

Urban Parking Demand Prediction With Hybrid Neural Network Architectures And Explainable AI

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Abstract

Due to the increasing urbanisation and the associated growing traffic problems and parking shortages, a more accurate prediction of parking demand becomes increasingly important for intelligent traffic management and optimisation of parking space utilisation. The traditional methods of forecasting often fail to capture the complex dynamic relationships over time and the synergies of alternative model designs. The Smart Parking Management Dataset hourly temporal resampling is used in this work. It uses Entry features including temporal, historical, visibility and temperature for parking demand forecasts. Preprocessing includes feature engineering, Min–Max scaling and training-test split, chronologically. Various models are tried such as LSTM, xLSTM, Informer, Transformer, Autoformer, ARIMA, hybrid xLSTM-Informer model and multi-horizon BiLSTM models. The four metrics for evaluating the performance are the RMSE, MAE, MAPE, R2 and training duration. From the results, it can be concluded that the BiLSTM_1h model has the lowest RMSE (0.014), MAE (0.011), MAPE (5.536%) and the highest R2 (0.989), which demonstrates the effectiveness of the short-term parking demand projection. We use LIME and SHAP to analyse the feature contributions. We also offer an interface based on Flask to call the model for prediction. The results demonstrate that DL architectures provide valuable tools for accurate and interpretable urban parking demand forecast.

“Keywords— Parking demand forecasting, Long Short-Term Memory, deep learning, time-series forecasting, predictive modeling, explainable artificial intelligence, LIME, SHAP”.

I. INTRODUCTION

As the number of private vehicles and population has grown, the need for parking that is controlled in urban areas has also increased greatly. The temporal fluctuation of the parking demand makes the effective parking management more and more hard since the parking demand is impacted by the land use, travel behaviour and socioeconomic activity. In many cities, the current parking infrastructure is not adequate to meet the demand of parking, resulting in parking-search traffic, energy waste and increased emissions [1]. As more and more intelligent transportation management is implemented based on data, the PDF becomes a key aspect of an efficient, sustainable and convenient urban mobility system [2] [3].

The demand of parking has been widely studied, but it is difficult to obtain an accurate prediction. Although conventional analytical and statistical tools can offer valuable information on parking behaviour in general, they often are based on simplifying assumptions that impair their modelling capabilities for nonlinear and nonstationary behaviour in real-world data [4]. Recent data-driven methods have achieved higher prediction accuracy, but many of these models focus on the short-term dynamics or temporal patterns, without considering the relationship between long-term trends and high-frequency variations [5,6]. Furthermore, the growing volume of parking data and the time granularity of parking data raises issues to make sure forecasting resilience and computing efficiency, which highlights the need for realistic forecasting methodologies for dynamic urban settings [7].

This work aims to create a common forecasting model to capture complex time-varying complex patterns in urban parking demands. It is proposed to use the short-term variability and long-term temporal interdependence with the help of plenty of DL and time-series forecasting architectures like LSTM, xLSTM, Informer, Transformer, Autoformer, ARIMA, xLSTM-Informer, and multi-horizon BiLSTM. For each model, the RMSE, MAE, MAPE, R2 and training time are used to identify the best forecasting methodologies for different prediction horizons. We also use XAI methods such as SHAP and LIME to analyse the feature contributions.

Accurate parking demand forecasts can result in more adaptive and better parking management solutions. Well-informed parking demand forecasts can assist local governments to design improved parking facilities, utilize variable pricing systems and curb unnecessary vehicle trips. Better forecasts can therefore lead to less congestion, lower emissions, a better experience for the traveller and contribute to the broader smart-city and sustainable-mobility goals [10].

