intelligent systems capable of integrating such variability into decision-support processes[7]. By systematically analyzing historical weather and traffic records, the study examines the influence of atmospheric factors on roadway congestion.

In addition to an extensive literature review, this paper details the methodology applied in the case study, with an emphasis on weather-based traffic speed prediction. It offers innovative operational recommendations aimed at improving predictive accuracy for intercity roads with diverse geographical profiles, thereby supporting

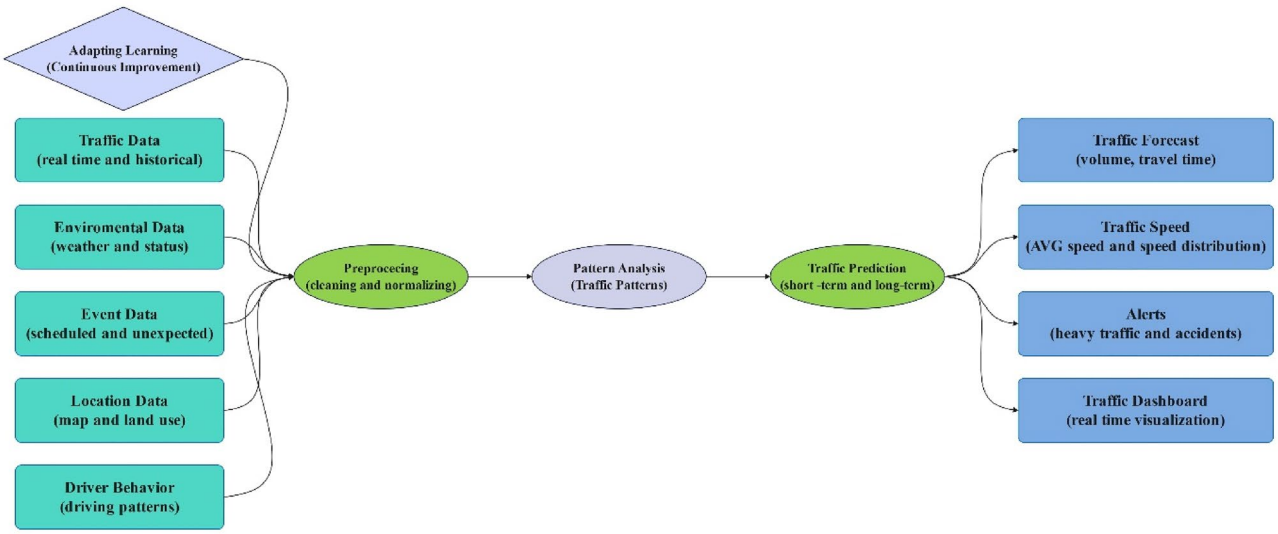


Fig. 1 Real-time traffic modeling framework.

intelligent transportation system (ITS) management. Moreover, a prototype intelligent application capable of responding to diverse weather scenarios has been developed as part of the proposed framework. The primary contributions of this study are threefold:

First, a unified spatiotemporal framework integrating weather and traffic data was proposed specifically for mountainous tourist corridors, which are highly sensitive to meteorological fluctuations, a context that has been largely overlooked in the existing literature, as it predominantly focuses on urban or freeway environments.

Second, following systematic feature engineering and preprocessing operations on the collected datasets, a comparative analysis of multiple predictive architectures (LSTM, Bi-LSTM, Conv-LSTM) alongside a classical time-series model (Prophet) was conducted on a unified dataset, providing empirical insights into model suitability for weather-sensitive traffic prediction.

Third, the gap between predictive outputs and operational decision-making was addressed by translating model predictions and feature importance analysis into an interpretable, rule-based Action Plan. This transformation converted the predictions into actionable, scenario-specific traffic management strategies, thereby enhancing the practical utility and interpretability of the proposed framework.

Literature review

It is important to clarify that the methodological innovation of this study lies in the development of an integrated framework that: (1) systematically incorporates weather variables for mountainous road traffic prediction, (2) employs SHAP-value figures for feature importance analysis to identify critical weather thresholds, and (3) translates these quantitative insights into interpretable, rule-based operational strategies. Traffic speed forecasting plays a pivotal role in traffic studies, as estimating a vehicle speed essentially means anticipating traffic flow. The advent of Smart Transportation Systems (STS) has contributed to the advancement of multiple traffic estimation techniques, encompassing analytical statistical approaches and artificial intelligence-based methods, depending on data availability. This study examines the possible advantages of leveraging STS to enhance traffic control and alleviate congestion.

Forecasting traffic within smart transportation systems (STS) has long been acknowledged as an essential approach for enhancing decision-making in route optimization, trip scheduling, and congestion management. Traditional approaches, such as autoregressive models and supervised learning methods like support vector regression and artificial neural networks, frame traffic speed estimation as a time series problem, which introduces distinct limitations. As a result, numerous studies have increasingly adopted deep learning frameworks over conventional methods.

Recently, remarkable developments have occurred in traffic speed estimation, enabled by incorporating deep learning approaches. In 2013, Cools and Creemers[8] examined how weather forecasts influence travel-activity behavior, focusing on the region of Flanders, and evaluated the role of weather predictions in changing travel behavior. In 2016, Jia et al.[9] pioneered the use of a data-based method grounded in a DNN structure to predict vehicle speed. This method involved combining representative features extracted from the data, ultimately developing predictive models that captured relevant correlations. In the same year, Wang et al.[10] introduced an AI model featuring an error feedback recurrent convolutional neural network (eRCNN) structure for real-time traffic speed forecasting. The simple structure of freeways, with minimal traffic signs or on/off ramps, allowed for improved prediction accuracy by increasing the dataset's temporal resolution, highlighting the significance of temporal over spatial correlation in freeway traffic speed forecasting. In 2017, Ma et al.[11] proposed an approach utilizing Convolutional Neural Networks (CNN), representing roadway conditions as visual data predicting traffic speed on a large scale with high accuracy at the network level. Li et al.[12] investigated data-driven traffic prediction by employing a diffusion convolutional recurrent neural network. To address these challenges, they formulated traffic flow as a diffusion process propagating over a directed graph. Similarly, Song et al.[13] introduced a CNN-driven framework capable of capturing local dependencies of traffic data while showing reduced susceptibility to data

disturbances. By 2018, Liu et al.[14] had designed an advanced fusion framework for space-mean-velocity estimation utilizing heterogeneous data. This method represented temporal and spatial attributes as raw inputs, initially extracted and processed by cumulative automatic encoders. The framework tackled forecasting difficulties triggered by unexpected road conditions, including peak-hour congestion and incidents, by integrating supplementary correction nodes into the iterative layer. In the same vein, Yao et al.[15] introduced a spatiotemporal diversified framework for demand estimation, integrating regional CNN, LSTM, and semantic embedding networks to simultaneously learn spatialtemporal dependencies. Cui et al.[16] leveraged time-series data to estimate traffic speed across the network, presenting an advanced stacked bidirectional and unidirectional LSTM (SBU-LSTM) neural network framework. The progression continued in 2019 when Wang et al.[17]presented a route-driven neural architecture for predicting traffic speed in large-scale cities. Essien et al.[18] also worked on enhancing metropolitan velocity estimation by combining traffic and meteorological data with deep learning techniques within an urban road network. In 2020, Guo and Yuan[19] introduced a new framework for short-term traffic speed prediction utilizing a Graph Attention Network (GAT) and a Temporal Convolutional Network (TCN). This framework aimed to enhance prediction accuracy by incorporating both spatial and temporal information. Concurrently, Cao et al.[20] proposed the CLM model, which integrated CNN and Long Short-Term Memory (LSTM) networks. This approach employed CNN to capture daily and weekly traffic speed patterns, with LSTM layers extracting spatiotemporal attributes alongside CNN output. James[21] later presented an innovative data-driven approach leveraging deep learning for predicting traffic speed across entire cities. This method captures the dependencies of traffic data using graph convolution and attention techniques, and incorporates an encoder-decoder structure within a generative adversarial framework. In 2022, Zafar et al.[22] introduced a combined LSTM-GRU model utilizing diverse data sources for predicting urban traffic speed. In 2022, Bi et al.[23] carried out a comparative study of travel time index (TTI) fluctuations influenced by weather conditions across four cities and discovered that meteorological factors could lead to notably worse traffic conditions on working days. In 2023, Tang et al.[24] introduced a traffic forecasting framework for severe weather events, combining disaster-related knowledge with advanced machine learning methods. Sharma et al.[25] addressed real-time traffic speed estimation for traffic management and congestion reduction in sustainable smart cities. Finally, in 2024, Ali[26] studied the impact of visibility on road traffic in foggy weather conditions. In 2025, Pen et al.[27] investigated the problem of traffic flow prediction at an urban intersection by employing a physics-guided stepwise framework based on spatiotemporal graph neural network architectures. This framework effectively captures the intricate spatiotemporal dependencies inherent in traffic networks through the integration of fundamental traffic flow physics with advanced spatiotemporal graph neural network algorithms. Ma et al. conducted an in-depth study in 2025 by constructing a traffic flow forecast that takes into account spatial and temporal characteristics[3]. To systematically organize the reviewed literature and highlight the evolution of traffic prediction methodologies, Table 1 categorizes the studies into four distinct methodological streams: (1) Classical time-series models, which rely on statistical approaches such as ARIMA; (2) Deep learning models, encompassing various neural network architectures including CNN, LSTM, and their hybrid variants; (3) Graph neural network-based models, which capture spatial dependencies through graph-based representations; and (4) Weather-aware traffic prediction models, which explicitly integrate meteorological variables into the forecasting framework. This categorization enables a clear identification of research gaps and demonstrates how the present study bridges multiple streams by combining weather-aware prediction with deep learning architectures for mountainous tourist corridors.

