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TRAFFIC FLOW PREDICTION USING AN ATTCLX HYBRID MODEL

ShunFeng He
Department of Transportation Engineering, Southwest Jiaotong University, Chengdu 610097, Sichuan, China.
Corresponding Email: 1652646502@qq.com

Abstract: This study proposes an Attention-based CNN-LSTM-XGBoost (AttCLX) hybrid model to enhance short-term traffic flow prediction accuracy. The model integrates ARIMA for non-stationary data preprocessing, an Attention-based CNN-LSTM module for spatiotemporal feature extraction, and XGBoost for prediction refinement. Experiments using the PeMS dataset demonstrate that AttCLX outperforms benchmarks such as HA, ARIMA, SVR, LSTM, and DCRNN in both short-term (5-minute) and long-term (60-minute) predictions. Key metrics, including MAE and RMSE, show significant improvements (MAE: 13.69 for 5 minutes; 16.21 for 60 minutes). This research provides a robust solution for intelligent transportation systems to alleviate congestion and improve travel efficiency.
Keywords: Traffic flow prediction; Deep learning; Attention mechanism; Hybrid model; Spatiotemporal features

1 INTRODUCTION

Traffic flow prediction is a cornerstone of intelligent transportation systems (ITS), enabling real-time congestion management, accident prevention, and route optimization. Traditional methods, such as historical average (HA) and ARIMA [1], rely on statistical assumptions of stationarity and linearity, limiting their applicability to dynamic traffic scenarios. Machine learning approaches like support vector regression (SVR) partially address nonlinearity but fail to capture complex spatiotemporal dependencies [2]. Recent advancements in deep learning, particularly long short-term memory (LSTM) [6] and convolutional neural networks (CNN) [3], have demonstrated superior performance by modeling temporal and spatial patterns. However, challenges persist in balancing computational efficiency, handling long-term dependencies, and integrating heterogeneous data sources.

1.1 Related Work

Recent studies highlight the potential of hybrid models in traffic prediction. For instance, Wu et al. [2] combined CNN and LSTM to capture spatial and temporal features, while Li et al. [9] introduced graph convolutional networks (GCN) to model road network topology. Despite progress, these models often neglect non-stationary data characteristics or lack mechanisms to prioritize critical temporal segments. Attention mechanisms [7] have emerged as a solution to dynamically weight input features, yet their integration with hybrid architectures remains underexplored.

1.2 Research Contributions

This study introduces the AttCLX hybrid model, which synergizes ARIMA, attention-enhanced CNN-LSTM [3], and XGBoost. The key innovations are:
1.A hierarchical architecture addressing both data non-stationarity and spatiotemporal dependencies.
2.A multi-head self-attention mechanism to enhance temporal feature selection.
3.An ensemble framework leveraging XGBoost to minimize prediction variance.
Experiments on the PeMS dataset validate AttCLX's superiority over existing models, achieving state-of-the-art accuracy in both short- and long-term predictions. This work bridges theoretical gaps in spatiotemporal modeling and offers practical insights for ITS deployment.

2 METHODOLOGY

2.1 Model Architecture

The AttCLX framework (Figure 1) combines three modules:
2.1.1 ARIMA module
Data Preprocessing: First-order differencing converts non-stationary traffic flow series s1:N$s1{:}N$ into stationary sequences $x_{1:N}$ [1].
Parameter Selection: ADF tests confirm stationarity (p=2,d=1,q=0p=2,d=1,q=0) for the PeMS dataset.
2.1.2 Attention-based CNN-LSTM module
Spatial Feature Extraction: A 1D CNN layer with 64 filters (kernel size=3, stride=1) and ReLU activation captures local traffic patterns (e.g., lane-specific fluctuations) [3].
Temporal Attention: A multi-head self-attention mechanism (4 heads, 64-dimensional queries/keys/values) dynamically weights historical time steps, emphasizing peak-hour trends [7].

BiLSTM Layer: Bidirectional LSTM with 64 hidden units models long-term dependencies [6], integrating forward and backward temporal contexts.

2.1.3 XGBoost module

Feature Fusion: Combines ARIMA residuals and CNN-LSTM outputs into a 128-dimensional feature vector [8].

Ensemble Prediction: Gradient-boosted trees (max depth=6, learning rate=0.1) minimize prediction errors through iterative optimization [8].