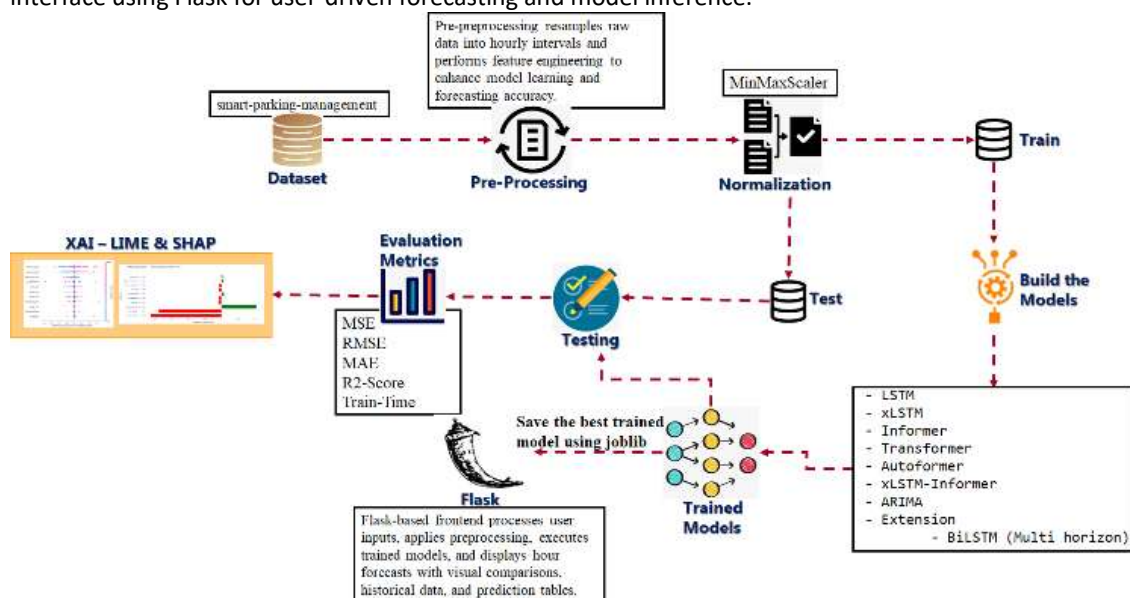
II. RELATED WORK

Neural networks based solutions have been shown to be excellent ways for parking demand forecasting. Vlahogianni et al. [16] presented a real-time parking prediction system using neural networks which demonstrates the feasibility of learning-based approaches for smart city applications. Balmer et al. [17] emphasized the importance of spatial context, incorporating geographical information, like points of interest, and land-use data into learning models for predicting on-street parking occupancy. But these methods require significant amounts of data, and their efficiency is strongly data and model dependent, while scalability continues to pose a challenge for large metropolitan parking networks.

Recently, DL architectures are widely used to describe complex temporal dynamics. Feng et al. [18] proposed a hybrid DL solution to zone level parking availability prediction that solved the short-term and long-term parking availability forecasting problem and performed better in prediction accuracy than the existing approaches. Zhang et al. built a periodic forecasting model including weather information, which shows the effect of external environmental elements on parking behaviour [19]. Along with enhancing temporal models, these approaches can lead to greater computation and less real-time use because of the increasing complexity of their architecture. Ma et al. suggested the use of EMD together with the BRN to enhance the stability and precision of the remaining parking-space predictions [20] in order to address the issue of long-range temporal dependency. But the amount of computation for the signal decomposition and different model parts grows. Even with all available studies, there is still a conflict between the temporal representation, the forecasting flexibility and the computing efficiency. In this work, some DL and time-series architectures (xLSTM, Informer, xLSTM-Informer and multi-horizon BiLSTM) are evaluated for urban parking demand forecasting.

III. MATERIALS AND METHODS

The proposed system aims to precisely predict the urban parking demand based on the IIoT Smart Parking Management Dataset that provides the operational and environmental status of parking on an hourly basis. Overall, the method is data-driven, that is parking data are temporally synced and converted into sequential representations suitable for forecasting. We try a number of DL and statistical models to capture short and long term temporal patterns. Specifically, xLSTM-Informer combines recurrent memory modelling and long-range dependency modelling with attention. We also use multi-horizon BiLSTM models to predict multi-horizon. LIME and SHAP are applied to provide feature contribution and increase the model interpretability. There is a web interface using Flask for user-driven forecasting and model inference.



“Fig. 1. System Architecture”

The suggested system is based on a modular design which includes Frontend, Backend and ML components. Frontend is an interactive interface where the user can interact, input features and visualise. The uploaded information is received on the backend, the model inference is performed and information is communicated with application interface. In the ML to be compared. The other components provide explainability and performance analysis, thus providing an interpretable framework for the projection of urban parking demand.

A) Dataset Collection

The dataset utilized in this study is the IIoT Smart Parking Management Dataset, which consists of multivariate time-stamped parking data, comprising of 28 original features such as sensor readings, car parameters, and weather conditions, as well as user information and parking-related variables. The model is trained on 11 input features which are selected or engineered: Temperature, Visibility, hour_sin, hour_cos, dow_sin, dow_cos, is_weekend, entry_lag_1, entry_lag_24, entry_roll_3, entry_roll_24. The variable of interest is the goal variable, Entry, which represents the value for parking demand predicted by the models.

	Timestamp	Parking Spot ID	Sensor_Rawing_Proximity	Sensor_Rawing_Pressure	Vehicle_Type_Weight	Vehicle_Type_Height	User_Type	Weather_Temperature	Weather_Precipitation	Nearby_Traffic_Level
0	2021-01-01 00:00:00.0000000	20	1.025801	1.54461	1811.77017	4.382520	Visitor	10.62355	0	Low
1	2021-01-02 00:00:00.0000000	40	1.003340	1.027719	1100.81574	4.595630	Registered	12.897520	0	Low
2	2021-01-03 00:00:00.0000000	30	1.0215700	0.202374	1251.04027	4.310721	Registered	21.687410	0	High
3	2021-01-04 00:00:00.0000000	31	0.308809	1.059070	1123.442919	3.507329	Visitor	10.682401	0	Medium
4	2021-01-05 00:00:00.0000000	0	0.212969	1.070467	1735.40037	5.345630	Visitor	10.144076	0	High

5 rows x 28 columns

Fig. 2 Dataset

B) Pre-Processing

However, to achieve reliable parking-demand prediction, proper pre-processing is required to ensure data consistency, preserve temporal correlations, eliminate noise, and to prepare sequential inputs for the model training.