Despite significant advances in deep learning-based traffic prediction and the review of emerging technologies (as summarized in Table 1), four major research gaps can be observed that limit the generalizability and real-world applicability of existing models. A review of previous studies reveals that most have been conducted in urban environments or on freeways with relatively stable conditions, lacking coverage of mountainous or tourist routes subject to pronounced weather-induced fluctuations. Moreover, comprehensive integration of meteorological data with traffic data within a multivariate framework has largely been absent, and when weather factors have been considered, they have typically been limited to very simple parameters such as air temperature or precipitation. Most approaches have focused predominantly on improving prediction accuracy, without translating model

Table 1 An overview of traffic speed prediction articles using deep learning techniques and classical models.

Number	Methodological category	Reference & Year	Dataset	Focus	Result	Evaluation index	Method
#1	Classical time-series	Ahmed & Cook.1979	-	Utilizing advanced techniques for analyzing time-series data in freeway traffic	Presentation of the configuration for travel time prediction on freeways	-	ARIMA
#2		Jia et al. 2016	Arterial in Beijing	Enhancing traffic speed prediction through deep learning methods	The DBN outperforms BPNN and ARIMA across all time horizons	DBN MAPE:5.8% ARIMA MAPE:5.97%	DNN & ARIMA
#3	Weather-aware traffic prediction	Cools & Creemers. 2013	Traditional paper and pencil questionnaires	How to adjust travel plans and daily activities based on weather forecasts	Deployment of a road weather monitoring system that is directly integrated with real-time weather forecasting tools	-	chi-square
#4		Essien, A., et al.2019		Short-term traffic speed forecasting with graph attention temporal convolutional networks	The influence of air temperature on traffic patterns during peak and non-peak hours	RMSE = 0.0892 MSE = 0.008	LSTM_ rainfall_temperature
#6		Tang et al., 2023	Real-world	Novel framework predicts urban traffic under extreme weather conditions	The model improves traffic prediction in extreme weather by integrating disaster attributes with deep learning	MAE = 6.47	GCN
#7		Ali et al., 2024	Real traffic data	The intelligent driver (ID) model employs a fixed acceleration parameter, leading to consistent traffic behavior regardless of varying conditions	The proposed model shows more accurate traffic dynamics with lower acceleration and deceleration rates than the ID model	-	ID

Table 1 (continued)

Number	Methodological category	Reference & Year	Dataset	Focus	Result	Evaluation index	Method
#8	Deep learning models	Wang et al 2016	GPS data & benchmark datasets	Deep learning-based traffic speed prediction and congestion source analysis	Experiments on real taxi data in Beijing show that eRCNN has stronger predictive power than several state-of-the-art competitors	MAPE = 0.25	eRCNN
#9		Ma et al. 2017	Microwave sensor	Interpreting traffic as images: scalable speed prediction with convolutional neural networks	The CNN method outperforms other algorithms, enhancing average accuracy with acceptable execution time	MSE = 0.939	CNN
#10		Song et al 2017	Temporal data & and speed data	Weekday traffic speed forecasting using convolutional neural networks	The CNN-based model outperforms the two MLP models in prediction performance	MAE = 5.23	CNN
#11		Liu et al. 2018	Infrastructures & Vehicles	Leveraging mobility data for urban traffic prediction via deep learning	Many hidden layers process input data, feeding it to subsequent layers to form higher levels	-	CNN & LSTM
#12		Wang et al 2019	Automatic vehicle identification (AVI) detectors	Improving urban traffic speed prediction through data fusion and deep learning	This survey organizes works to show how deep learning models are applied in transportation	MSE = 10.51	Bi-LSTM NN
#13		Cao et al. 2020	Eal-time and historical average traffic speed	Network-wide traffic speed forecasting with deep bidirectional and unidirectional lstm recurrent neural networks	The CLM model outperforms five other methods in predicting traffic speed	MAE = 1.9	CNN-LSTM
#14		Cui et al.2020	DRIVE Net	Citywide traffic speed estimation using geometric deep learning approaches	The SBU-LSTM neural network outperforms in both accuracy and robustness for traffic network prediction	MAPE = 5.674 MAE = 2.46	SBU-LSTM
#15		James .2021	visual	Application of hybrid LSTM-GRU models with heterogeneous data sources for urban traffic speed prediction	The SBU-LSTM network demonstrates exceptional accuracy and resilience in predicting traffic conditions.	MAPE = 5.4%	Bi-LSTM NN
#16		Zafar, N., et al.,2022	A real-time traffic	Enhanced short-term urban traffic speed prediction through complex accident data fusion	Combining diverse data sources during preprocessing results in a unified and enriched feature space	RMSE = 4. 5	LSTM–GRU
#17	Graph neural network-based models	Ma et al., 2025	Real-world spatiotemporal datasets	A hybrid model with a transformer and self-attention mechanism is proposed to address spatiotemporal illusion in traffic prediction	dynamically adjusts and analyzes short-term spatiotemporal features	MAPE = 14.25	ODE

Table 1 (continued)

Number	Methodological category	Reference & Year	Dataset	Focus	Result	Evaluation index	Method
#18		Li et al. 2017	METR-LA PEMS-BAY	Modeling spatial dependence of traffic as a diffusion process on a directed graph and overcoming the long-term prediction problem	Better performance of directed graphs modeling asymmetric traffic correlation (impact of downstream and upstream traffic) than undirected graphs	MAPE = 2.9%	DCRNN
#19		Guo, G. and W. Yuan,2020	A real-world traffic	A Hybrid CNN-LSTM Model for Accurate Traffic Speed Prediction	The GAT and TCN fusion layer allows the model to learn Spatio-temporal traffic flow characteristics while accounting for exogenous factors	RMSE = 4.35	GATCN
#20		Sharma et al 2023	PeMS	Modeling spatial dependencies (road network topology) and temporal dynamics using graph neural networks	Proposing a graph-based road topology feeding mechanism to a neural network for refined traffic speed prediction	MAPE = 12.45%	STG-GAN
#21		Pan et al., 2024	Real-world	Integrating traffic physics laws with spatiotemporal graph neural networks to increase model accuracy and interpretability	Integrating STGNN with physics-based modeling can indeed lead to high computational complexity, especially for large-scale urban traffic networks	MAPE = 9.452%	PG-STGNN

outputs into operational planning or managerial decision-making. In addition, the simultaneous comparison of multiple deep learning architectures with a classical time-series model on a unified dataset represents a methodological perspective that has not been explored in the existing literature.

Methodology

Drawing from comparable research, it is evident that each proposed model possesses distinct attributes, making it suitable for specific datasets. This section presents a framework for traffic speed forecasting on a mountainous tourist route, integrating traffic and meteorological data within a unified modeling process. The framework implements and compares multiple deep learning architectures with a classical time-series model, designed to achieve high predictive accuracy while generating interpretable outputs for operational planning and managerial decision-making. The methodological design addresses a notable gap in the literature and is structured to ensure adaptability to similar environments. During the design phase, a dynamic prediction model is developed, which thoroughly addresses multiple facets of the problem. This model is then fine-tuned to align with the unique characteristics of the dataset under study. After gathering the necessary data, preprocessing is applied to both historical and current data. At this stage, the Systematic Literature Review (SLR) results serve as the foundation for defining and synchronizing the model's variables, parameters, and constraints in traffic prediction techniques. Subsequently, the most appropriate algorithm is selected to address the research problem effectively. The final model is tailored to the dataset and refined using the chosen solution method. Validation is conducted using standard techniques, such as benchmarking against existing models, gap analysis, and emphasizing the model's strengths. Sensitivity analysis is also performed to evaluate the robustness of the results.

The next objective is to construct a model capable of predicting the problem's future parameters, which is validated using standard validation indices such as Mean Squared Error (MSE). At this stage, the predictive model is

used to forecast the future behaviors of the system, and its accuracy is confirmed using additional relevant prediction accuracy metrics. Figure 2 illustrates the research's implementation steps in the modeling process. Moreover, to improve prediction accuracy, the study incorporates the latest machine learning algorithms and more complex models for data analysis. These approaches not only enhance the accuracy of traffic speed predictions but also enable more precise simulations of complex and variable conditions within intelligent transportation systems.

In this study, three distinct methodologies basic LSTM, bidirectional LSTM, and Conv-LSTM were chosen for analysis, tailored to the specific traits of the dataset in question. Each approach is thoroughly examined and discussed, with particular attention to the dataset's unique features.