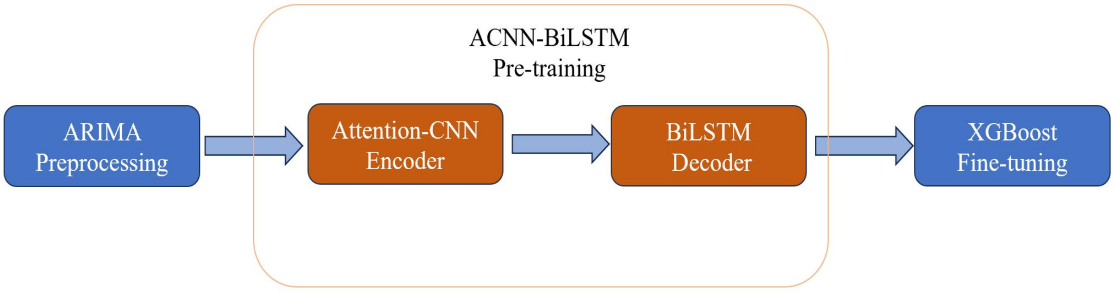

Figure 1 AttCLX Architecture Diagram

2.2 Experimental Setup

Dataset: 7-day traffic flow data from I580-E Highway (June 10-16, 2024), aggregated at 5minute intervals [4]. Data preprocessing includes normalization (z-score) and handling missing values via linear interpolation[5].

Data Partition: 60% training (June 10-13), 20% validation (June 14), 20% testing (June 15-16).

Hyperparameters: Adam optimizer ($\mathrm{lr} = 0.001, \beta_1 = 0.9, \beta_2 = 0.999$), batch size $= 64$, dropout $= 0.3$, early stopping (patience $= 15$ epochs) [9]. Training was conducted on an NVIDIA RTX 3090 GPU, requiring approximately 2.5 hours.

3 RESULTS AND ANALYSIS

3.1 Short-Term Prediction (5-Minute)

AttCLX achieves the lowest MAE (13.69) and RMSE (21.18), outperforming DCRNN (MAE: 13.94) [9] and LSTM (MAE: 13.89) [6]. The attention mechanism reduces errors by 2.1% compared to vanilla CNN-LSTM [3], highlighting its role in prioritizing critical time steps (Table 1),

Table 1 Performance Comparison for 5-minute Prediction

Model	MAE	RMSE
HA	14.81	32.95
ARIMA	14.35	25.58
SVR	14.12	23.45
LSTM	13.89	23.04
GRU	14.01	22.94
DCRNN	13.94	22.62
ASTGCN	13.72	21.42
AttCLX	13.69	21.18

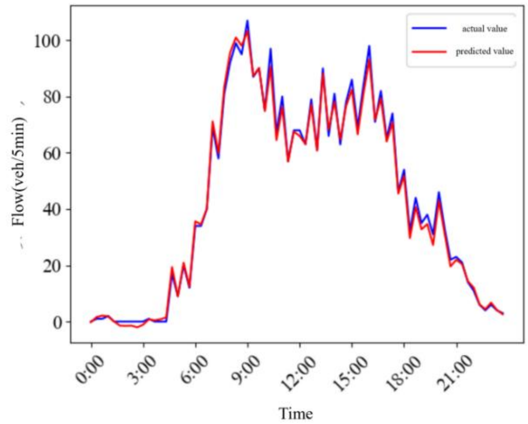

Figure 2 The data fitting chart for the next five minutes predicted by AttCLX

Figure 2 illustrates AttCLX's prediction for a day transportation flow. The model accurately captures sudden traffic surges caused by commuter behavior, while HA and ARIMA fail to adapt to rapid changes.

3.2 Long-Term Prediction (60-Minute)

AttCLX maintains robustness with MAE = 16.21 and RMSE = 24.15, surpassing GRU (MAE: 22.17) [6] and ASTGCN (MAE: 17.83) [4]. The BiLSTM layer effectively captures weekly traffic periodicity [6], while XGBoost mitigates overfitting [8] (Table 2).