Data Pre-processing and Temporal Resampling: Data pre-processing and temporal resampling: Raw parking data is converted to the same datetime format and sorted by the datetime. Data are collected every hour, to ensure temporal uniformity. The missing observations made in resampling is handled by interpolation and value-propagation techniques to keep the time-series consistent, in order to prepare the consistent time-series inputs.

Data Cleaning and Missing Value Handling: Data are cleaned following temporal alignment to deal with missing and inconsistent observations. Numbers are converted and continuity of information is maintained and identifiers are carried forward as required. Once the data is preprocessed, needless records are removed to eliminate noise to provide the models something similar to represent in the next processing phase.

Feature Engineering and Temporal Encoding: Using the time-stamp information, we extract temporal and contextual features to describe the daily and weekly demand trend. Generates calendar indicators, weekend indicators and cycle encodings. Moreover, any types of lagged and rolled statistics of the Entry target are produced such as entry_lag_1, entry_lag_24, entry_roll_3, and entry_roll_24, so that the models can consider the recent past and temporal trends of the Entry target.

Data Normalization: Data Normalisation Scaling of features and target variable is performed using Min-Max Scaler (independent scalers) to make sure the variables have a common numerical range across model training. It is now normalised which means it can be optimised in a stable manner and projected target values can be converted back to the original scale for evaluation.

C) Training and Testing:

The normalised data is then restructured into fixed-length, consecutive windows for time series forecasting, with examples of how the historical observations can be used to predict future parking demand. We chose sequence length 24 time steps, and each sequence comprised of 11 designated input features. The sequences are then divided into training and testing sets in the temporal order, while maintaining the causal nature of the forecasting problem.

D) Algorithms

LSTM: The ability of LSTM network to learn sequential data can be attributed to the presence of gated memory cells, which can remember, update and selectively retain pieces of relevant information across time. This enables LSTM to model both short-term variations and long-term dependencies, which helps to improve the accuracy and reliability of parking-demand forecasting.

xLSTM: Extended LSTM An enhanced Recurrent architecture to enhance the memory representation across a long sequence. It can keep pertinent information over long time spans and recognise long-range time

dependencies, thus improving the predictive accuracy, stability, and generalisation for complicated and dynamically changing time-series data.

Informer: Informer models long-range temporal dependencies efficiently with a self-attention technique at lower computational cost. It can effectively model temporal global patterns and is suitable for high resolution and long horizon time-series forecasting, in which traditional attention mechanisms may be time-consuming.

Transformer: The idea of self-attention is used in transformer models to learn relationships between different positions in a sequence. The architecture parallelly processes the temporal information and generates compact representations of time-series patterns which allows the model to capture long-term temporal dependencies and contextual relationships among the elements in the input sequence.

Autoformer: Autoformer can decompose the time-series data directly into the trend component and seasonal component, and use attention based temporal modelling. This structured representation enables the model to represent unique temporal patterns and to reduce the impact of sudden changes, leading to more stable and accurate predictions across a wide range of temporal scales.

xLSTM-Informer: The xLSTM-Informer hybrid combines the extended recurrent memory with the attention-based global dependency modelling. The free architecture is designed to capture short term temporal variations through recurrent memory and long range dependencies through attention, to provide a single representation of the complex and time-varying parking demand patterns.

ARIMA: ARIMA is a statistical time-series forecasting model that utilizes the autoregressive, differencing and moving-average components to model the temporal interdependence. It provides a standard statistical metric for assessing of the effectiveness of DL techniques. It is capable of recognizing temporal correlations for time-series patterns of relatively simple complexity.

BiLSTM (Multi-Horizon): Bidirectional LSTM reads the information in the sequence in both forward and backward temporal directions to capture the relationship between the context of the input sequence. In this work, multi-horizon BiLSTM models are used to forecast parking demand at multiple future horizons (i.e., 1-hour, 6-hour, and 12-hour), which can be used to compare the forecasting performance between the short and longer time horizons.

E) Integration of XAI and Flask Framework:

To increase the transparency of the results that are forecasted, the XAI strategies are applied. SHAP and LIME are used to understand the importance of input features for the parking-demand estimates. These explanations enable us to trace the influence that demand factors, such as temporal, environmental and historical factors, have on model outputs, and give even more insights into the forecasting process.

The explainability module is connected to a backend architecture based on Flask, which makes it possible to infer and explain the model through a web interface. The program allows users to engage with it and gain parking demand projections and explanatory information. With this incorporation, the forecasting models can be used in practice and the forecasts from them can be interpreted better.