LSTM networks

LSTM networks, a specialized form of recurrent neural networks (RNNs), excel in sequence analysis by mitigating the vanishing gradient issue through innovative "gate" mechanisms that manage data flow[28–30]. These networks are structured in layers of LSTM units, where the quantity of layers and units significantly influences efficacy. Predominantly, sigmoid and tanh functions are utilized for activation. Central to LSTM is the state unit, governed by gates that regulate information retention or disposal. Three pivotal gates oversee the state unit[31]:

A. Forget Gate: Decides which prior state unit information to eliminate.

$$f_t = \sigma\left(W_t.[C_{t-1}, h_{t-1}, x_t] + b_t\right) \tag{1}$$

B. Input Gate: Determines new information to retain in the state unit.

$$C_t = f_t * C_{t-1} + i_t * \widetilde{C}_t \tag{2}$$

$$i_t = \sigma(W_{\ i}.[h_{t-1}, x_t] + b_i \tag{3}$$

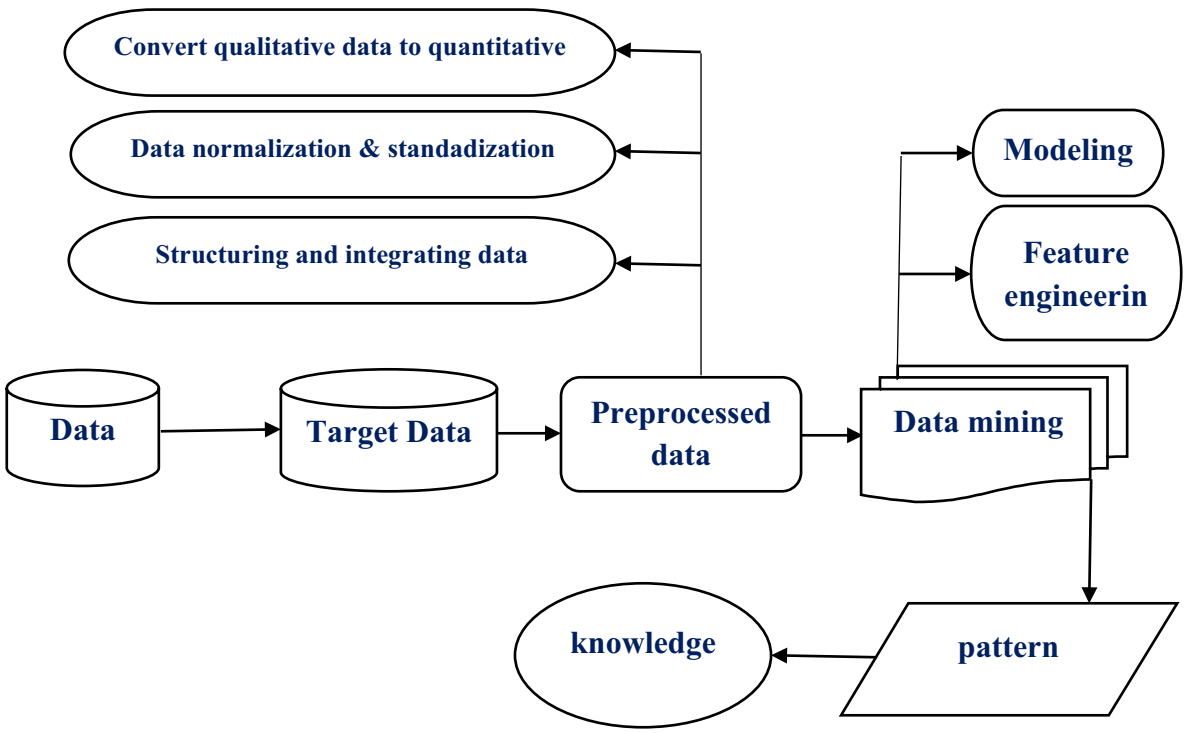


Fig. 2 Research performance stages.

$$\widetilde{C_t} = tanh(W_c.[h_{t-1}, x_t]) + b_c) \tag{4}$$

C. Output Gate: Manages which state unit information to emit.

$$o_t = \sigma(W_o.[C_{t-1}, h_{t-1}, x_t] + b_o \tag{5}$$

$$h_t = o_t * tanh(C_t) \tag{6}$$

These gates employ sigmoid layers and multiplicative operations to modulate data flow, with outputs of zero or one respectively blocking or permitting information passage. The LSTM sequence involves the forget gate, input gate, and output gate to refresh the cell state and produce the output.

Bidirectional LSTM

A bidirectional LSTM analyzes the input sequence in both chronological and reverse order, allowing the model to understand temporal relationships in both directions. A study by Greff et al. (2016) demonstrated that bidirectional LSTMs enhance the performance of speech recognition systems. The output of a bidirectional LSTM is formed by merging the results of two independent LSTMs one processing the sequence forward and the other backward. This combined output encapsulates information from both preceding and subsequent contexts. The outputs of the two LSTMs are merged at each time step to generate the final result. The Bi-LSTM formulas are as follows[32]:

First, forward hidden states are calculated using:

$$h_t^f = f(w_f * \left[h_{t-1}^f - x_t\right] + b_f) \tag{7}$$

$$c_t^f = i_t^f * g\left(w_c^f * \left[h_{t-1}^f.x_t\right] + b_c^f\right) + f_f^t * c_{t-1}^f \tag{8}$$

$$o_t^f = \sigma(w_o^f * [h_{(t-1)}^f \cdot x_t] + b_o^f) \tag{9}$$

$$y_t^f = o_t^f * h_t^f \tag{10}$$

where:h_t^f: Forward hidden state at time step tc_t^f: Forward cell state at time step ti_t^f, f_f^t, o_t^f: Input, forget, and output gates, respectively$g$: Activation function for the cell state$w_f, w_c^f, w_o^f, b_f, b_c^f, b_o^f$: Learnable parameters

Next, backward hidden states are calculated similarly:

$$h_t^b = f(w_b * \left[h_{t-1}^b - x_t\right] + b_b) \tag{11}$$

$$c_t^b = i_t^b * g\left(w_c^b * \left[h_{t-1}^b.x_t\right] + b_c^b\right) + f_f^b * c_{t-1}^b \tag{12}$$

$$o_t^b = \sigma(w_o^b * [h_{(t-1)}^b \cdot x_t] + b_o^b) \tag{13}$$

$$y_t^b = o_t^b * h_t^b \tag{14}$$

where:h_t^b: Backward hidden state at time step tc_t^b: Backward cell state at time step ti_t^b, f_f^b, o_t^b: Input, forget, and output gates, respectively$w_f, w_c^b, w_o^b, b_f, b_c^b, b_o^b$: Learnable parameters

Finally, the forward and backward hidden states are concatenated to produce the final output for each time step:

$$y_t = \left[y_t^f, y_t^b\right] \tag{15}$$

This allows the network to incorporate information from both past and future contexts as it processes each element in the input sequence.

Conv-LSTM

Integrating convolutional layers with LSTM layers enables the model to discern local patterns within sequences and enhances feature extraction. Yao et al.'s 2020[33] study highlighted that merging CNNs with LSTMs boosts time series forecasting accuracy. CNNs utilize convolutional layers to derive features from input data through filters, generating feature maps. When paired with LSTM layers, CNNs serve as feature extractors for sequential data, allowing the CNN-LSTM model to identify intricate Spatio-temporal patterns by amalgamating spatial and temporal data. This architecture is particularly beneficial for sequential data with spatial/temporal structures, aiming to extract significant features.

In the Conv-LSTM model, an input sequence of length "T" is assumed, with each element represented by $x_{t,}$ and a filter bank of size k with learnable parameters[28,34]. The convolution operation's output at time step t is:

$$Y_t = Conv(x_t, W) \tag{16}$$

where:Y_t: Output of the convolution operation at time step t.W: Learnable filter weights.

Then, using the following equations, the input, forgetting and output gates are calculated:

$$i_t = \sigma(Conv\,(Y_t, U_i) + Conv\,(h_{t-1}, V_i) + b_i) \tag{17}$$

$$f_t = \sigma(Conv\,(Y_t, U_f) + Conv\,(h_{t-1}, V_f) + b_f) \tag{18}$$

$$o_t = \sigma(Conv\,(Y_t, U_o) + Conv\,(h_{t-1}, V_o) + b_o) \tag{19}$$

Then, the state of the candidate cell is calculated using the convolution operation:

$$g_t = tanh(Conv\,(Y_t, U_g) + Conv\,(h_{t-1}, V_g) + b_g) \tag{20}$$

Finally, the cell state and the hidden state are updated using input, forget, and output gates:

$$c_t = f_t * c_{t-1} + i_t * g_t \tag{21}$$

$$h_t = o_t * \tanh(c_t) \tag{22}$$

where:i_t, f_t, o_t: Input, forget, and output gates, respectively.U, V, b: Learnable parameters for gates and candidate states.c_t: Cell state at time step t.h_t: Hidden state at time step t.

This architecture enables the model to extract Spatio-temporal features, making it suitable for tasks like video prediction and time-series forecasting.