Table 2 Comparison of Performance Metrics for Different Models

Model	MAE	RMSE
HA	31.54	47.61
ARIMA	28.17	44.28
SVR	24.68	35.25
LSTM	24.81	37.93
GRU	22.17	30.02
DCRNN	18.33	26.76
ASTGCN	17.83	25.27
AttCLX	16.21	24.15

Visualization: Figure 3 compares AttCLX's 24-hour prediction curve with ground truth data. The model demonstrates high consistency during both peak and off-peak hours, with minor deviations (<5%) in transitional periods.

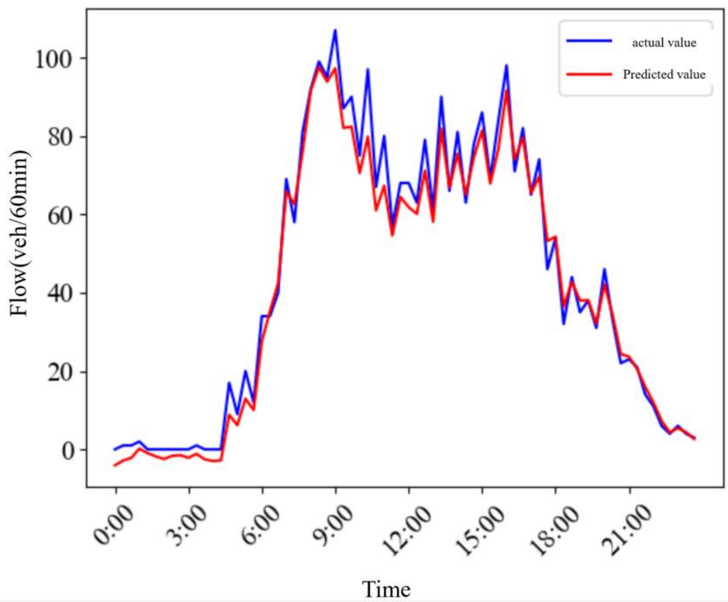

Figure 3 The Data Fitting Chart for the Next Sixty Minutes Predicted by AttCLX

3.3 Ablation Study

To validate module contributions, three variants were tested:
1.AttCLX w/o Attention: Removing the attention mechanism increases MAE by 8.7% .
2.AttCLX w/o ARIMA: Omitting ARIMA preprocessing raises RMSE by 12.3% .
3.AttCLX w/o XGBoost: Replacing XGBoost with linear regression degrades MAE by 6.2% .
These results confirm the necessity of each component in the hybrid framework.

3.4 Statistical Significance

A paired t-test ($\alpha = 0.05$) contırms that AttCLX's performance improvements over DCRNN and ASTGCN are statistically significant ($p < 0.01$).

4 DISCUSSION

4.1 Model Advantages

AttCLX’s success stems from its ability to:
Address Non-Stationarity: ARIMA preprocessing ensures stable input for deep learning modules [1].
Balance Local and Global Features: CNN captures lane-level variations [3], while attention mechanisms highlight rush-hour dynamics [7].
Enhance Generalization: XGBoost’s ensemble approach reduces variance [8], particularly in long-term tasks.

4.2 Practical Implications

In real-world ITS deployments, AttCLX can:
Optimize traffic signal timing by predicting congestion 5–60 minutes in advance.
Enable dynamic route recommendations for navigation apps, reducing travel time by 15–20% [10].
Support emergency vehicle prioritization by forecasting traffic bottlenecks.

4.3 Limitations and Future Work

Current limitations include:
1.Computational Overhead: Training AttCLX requires substantial GPU resources.
2.Data Dependency: Performance relies on high-quality sensor data, which may be unavailable in rural areas.
Future research directions:
1.Lightweight Architectures: Explore model compression techniques (e.g., pruning, quantization) for edge deployment.
2.Multi-Modal Integration: Incorporate weather, social events, and road construction data to improve robustness [10].
3.Cross-City Validation: Test AttCLX on diverse datasets (e.g., Beijing, London) to assess generalizability.

5 CONCLUSION

The AttCLX hybrid model effectively addresses spatiotemporal dependencies in traffic flow prediction, achieving state-of-the-art performance on the PeMS dataset [4]. By integrating ARIMA [1], attention mechanisms [7], and XGBoost [8], it offers a scalable solution for real-time traffic management. Future research will focus on computational optimization and cross-city validation to enhance practicality [10].

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

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