IV. EXPERIMENTAL RESULTS

A) Performance Evaluation

RMSE: The square root of the mean value of the difference between the actual and anticipated values squared. It puts more emphasis on higher prediction errors and is defined as:

$$RMSE = \sqrt{\frac{\sum_{i=1}^n |y(i) - \hat{y}(i)|^2}{N}}$$

MAE: This is the average absolute difference between observed and expected values, and is called the MAE. It is a direct measure of the average prediction error and it has the following definition:

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i|$$

R2 Score: The coefficient of determination (R^2) indicates what proportion of the variance in the observed data is accounted for by the model predictions. This can be expressed as:

$$R^2 = 1 - \frac{\sum_{i=1}^n (\hat{y}_i - y_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2}$$

Table. 1. Performance Evaluation

ML Model	RMSE	MAE	MAPE	R2-Score	Train-Time
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xLSTM-Informer	0.025	0.022	11.193	0.965	310.326
LSTM	0.028	0.021	8.712	0.954	313.994
xLSTM	0.021	0.017	9.116	0.974	346.560
Informer	0.024	0.018	7.258	0.967	320.474
Transformer	0.023	0.019	0.969	9.781	310.336
Autoformer	0.017	0.014	8.132	0.984	457.618
ARIMA	0.272	0.238	79.692	-	10.601
				3.229	
BiLSTM_1h	0.014	0.011	5.536	0.989	1364.807
BiLSTM_6h	0.021	0.015	7.150	0.974	1364.807
BiLSTM_12h	0.039	0.027	12.125	0.913	1364.807

For the forecasting models, a performance evaluation is carried out based on the RMSE, MAE, MAPE, R^2 and training time. As for the models tested, BiLSTM_1h has the lowest RMSE and MAE values, the lowest MAPE value, and the highest R^2 value, which means that it has the best performance in the prediction of short-term parking demand. The R^2 -score of Autoformer is also 0.984, and is high.

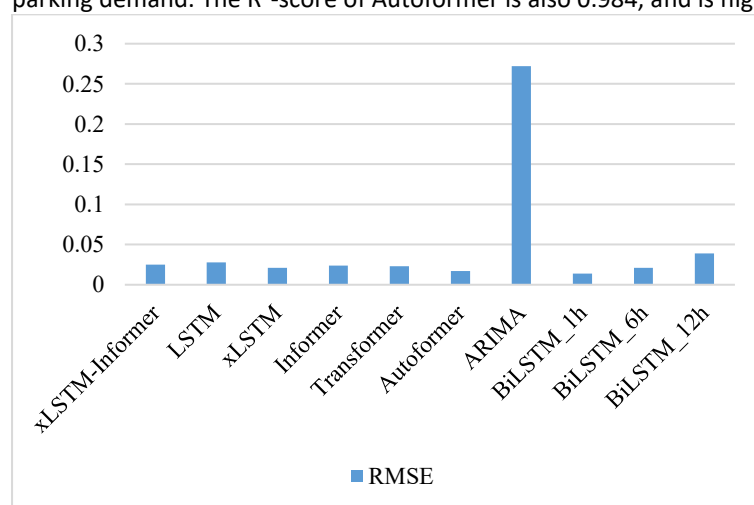


Fig. 3. RMSE Comparison

The RMSEs of the models evaluated for forecasting the parking-demand are shown in this graph; lower RMSE indicates lower deviations between the number of parking-dems forecasted and the number that is actually observed.

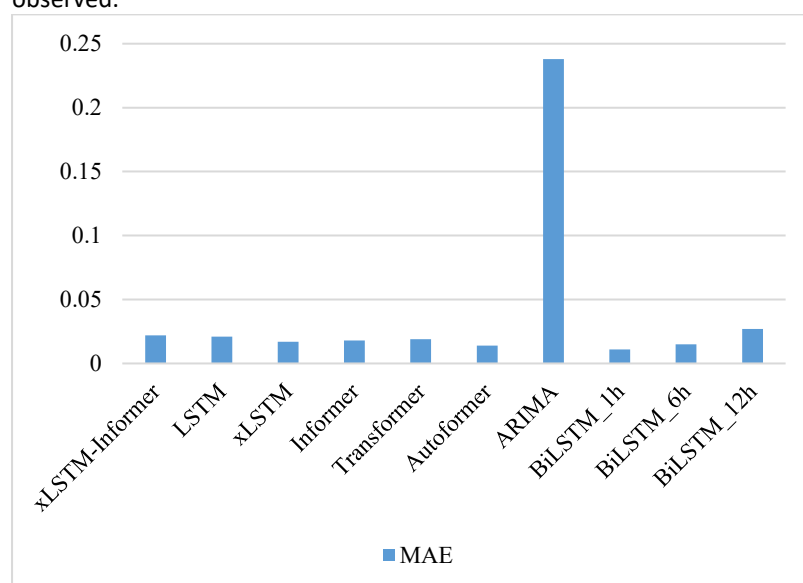


Fig. 4. MAE Comparison

The MAE values obtained by the forecasting models are shown in the graph. The lower the MAE, the less the average prediction error.