Performance evaluation

To evaluate the performance of different traffic forecasting techniques, four primary metrics are utilized: Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Squared Error (MSE). These metrics are defined as follows[35]:

Root mean square error (RMSE)

RMSE measures the average difference between the model's predictions and the actual values, with lower values indicating higher accuracy.

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \overline{y}_i)^2} \quad (23)$$

Mean squared error (MSE)

MSE calculates the average of the squared differences between predicted and actual values, offering a sense of the scale of prediction errors.

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \overline{y}_i)^2 \quad (24)$$

Mean absolute error (MAE)

MAE measures the average absolute difference between predicted and actual values, reflecting the models overall error magnitude.

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \overline{y}_i| \quad (25)$$

In these equations:y_i: represents the ground truth (actual value).$\overline{y_i}$: denotes the predicted value.n: is the number of observed samples.

Proposed weather-aware spatiotemporal framework

The main methodological novelty of this study lies in the integrated data fusion pipeline and its specific configuration within the evaluated deep learning architectures. While Sects. "LSTM networks:" through "Performance evaluation:" detail the baseline deep learning architectures, this section explicitly describes the proposed framework tailored to mountainous tourist routes. This framework processes data through a structured spatiotemporal pipeline. Since meteorological data is recorded at 3-h synoptic intervals and traffic data is hourly, the traffic speed and flow variables were temporally aggregated into 3-h averages to ensure strict alignment with weather parameters. Following dimensionality reduction via Principal Component Analysis (PCA) to mitigate multicollinearity, the structured tensor is processed by three distinct architectures: the standard LSTM captures long-term temporal dependencies; the Bi-LSTM extends this by bidirectionally processing sequences to capture both historical and subsequent contextual patterns; and the Conv-LSTM integrates convolutional operations into state transitions, enabling simultaneous extraction of local spatial features across the sequence and temporal dynamics. The modular design of this framework supports its transferability to other weather-sensitive road networks. Although the current hyperparameters are optimized for a mountainous corridor, the methodology can be systematically adapted to new geographical contexts through a straightforward process: (1) redefining the spatial dimension to match the new road sensor layout, (2) synchronizing local traffic and meteorological data at consistent intervals, and (3) employing the SHAP-based approach to identify the dominant local weather variables. By recalibrating the selected architecture on the new local datasets, this framework provides a practical and adaptable method for traffic speed prediction across various mountainous or weather-sensitive corridors.

Table 2 Variables used in the research.

Summary title	Variable name	Summary title	Variable name	Summary title	Variable name
vv	Horizontal view	ess	Snow depth	Station_id	Station number
n	Cloudy sky	u	Relative humidity	Station_name	Station name
dd	Wind direction	ew	Steam pressure	Region_id	District number
ff	Wind speed	ews	Saturated vapor pressure	Region_name	Name of the region
t	Temperature	pqnh	Pressure QNH	Lat	Latitude
td	Dew point	ss	Snowfall	Lon	Longitude
p	Sea level pressure	ww	Current weather	Date	Date and time
p0	Station pressure	h	The lowest cloud	Vehicle	Number of vehicles
geops	Geopotential pressure		Speed	Average speed of the vehicle	
e	The condition of the ground without snow cover		rrr	Rainfall in 6 h	

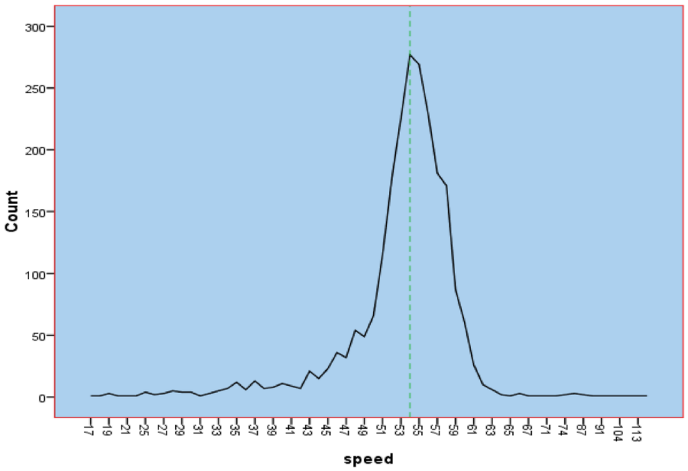


Fig. 3 Graphical depiction of temporal speed variations.

Case study

Chalus Road, officially recognized as Road 59, is a vital access route to the northern regions of Iran for the inhabitants of Tehran and Karaj. It commences from Karaj city in Alborz province and extends towards Chalus city in Mazandaran. This mountain road in northern Iran links the capital city of Tehran to Chalus, situated on the coast of the Caspian Sea. Spanning approximately 180 km, the road traverse's picturesque mountainous terrain, making it a favored tourist destination.

Dating back to the 1930s, Chalus Road adapts to its rugged environment with features like severe gradients, sharp bends, and narrow roadways. Safety and usability improvements have been implemented over time. The road's complex network of tunnels and bridges is a testament to its design, enabling passage through the difficult terrain.

Chalus Road experiences diverse climate conditions, including clear, cloudy, foggy, rainy, snowy, and stormy conditions. The air temperature along the road typically remains low, even during hot summer days, occasionally accompanied by winds. Despite the challenges presented by its geometric characteristics, Chalus Road remains an essential transportation artery in northern Iran and a popular tourist attraction.

Table 2 displays the variables employed in this research, obtained from the studied area on Chalus Road, between Kandavan and the Siah-Bisheh tunnel. Figures 3 and 4 showcase the time series graph and grouped graph of vehicle speeds in the studied area, utilized as the target variable in this research. The normal distribution curve in Fig. 3. indicates that 95% of vehicle speeds range between 43 and 63 km/h. Additionally, Fig. 4. reveals that the average speed of 51.5 km/h was the most frequently observed speed(Fig. 5).

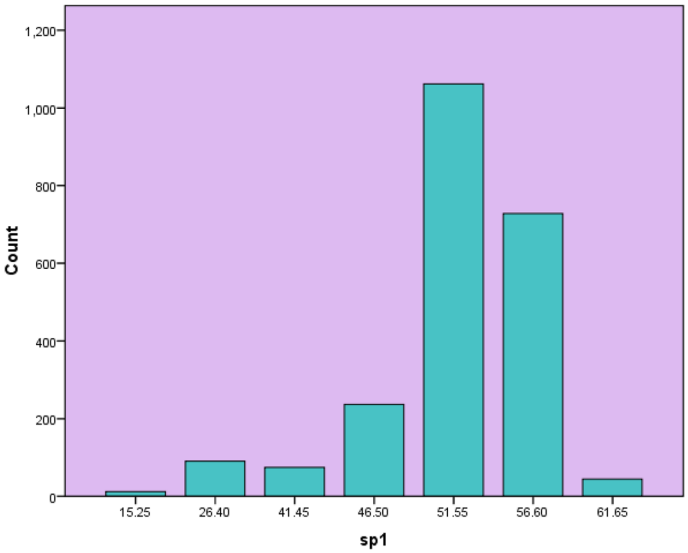


Fig. 4 Segmented speed distribution of traffic flow along Chalus route.

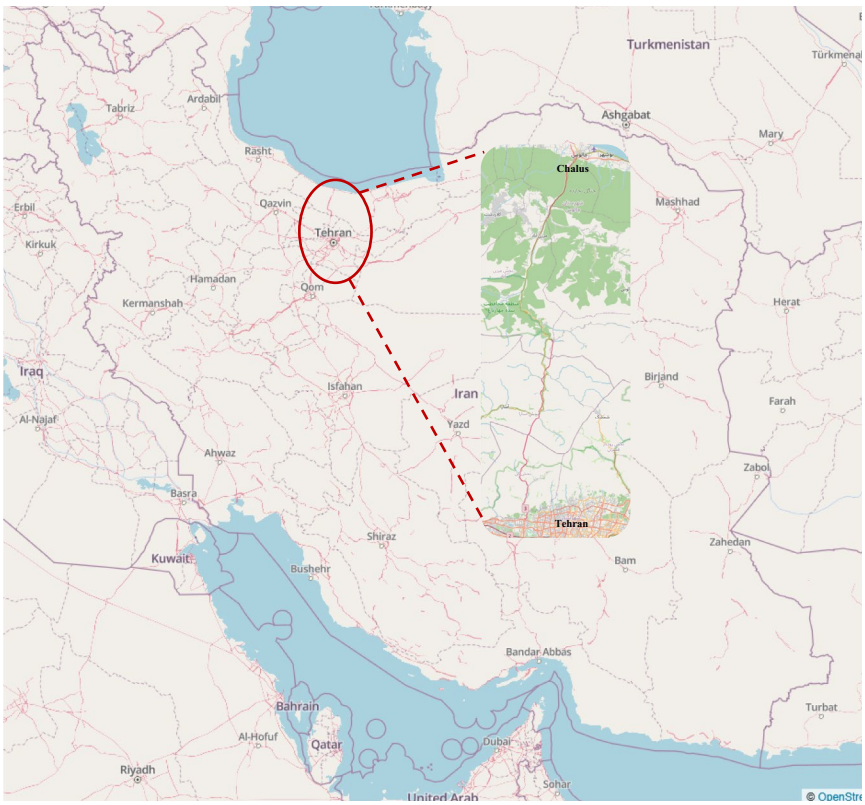


Fig. 5 Chalus road.