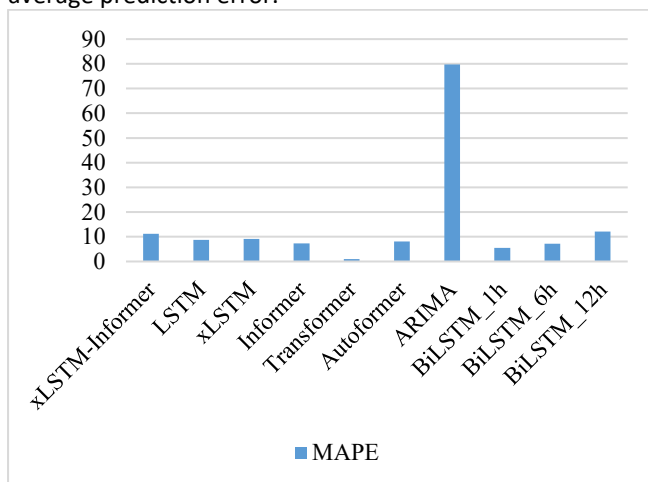


Fig. 5. MAPE Comparison

This graph shows the MAPE of the modeled assessed models which represents the relative percentage error in prediction. Forecasts performance is better the closer the MAPE value is to zero.

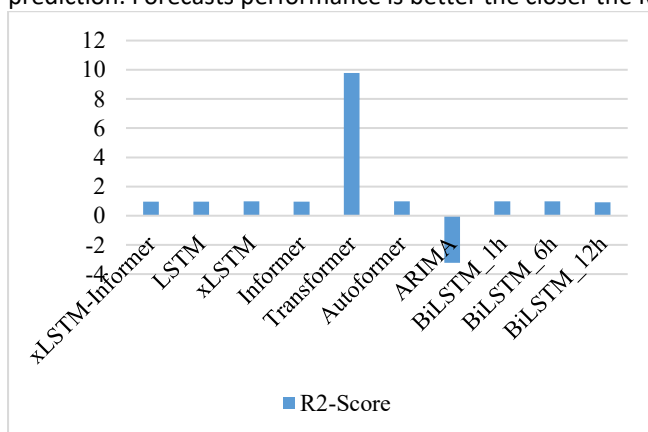


Fig. 6. R²-Score Comparison

The graph below shows the comparison of the R2-scores of the forecasting models. The closer R^2 is to one the better the fit of the model to the variability of the observed parking-demand value.

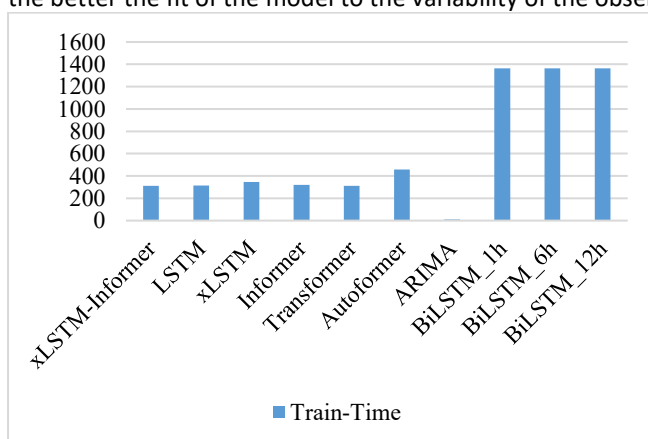


Fig. 7. Training Time Comparison

The graph shows the training duration of each model, and the relative computational cost of the studied forecasting methodologies.

B) Explainable AI Results

LIME Explanation → (h: Forecast, Sample #5)

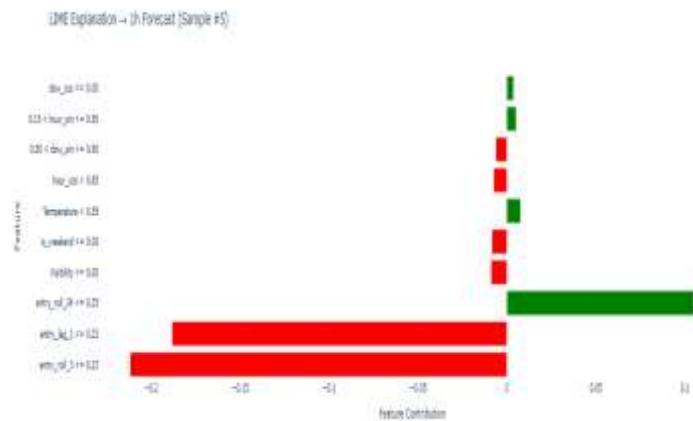


Fig. 8. LIME Feature Contribution Explanation

The LIME explanation shows the contribution of the individual input features to a representative parking-demand prediction. Identifies which features are favouring or adverse to the specified prediction and provides a local explanation of the model output.

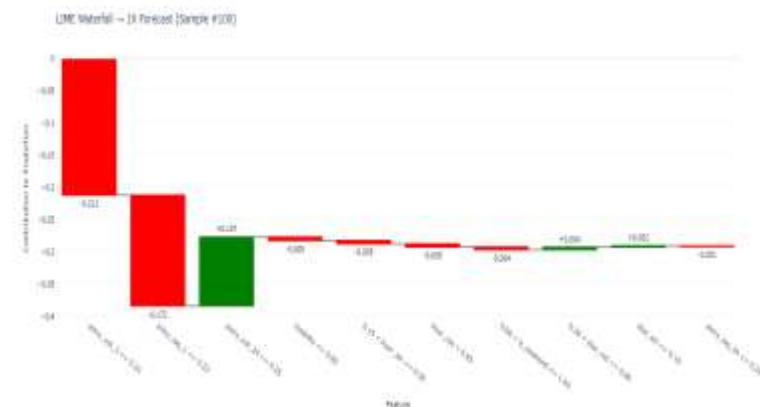


Fig. 9. LIME Waterfall Explanation

The LIME waterfall visualisation shows the contribution of the input features in the resultant prediction in steps. It shows how the individual feature effect on the expected parking demand of the model.