Meteorological data for this study were extracted from the synoptic stations of the Islamic Republic of Iran Meteorological Organization (IRIMO) in accordance with the standards of the World Meteorological Organization (WMO). The dependent variable, average vehicle speed (speed), was aggregated from hourly measurements into three-hourly averages to temporally align with the meteorological data recorded at 3-h synoptic intervals. The raw dataset initially comprised numerous parameters. During the preprocessing stage, missing values were handled through linear interpolation, averaging adjacent data points, or by dropping rows with minimal missing data. Resampling techniques were applied to address data imbalance, categorical variables (such as station and

region names) were converted using one-hot encoding, and numerical features were normalized. Additionally, data noise was mitigated using moving average filters and the removal of outliers. To select the most relevant features and address multicollinearity, a stepwise approach incorporating domain-knowledge-based filtering, correlation analysis, and statistical multicollinearity evaluation was employed. These variables were selected based on their direct physical relevance to road safety and traffic flow in mountainous areas. Subsequently, Principal Component Analysis (PCA) was utilized for dimensionality reduction to simplify the dataset. In the modeling phase, the hyperparameters for the LSTM and Prophet models (Table 2) were optimized using a grid search. Various configurations, including layer depth, number of neurons, batch size, and learning rate were evaluated using a validation split (Table 3). The optimal configuration was selected based on the lowest validation MAE and RMSE to ensure model stability and prevent overfitting.

Discussion and result

For fine-tuning the model's hyperparameters, the optimal configuration that enhances its effectiveness was selected. Initially, the parameter space was outlined, specifying possible values for each variable.

This paper presents a prediction model for how weather conditions influence traffic speed and flow. During the stage of area identification and data verification, the speed model yielded more acceptable results than the flow model. Consequently, the average traffic speed was selected as the target variable. The available data consisted of two components: weather-related data recorded every three hours from meteorological and optical stations, and traffic data comprising hourly flow and speed recordings. Traffic data was converted into a three-hour average, combined with meteorological data based on date and time, and finally standardized and normalized. In the feature extraction stage, raw data was transformed into numerical features that retain the original dataset's information while removing less significant data and equalizing interrelated data. This section employed deep learning

Table 3 A Comprehensive overview of hyperparameter optimization across models.

Model	Optimization technique	Key hyperparameters		value
LSTM	Grid search	Configuration details	Epochs	100
			Batch size	32
			Neurons	64
			Layers	2
			Learning rate	0.001
			Dropout	0.2
Bi- LSTM	Random search		Epochs	100
			Batch size	32
			Neurons	128
			Layers	2
			Learning rate	0.001
			Dropout	0.3
Conv- LSTM	Grid search		Epochs	150
			Batch size	32
			LSTM units	64
			Kernel size	3*3
			Conv filters	32
			Learning rate	0.001
			Dropout	0.2
prophet	Grid search		Changepoint_prior_scale	0.05
			Seasonality_prior_scale	10
			Holidays_prior_scale	10
			Seasonality_mode	additive
			Yearly_seasonality	True
			Weekly_seasonality	True

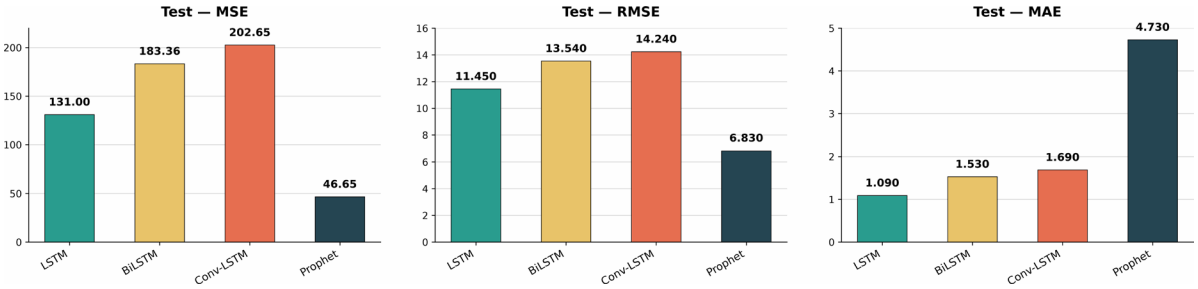


Fig. 6 Model performance evaluation findings (Test).

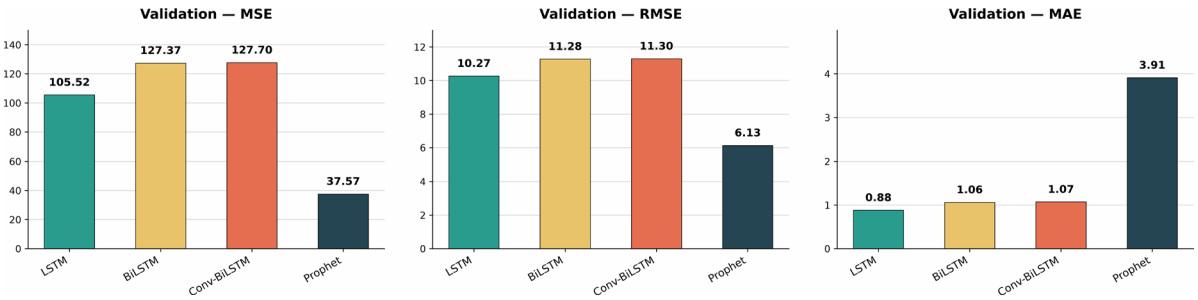


Fig. 7 Model performance evaluation findings (validation).

techniques to create models predicting traffic speed. The target parameter for the models was traffic speed, and their performance was evaluated using various criteria. Hyperparameter tuning was performed to determine the most effective configuration that enhanceed the model's accuracy. The optimization methods for hyperparameters were chosen based on needs and resources. By comparing the prediction accuracy using these criteria, the best model was selected. The chosen models (Simple LSTM, Bi-LSTM, and Conv-LSTM) were trained, tested, and validated, with a prediction model extracted from each. The dataset was divided into an 80% training set and a 20% testing set. All computations were carried out using Python 3 within the Jupyter Notebook 6.0.3 framework. Furthermore, performance assessment criteria for various hyperparameter settings were specified. The experimental dataset for this study ranges from April 10, 2017, to December 7, 2022. MSE, RMSE, and MAE are the evaluation criteria employed in forecasting and estimation problems within this article. MSE quantifies the mean squared errors by measuring prediction errors, squaring them, and calculating their average. MSE evaluates a model's accuracy, with a value of zero indicating perfect accuracy. The Root Mean Squared Error (RMSE) metric is derived by squaring residuals before computing their mean, ensuring consistency with the original data scale. It shares mathematical properties with Mean Squared Error (MSE), though RMSE provides clearer insights into prediction deviations. Meanwhile, Mean Absolute Error (MAE) determines forecasting inaccuracies by averaging absolute errors. These measures are fundamental for evaluating prediction model effectiveness. This article's primary objective is to forecast traffic speed on an hourly basis over 24 h. LSTM models have been combined with other models to generate predictions. Figure 6. displays test results for the three models, while Fig. 7. showcases their validation results. This superiority can be attributed to the hybrid nature of the model; specifically, the utilization of convolutional layers to extract spatio-temporal patterns, combined with bidirectional long short-term memory, provides a unique capability to identify hidden correlations between traffic and meteorological variables correlations that are difficult for other models to discern. The outcomes demonstrate the strong performance of deep learning models. The MSE value reveals that the Conv-LSTM architecture achieves the highest forecasting accuracy, whereas the Prophet model performs the worst due to its elevated MSE score. The Conv-LSTM framework outperforms other methods in identifying complex patterns and temporal relationships within the dataset. By integrating the LSTM structure with convolutional operations, this model can extract

more valuable insights from the data. The Prophet model is specifically developed for forecasting time series with prominent trends and seasonal patterns. However, in this research, other models have outperformed it, indicating that the data used has specific characteristics that are not suitable for the Prophet model. Additionally, the MAE value in Fig. 6. shows that the Prophet model is not suitable for the data used in this analysis. The elevated MAE value suggests that the model's predictions consistently differ substantially from the actual values on average. The LSTM, BI-LSTM, and Convolutional LSTM architectures, which are designed based on recurrent neural network (RNN) architectures, are more suitable for this type of data. The similar performance of these three models suggests that, for this particular dataset, they exhibit comparable results. Furthermore, the RMSE values show that the Conv-LSTM model has the lowest RMSE, providing the most accurate predictions. In summary, based on the presented chart, it can be concluded that the Conv-LSTM model has demonstrated the best performance for the experimental data used in this study. The Conv-LSTM model, with an r2 value of 0.91, demonstrates superior performance compared to the other models. A high R-squared value of 0.91 suggests that 91% of the data's variability is accounted for by the Conv-LSTM model, highlighting its effectiveness in capturing underlying trends and temporal dynamics.