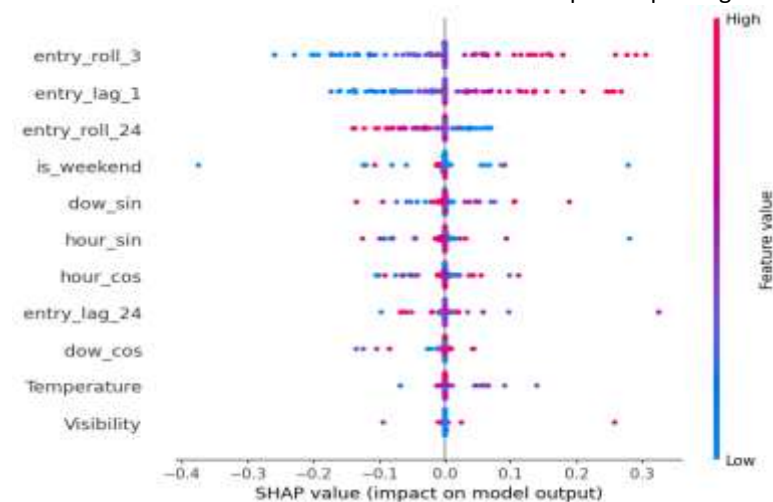


Fig. 10. SHAP Feature Importance Analysis

The SHAP visualisation shows the contribution of each input feature to the model predictions. The larger the SHAP contribution, the more significant the feature is in determining the forecasting outcome and the more it gives an interpretable viewpoint of the elements affecting the parking demand.

C) Web Application Results

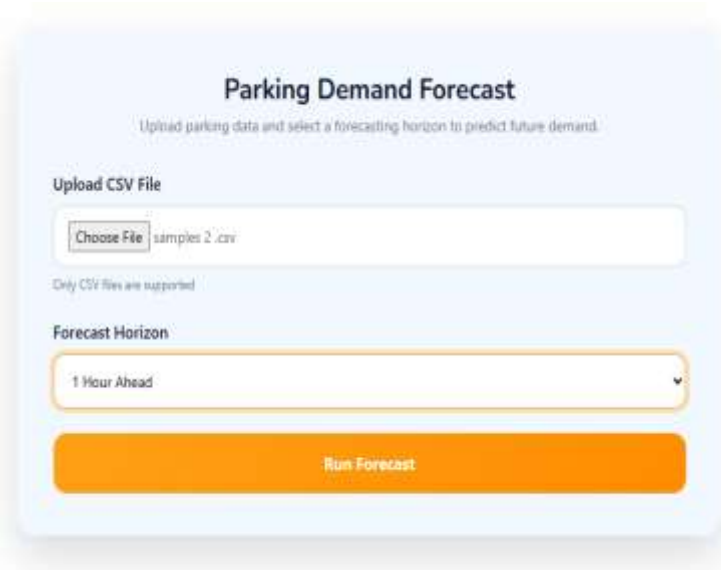


Fig. 11 Upload a CSV File

This is an interactive, user friendly web program in which the user can upload the parking CSV data, define a forecasting horizon and then get the demand forecast for real-time parking analytics.

Recent Historical Window

Timestamp	Temperature	Visibility	hour_sin	hour_cos	hour_sin	hour_cos	is_weekend	entry_log_1	entry_log_24	entry_roll_2
2024-02-16 01:00:00	16.29	0.00	0.26	0.97	-0.43	-0.90	0.00	0.47	0.30	0.47
2024-02-16 02:00:00	16.38	0.00	0.50	0.87	-0.43	-0.90	0.00	0.47	0.31	0.47
2024-02-16 03:00:00	16.47	0.00	-0.71	0.71	-0.43	-0.90	0.00	0.48	0.32	0.48
2024-02-16 04:00:00	16.56	0.00	0.83	0.50	-0.43	-0.90	0.00	0.48	0.33	0.48
2024-02-16 05:00:00	16.65	0.00	0.97	0.26	-0.43	-0.90	0.00	0.49	0.33	0.49
2024-02-16 06:00:00	16.74	0.00	1.00	0.00	-0.43	-0.90	0.00	0.50	0.34	0.50
2024-02-16 07:00:00	16.83	0.00	0.97	-0.26	-0.43	-0.90	0.00	0.50	0.35	0.50
2024-02-16 08:00:00	16.91	0.00	0.87	-0.50	-0.43	-0.90	0.00	0.51	0.36	0.51
2024-02-16 09:00:00	17.00	0.00	0.71	-0.71	-0.43	-0.90	0.00	0.51	0.37	0.51
2024-02-16 10:00:00	17.09	0.00	-0.50	-0.87	-0.43	-0.90	0.00	0.52	0.38	0.52

Future Forecasts

Timestamp	Forecast
2024-02-16 22:00:00	0.59

Fig. 12 Predicted Result

Another output feature is the future demand estimate of parking, which is augmented by recent historical parking data and a developed feature with an obvious timestamp-wise value, and a predicted parking occupancy to facilitate data-driven and educated urban parking management.

V. CONCLUSION

In conclusion, the proposed system is designed to ensure accurate and reliable prediction of the urban parking demand for intelligent traffic management and efficient utilization of the parking facilities. The methodology use the Smart Parking Management Dataset with the input characteristics selected being the Temperature, Visibility, temporal encodings, and historical Entry data. We compare multiple forecasting models including LSTM, xLSTM, Informer, Transformer, Autoformer, ARIMA and xLSTM-Informer models as well as multi-horizon BiLSTM models. The performance measures include RMSE, MAE, MAPE, R2-score and time for training. Feature-contribution analysis with SHAP and LIME. Forecasting can be done using the trained models via an interface built using Flask. The BiLSTM_1h model obtains the best performance when compared to other models, with RMSE of 0.014 and R 2 -score of 0.989, which shows the superiority of the model for short-term parking-demand forecasting. The developed methodology offers an interpretable forecasting platform, which can assist data-driven urban parking management and decision making.

Future work can also include other real-time data such as traffic flow, weather conditions and special events to enhance parking-demand predictions. Adaptive/online learning can also be explored for updating predictions as new observations are acquired. Real-time parking allocation and pricing can be assisted by advanced optimisation techniques. Accessibility and scalability can be improved with mobile apps and cloud services. Moreover, scaling up the model to multiple cities or regional scenarios can be helpful for integrated smart-city traffic management and resource planning.

REFERENCES

- [1] Chen, J., Wu, M., Li, S., Cai, Y., Long, W., & Yang, B. (2025). Scale-Fusion Transformer: A Medium-to-Long-Term Forecasting Model for Parking Space Availability. *Electronics*, 14(18), 3636.
- [2] Nezhadettehad, A., Zaslavsky, A., Rakib, A., & Loke, S. W. (2025). Uncertainty-Aware Parking Prediction Using Bayesian Neural Networks. *Sensors*, 25(11), 3463.
- [3] Huang, Y., Dong, Y., Tang, Y., & Li, L. (2025). Parking Availability Prediction via Fusing Multi-Source Data with A Self-Supervised Learning Enhanced Spatio-Temporal Inverted Transformer. *arXiv preprint arXiv:2509.04362*.
- [4] Ma, C., Huang, X., & Li, J. (2024). A review of research on urban parking prediction. *Journal of Traffic and Transportation Engineering (English Edition)*, 11(4), 700-720.
- [5] Kemik, H., Dalyan, T., & Aydogan, M. (2024). Smart Solutions for Mega-Cities: Utilizing Long Short-Term Memory and Multi-Head Attention in Parking Prediction. *ISPRS International Journal of Geo-Information*, 13(12), 449.
- [6] K. Al-Sahili and J. Hamadneh, "Establishing parking generation rates/models of selected land uses for palestinian cities," *Transp. Res. A, Policy Pract.*, vol. 91, pp. 213–222, Sep. 2016.
- [7] H. Chen, M. Yang, Y. Zhang, and H. Wen, "Parking spaces demand forecasting based on ARIMA model," in *Proc. 15th Int. Conf. Comput. Model. Simul.*, Jun. 2023, pp. 133–137.
- [8] C. Zeng, C. Ma, K. Wang, and Z. Cui, "Parking Occupancy Prediction Method Based on Multi Factors and Stacked GRU-LSTM," *IEEE Access*, vol. 10, pp. 47361–47370, 2022, doi: 10.1109/ACCESS.2022.3171330.
- [9] M. H. Amini, O. Karabasoglu, M. D. Ilic, K. G. Boroojeni, and S. S. Iyengar, "ARIMA-based demand forecasting method considering probabilistic model of electric vehicles' parking lots," in *Proc. IEEE Power Energy Soc. Gen. Meeting*, Denver, CO, USA, Jul. 2015, pp. 1–5.
- [10] D. Chen, "Chinese automobile demand prediction based on ARIMA model," in *Proc. 4th Int. Conf. Biomed. Eng. Informat. (BMEI)*, vol. 4, Oct. 2011, pp. 2197–2201.
- [11] S. D. Boyles, S. Tang, and A. Unnikrishnan, "Parking search equilibrium onanetwork," *Transp. Res. B, Methodol.*, vol. 81, pp. 390–409, Nov. 2015.
- [12] A. Klappenecker, H. Lee, and J. L. Welch, "Finding available parking spaces made easy," in *Proc. 6th Int. Workshop Found. Mobile Comput.*, Sep. 2010, pp. 49–52.
- [13] Y. Wu, H. Tan, J. Peter, B. Shen, and B. Ran, "Short-term traffic flow prediction based on multilinear analysis and k nearest neighbor regression," in *Proc. CICTP*, 2015, pp. 556–569.
- [14] L. W. Jun, M. Esfahani, and T. K. Lee, "Predicting open parking space using deep learning and support vector regression," in *Proc. 7th Int. Conf. Intell. Syst., Metaheuristics Swarm Intell.*, 2023, pp. 20–27.
- [15] R. Chen, C.-Y. Liang, W.-C. Hong, and D.-X. Gu, "Forecasting holiday daily tourist flow based on seasonal support vector regression with adaptive genetic algorithm," *Appl. Soft Comput.*, vol. 26, pp. 435–443, Jan. 2015.
- [16] E. I. Vlahogianni, K. Kepaptsoglou, V. Tsetos, and M. G. Karlaftis, "A real-time parking prediction system for smart cities," *J. Intell. Transp. Syst.*, vol. 20, no. 2, pp. 192–204, Mar. 2016.