Table 4 presents performance evaluation index values for each model. These models evaluate future traffic speed estimates, with the Conv-LSTM model outperforming others, aligning with the available research data. The RMSE for the validation set is 11.30, indicating average accuracy in speed value predictions. RMSE, presented in the original data unit, shows lower values for improved model accuracy. RMSE suits models tolerating significant errors. The mean squared error (MSE) for the validation set is 127.70, indicating variations in model predictions. The model is tested using the selected meta-parameters to obtain an unbiased performance estimate and is then established for predicting new, unseen data. In this paper, MAE, expressed in the original data unit, displays lower values for improved model performance. The MAE value for the validation dataset is only 1.07, demonstrating the model's comparatively small average prediction error. The Conv-LSTM model's speed error for the test data is 1.69 km/h. Although the simple LSTM model exhibits lower absolute error values (MAE = 1.09 km/h) in the test set, the Conv-LSTM model was designated as the superior architecture for three critical reasons. First, it achieves the highest coefficient of determination ($R^2 = 0.91$), indicating that it explains 91% of the variance in traffic speed data. Second, the mountainous tourist corridor under study is characterized by highly non-linear, weather-induced fluctuations; in such an environment, prediction stability and the ability to accurately track speed trajectories under critical conditions take precedence over marginal improvements in average error. Third, the hybrid architecture of Conv-LSTM enables physically meaningful extraction of spatio-temporal patterns and more effectively captures the complex interactions between meteorological variables and traffic dynamics.

Figure 8. presents the SIMPLE Test chart for a time period in 2018, comparing actual and predicted values of a speed variable over time using the simple LSTM model. The actual and predicted speed values exhibit significant fluctuations during the analyzed period. This indicates that the speed variable is influenced by various factors that may change over time. The green line denotes prediction errors. Positive errors indicate overestimation, while negative errors reflect underestimation compared to actual values. Significant fluctuations in the prediction error suggest that the prediction model had high accuracy at certain points and lower accuracy at others. In some time intervals, the actual and predicted lines show high correlation (i.e., they rise and fall almost simultaneously), indicating good performance of the prediction model during those periods. Conversely, in other time intervals,

Table 4 Assessment of model effectiveness.

Method	Test			Validation			
	RMSE	MSE	MAE	RMSE	MSE	MAE	$_R2$
LSTM	11.44	131	1.09	10.27	105.52	0.88	0.85
Bi-LSTM	13.54	183.36	1.52	11.28	127.37	1.06	0.88
Conv-LSTM	**14.24**	**202.65**	**1.69**	**11.30**	**127.70**	**1.07**	**0.91**
Prophet	6.83	46.65	4.73	6.13	37.57	3.91	0.71

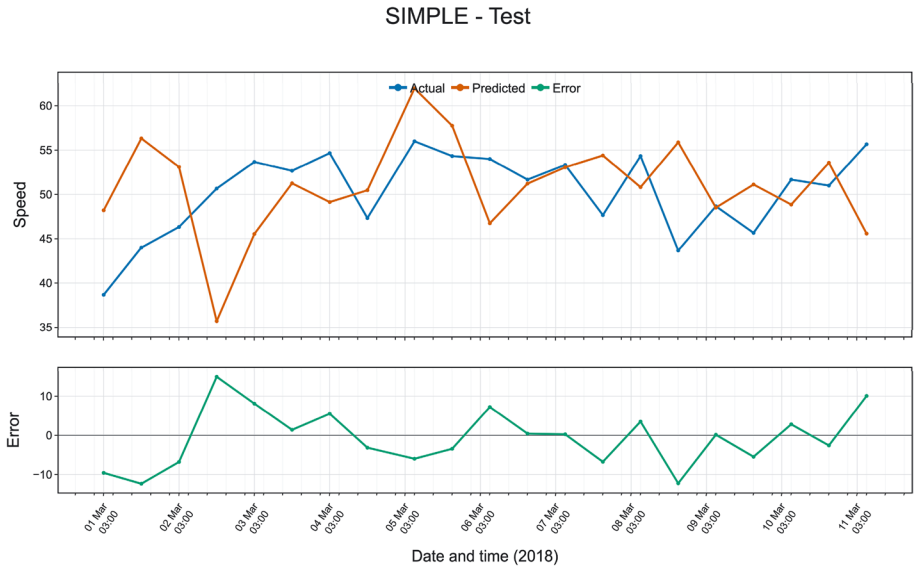


Fig. 8 Performance metrics of LSTM speed prediction.

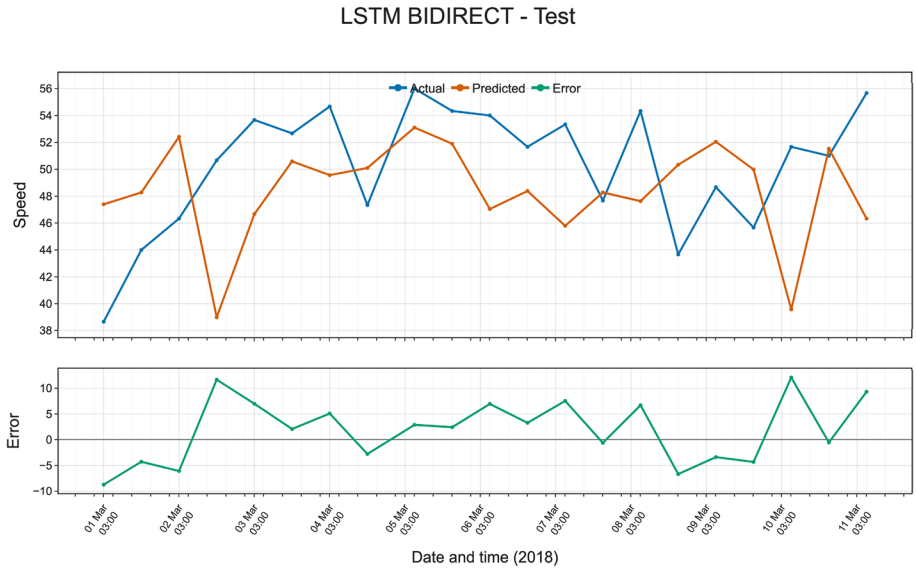


Fig. 9 Performance metrics of LSTM-Bi speed prediction.

the actual and predicted lines show low correlation, reflecting poor performance of the prediction model in those periods. Figure 9. shows that the BI-LSTM model also demonstrates significant fluctuations in both actual and predicted speed values, suggesting that various factors influence speed. The large fluctuations in prediction error, similar to the simple LSTM model, indicate that the model performed with high accuracy in some points and lower accuracy in others. Periods of correlation and lack of correlation between the actual and predicted lines reveal that the BI-LSTM model performed well in certain time periods but poorly in others. According to the chart, this model has not effectively captured speed variations, highlighting the need for more complex models to improve prediction accuracy. The subsequent section introduces the Conv-LSTM model. Figure 10. presents the speed prediction chart based on the Conv-LSTM model. Visual analysis of Fig. 10. further corroborates the superiority of this model, as the predicted curve closely tracks the fluctuations of the actual data with high precision, particularly at the peaks and troughs of speed, while the instantaneous error remains within a stable range with a limited amplitude of fluctuation. This indicates that the Conv-LSTM model achieves high accuracy in many instances, and during most time periods, the actual and predicted lines demonstrate high correlation,

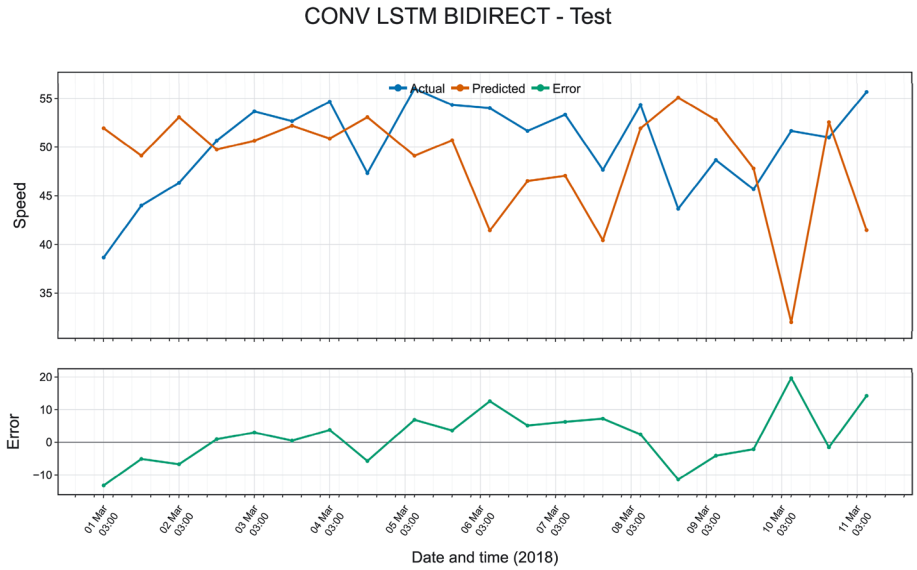


Fig. 10 Performance metrics of Conv- LSTM speed prediction.

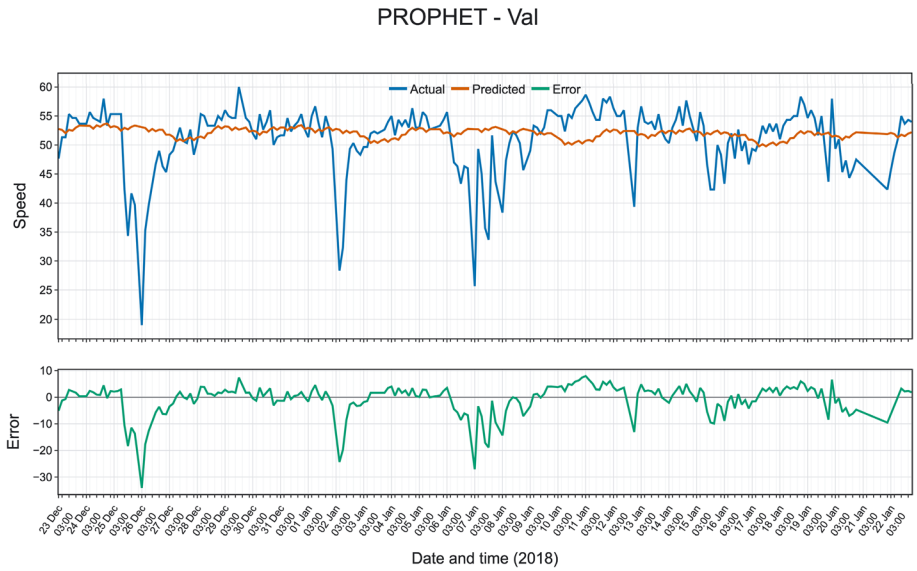


Fig. 11 Performance metrics of Prophet speed prediction.

reflecting robust model performance across diverse conditions. In contrast, in Fig. 8 (LSTM) and Fig. 9 (Bi-LSTM), the error increases significantly at critical points, and in Fig. 11. (Prophet), a substantial deviation is observed between the actual and predicted curves, indicating the limitation of this classical model in handling non-linear and weather-dependent dynamics. Figure 11, which represents the Prophet model, shows severe fluctuations due to discrepancies between actual and predicted speed values, indicating high prediction error. There is also low correlation between actual and predicted values in this model. Ultimately, it has been found that the Conv-LSTM model has the lowest overall error, while the Prophet model has the highest error. Generally, as the complexity of the model increases (from LSTM to Conv-LSTM), the prediction accuracy improves. (https://doi.org/10.5281/zenodo.21224998).

Figure 12. demonstrates the influence of each weather parameter on traffic speed. The results indicate that wet-bulb temperature has the most substantial impact on traffic speed along the study corridor. This temperature represents the equilibrium at which air interacts with a moist surface, with air humidity significantly affecting behavior and environmental conditions. Increased air humidity elevates the likelihood of rain and cloud formation. In high

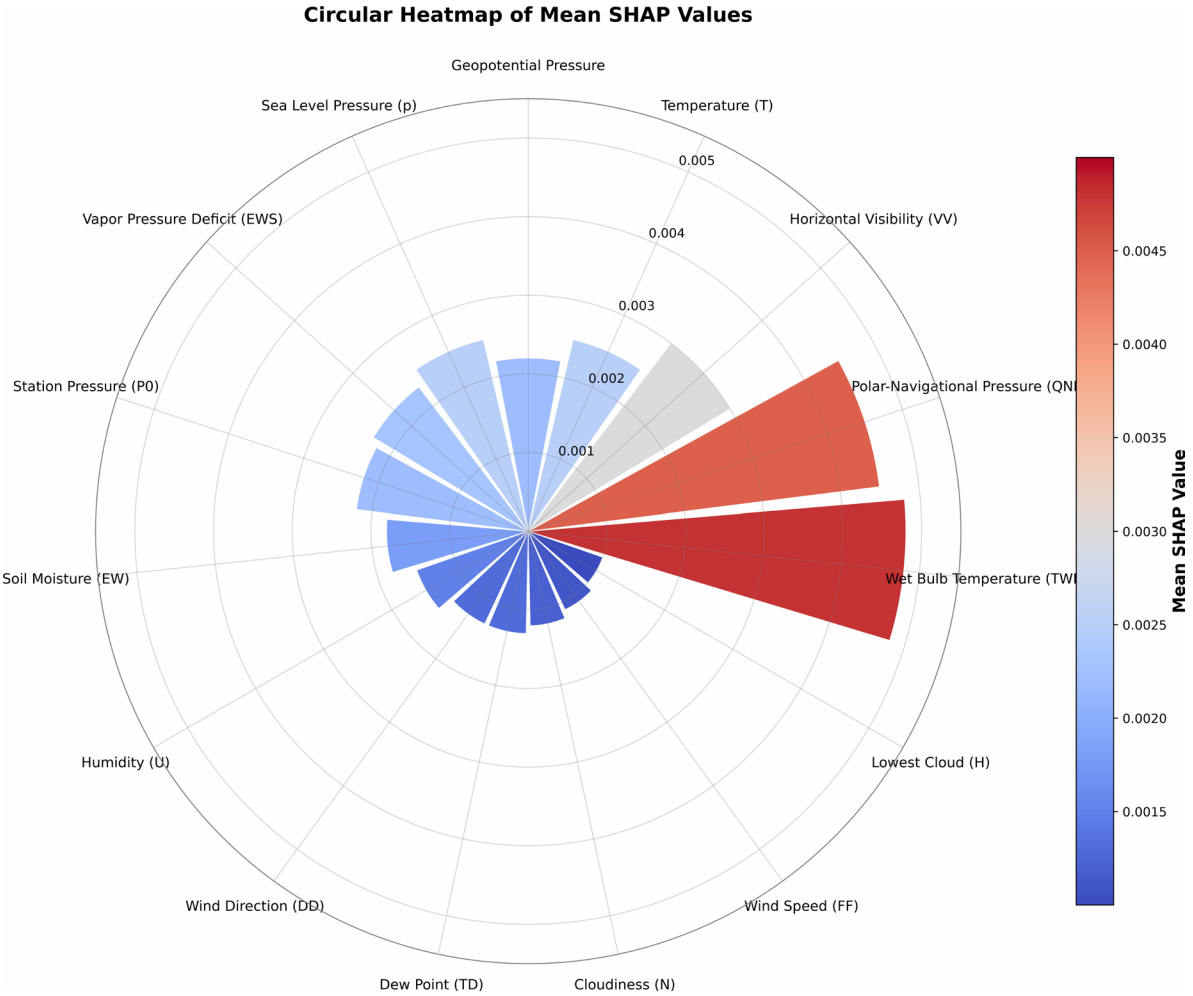


Fig. 12 The influence of weather conditions on traffic speed.

wet-bulb temperature conditions, the risk of slipping increases, and road surface traction decreases. Wet-bulb temperature directly affects vehicle speed and driving behavior, as drivers tend to slow down and exercise additional caution while driving on slippery roads. Furthermore, air humidity and wet-bulb temperature affect driver visibility and overall driving conditions.

Following wet-bulb temperature, QNH pressure exhibits the next most significant influence on traffic speed. QNH pressure, a concept within meteorology and atmospheric pressure, signifies the corrected atmospheric pressure at sea level. This pressure fluctuates with altitude, causing atmospheric pressure to decrease as altitude increases. The corrected atmospheric pressure at sea level enables accurate comparisons of atmospheric pressure across various regions. A case study on a cold suburban mountain road reveals that variations in atmospheric pressure impact road conditions and traffic speed. Severe weather conditions and high atmospheric pressure reduce traffic speeds and affect the overall performance of the traffic network.

After QNH pressure, horizontal view emerges as the subsequent critical factor affecting traffic speed. This aspect permits drivers to observe clouds, terrain features, natural landscapes, and weather conditions on the horizon. Within the context of driving, horizontal view relates to having a clear perspective of the road and surrounding environment horizontally. This visibility significantly impacts a driver's decision-making process concerning suitable speed adjustments and maneuvering. It enables drivers to observe road markings, traffic conditions, road

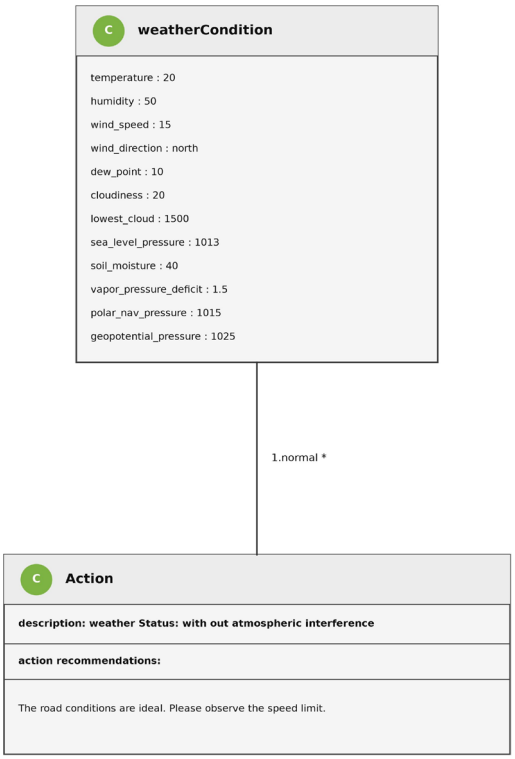


Fig. 13 Traffic action plan in a normal condition.