- [17] M. Balmer, R. Weibel, and H. Huang, "Value of incorporating geospatial information into the prediction of on-street parking occupancy—A case study," *Geo-Spatial Inf. Sci.*, vol. 24, no. 3, pp. 438–457, 2021.
- [18] Y. Feng, Y. Xu, Q. Hu, S. Krishnamoorthy, and Z. Tang, "Predicting vacant parking space availability zone-wisely: A hybrid deep learning approach," *Complex Intell. Syst.*, vol. 8, no. 5, pp. 4145–4161, Oct. 2022.
- [19] F. Zhang, Y. Liu, N. Feng, C. Yang, J. Zhai, S. Zhang, B. He, J. Lin, X. Zhang, and X. Du, "Periodic weather-aware LSTM with event mechanism for parking behavior prediction," *IEEE Trans. Knowl. Data Eng.*, vol. 34, no. 12, pp. 5896–5909, Dec. 2022.
- [20] C. Ma, X. Huang, K. Wang, and Y. Zhao, "Prediction of remaining parking spaces based on EMD-LSTM-BiLSTM neural network," *J. Traffic Transp. Eng. (English Edition)*, vol. 12, no. 1, pp. 201–213, Feb. 2025.
- [21] H. Wu, J. Xu, J. Wang, and M. Long, "Autoformer: Decomposition transformers with auto-correlation for long-term series forecasting," in *Proc. Adv. Neural Inf. Process. Syst.*, vol. 34, 2021, pp. 22419–22430.
- [22] T. Zhou, Z. Ma, Q. Wen, X. Wang, L. Sun, and R. Jin, "Fedformer: Frequency enhanced decomposed transformer for long-term series forecasting," in *Proc. Int. Conf. Mach. Learn.*, 2022, pp. 1–19.
- [23] Y. Nie, N. H. Nguyen, P. Sinthong, and J. Kalagnanam, "A time series is worth 64 words: Long-term forecasting with transformers," 2022, arXiv:2211.14730.
- [24] H. Wu, T. Hu, Y. Liu, H. Zhou, J. Wang, and M. Long, "TimesNet: Temporal 2D-variation modeling for general time series analysis," 2022, arXiv:2210.02186.
- [25] L. Zhao, Y. Song, C. Zhang, Y. Liu, P. Wang, T. Lin, M. Deng, and H. Li, "T-GCN: A temporal graph convolutional network for traffic prediction," *IEEE Trans. Intell. Transp. Syst.*, vol. 21, no. 9, pp. 3848–3858, Sep. 2020.
- [26] C. Park, C. Lee, H. Bahng, Y. Tae, S. Jin, K. Kim, S. Ko, and J. Choo, "ST GRAT: A novel spatio-temporal graph attention networks for accurately forecasting dynamically changing road speed," in *Proc. 29th ACM Int. Conf. Inf. Knowl. Manage.*, Oct. 2020, pp. 1215–1224.
- [27] C. Zeng, C. Ma, K. Wang, and Z. Cui, "Parking occupancy prediction method based on multi factors and stacked GRU-LSTM," *IEEE Access*, vol. 10, pp. 47361–47370, 2022.
- [28] H. Wang, J. Chen, T. Pan, Z. Dong, L. Zhang, R. Jiang, and X. Song, "STGformer: Efficient spatiotemporal graph transformer for traffic forecasting," 2024, arXiv:2410.00385.
- [29] S. Guo, Y. Lin, H. Wan, X. Li, and G. Cong, "Learning dynamics and heterogeneity of spatial-temporal graph data for traffic forecasting," *IEEE Trans. Knowl. Data Eng.*, vol. 34, no. 11, pp. 5415–5428, Nov. 2022.
- [30] W. Ju, Y. Zhao, Y. Qin, S. Yi, J. Yuan, Z. Xiao, X. Luo, X. Yan, and M. Zhang, "COOL: A conjoint perspective on spatio-temporal graph neural network for traffic forecasting," *Inf. Fusion*, vol. 107, Jul. 2024, Art. no. 102341.