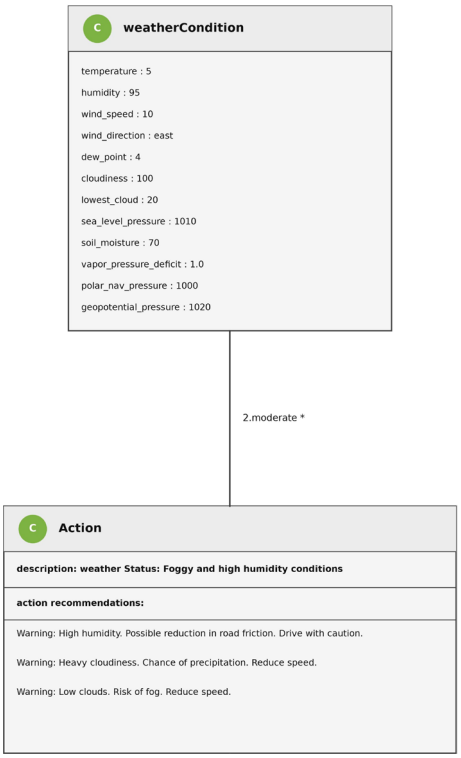


Fig. 14 Traffic action plan in a foggy and humidity condition.

conditions, and environmental factors on the horizon. However, variables such as road fog, narrow roads, and curves impact the effectiveness of this visibility, causing its value to either decrease or increase.

Action plan

One of the fundamental limitations in most deep learning-based traffic forecasting studies is the inability to convert model outputs into actionable and interpretable operational strategies. To address this critical gap, the present study develops an interpretable framework that systematically transforms Conv-LSTM predictions into quantitative, rule-based actions grounded in objective evidence. This operational framework constitutes the applied extension of the proposed weather-aware spatiotemporal traffic speed forecasting methodology. As established in the Introduction, the lack of interpretable operational planning remains a critical limitation in prior mountainous-road studies. Building on the SHAP-based feature importance analysis, the Action Plan translates model outputs such as the identified significance of Wet-Bulb Temperature (TWET) and Polar-Navigational Pressure (QNH) into rule-based, actionable strategies tailored for diverse meteorological scenarios on Chalus Road. The framework, implemented using Python programming language, details the steps and strategies designed to enhance safety, efficiency, and environmental sustainability on mountainous roads. The interpretability of the proposed approach is corroborated by the inherent traceability of each operational decision to its corresponding SHAP values and feature importance rankings. Such transparency enables traffic management authorities to conduct audits and adjust decision-making logic in response to contextual conditions. Using PlantUML, the operational protocols are visualized in Figs. 13,14,15,16 as class diagrams.

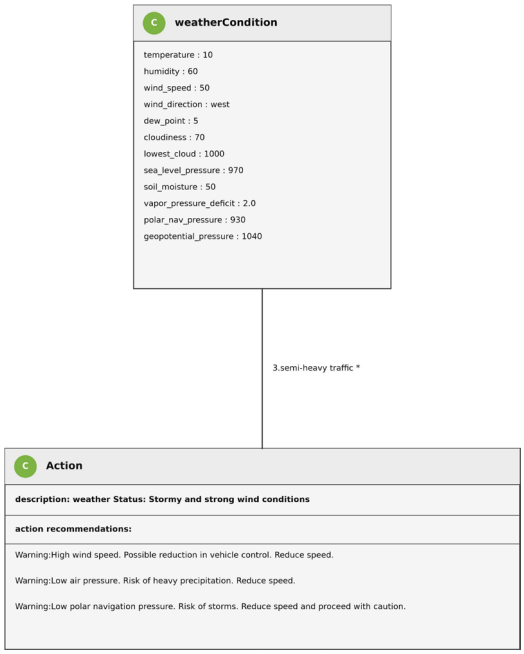


Fig. 15 Traffic action plan in an stormy and strong wind condition.



Fig. 16 Traffic action plan in a heavy rainfall condition.

In the first scenario (Fig. 13.), representing normal conditions without atmospheric interference, the system registers baseline values: temperature of 20°C, relative humidity of 50%, sea-level pressure of 1013 hPa, and polar navigation pressure of 1015 hPa. Under these optimal conditions, the recommendation is straightforward: road conditions are ideal, and drivers should observe the standard speed limit. In contrast, the second scenario (Fig. 14.) triggers a foggy and high humidity protocol when critical thresholds are breached: temperature drops to 5°C, humidity reaches 95%, dew point approaches 4°C, lowest cloud base descends to 20 m, and polar navigation pressure drops to 1000 hPa. The system automatically issues sequential warnings regarding reduced road friction, precipitation risk, and fog, mandating speed reduction and cautious driving. The third scenario (Fig. 15.) addresses stormy and strong wind conditions, characterized by wind speeds reaching 50 m/s, sea-level pressure dropping to 970 hPa, and polar navigation pressure falling to 930 hPa. These quantitative indicators activate high-risk alerts for reduced vehicle control and storm hazards, prompting drivers to reduce speed and proceed with extreme caution. Finally, the fourth scenario (Fig. 16.) manages heavy rainfall and high soil moisture conditions, quantitatively defined by temperature of 8°C, humidity of 85%, wind speed of 25 m/s, sea-level pressure of 990 hPa, soil moisture at 90%, and vapor pressure deficit of 0.5. The framework responds by generating multi-layered warnings for reduced road grip, slippery surfaces, and heavy precipitation, enforcing strict speed reduction protocols. By explicitly linking numerical thresholds to operational actions, the proposed framework ensures that every managerial decision is auditable, reproducible, and directly traceable to the model's interpretability outputs.

Conclusion

This study underscores the significant role weather plays in traffic forecasting, emphasizing the importance of considering weather parameters as non-constant and dynamic factors. Unlike most traffic forecasting studies focusing on traffic flow, this research highlights the crucial impact of weather on traffic speed, particularly on suburban roads. By integrating traffic and weather data, a more accurate prediction of traffic conditions can be obtained.

The findings of this study hold practical applications for transportation planning and policy-making. A comprehensive understanding of weather's influence on traffic speed allows transportation agencies to make informed decisions about road maintenance, construction, and the implementation of strategies aimed at minimizing delays and improving safety. Furthermore, drivers can leverage this information to plan their trips and adjust their driving behavior accordingly, ultimately enhancing overall travel experiences and reducing accident risks.

This article employs three LSTM, Bi-LSTM, and Conv-LSTM models and one time series model (Prophet) for traffic speed prediction utilizing deep learning techniques and historical weather and traffic data. The models were trained and tested using functional criteria and Spatio-temporal characteristics. The methodological innovation of this study lies in the development of an integrated, weather-aware spatiotemporal framework specifically designed for mountainous tourist routes, an area that has been systematically overlooked in previous literature. Within this framework, the Conv-LSTM model was selected as the optimal architecture based on a multi-criteria evaluation. Although the simple LSTM achieved a slightly lower MAE (1.09 km/h) on the test set compared to the Conv-LSTM (1.69 km/h), the Conv-LSTM model was identified as the superior model due to its significantly higher coefficient of determination ($R^2 = 0.91$ versus 0.85 for the simple LSTM), indicating that it explains 91% of the variance in the traffic speed data. This superiority, coupled with the model's enhanced robustness in capturing weather-induced nonlinear fluctuations and its ability to extract meaningful spatiotemporal patterns through the integration of convolutional and recurrent layers, establishes it as the better-performing model for operational analysis and planning.

According to the model outputs, wet-bulb temperature exerts the most significant influence on the traffic speed of Chalus Road. Although deep learning algorithms provide effective solutions when information about data distribution and relationship shape is limited, prioritizing prediction model accuracy and precision over speed, stability, interpretability, and scalability is essential. These algorithms may have inherent flaws, which can be mitigated by combining multiple algorithms. Consequently, future studies should focus on addressing weak points in algorithm development. It is crucial to acknowledge that each learning model may not be the optimal modeling technique for every scenario, emphasizing the importance of considering factors that have been overlooked thus far. Including accident data and road operations in future studies may further refine traffic prediction accuracy.

To summarize, traffic speed prediction based on weather parameters provides valuable insights for various aspects of transportation management, including travel time estimation, incident management, public transportation optimization, and transport planning. Ultimately, to control traffic speed and mitigate the impact of weather-related crises on traffic flow, the action plan is proposed. These measures assist managers in significantly improving safety, efficiency, flexibility, and sustainability in urban transportation systems.

Author contributions Shahriar Afandizadeh: Conceptualization, Supervision, Methodology, Writing—Review & Editing. Saeid Abdolahi: Data Curation, Formal Analysis, Writing—Original Draft, Visualization. Hamid Mirzahossein: Software Development, Validation, Writing—Review & Editing. All authors have read and approved the final manuscript.

Data availability The data that support the findings of this study are available from Prof. Shahriar Afandizadeh upon reasonable request.

Declarations

Competing interests The authors declare no competing interests.

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