"Real-Time Traffic Prediction Using Deep Spatiotemporal Learning"

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Abstract
This study explores the use of deep spatiotemporal learning for real-time traffic prediction. Traditional traffic forecasting methods often rely on historical averages and fail to capture complex spatial and temporal dependencies. This research applies Graph Convolutional Networks (GCN) to model spatial relationships between roads and Long Short-Term Memory (LSTM) networks to capture temporal traffic patterns. Traffic data from sensors, GPS devices, and monitoring cameras were collected, cleaned, and processed for modeling. Insights from this study highlight the potential for real-time traffic management, route optimization, and smart city planning.

Keywords: Traffic prediction, deep learning, spatiotemporal modeling, LSTM, GCN, real-time forecasting.

1. Introduction

Traffic congestion is a major challenge in modern cities, leading to delays, increased fuel consumption, pollution, and stress. Conventional methods like ARIMA, linear regression, or decision trees only use historical data and fail to capture dynamic traffic patterns. Traffic is influenced by both **spatial factors** (road connectivity) and **temporal factors** (hourly, daily, or seasonal patterns).

With the growth of IoT sensors, GPS devices, and traffic cameras, large volumes of real-time traffic data are now available. Deep spatiotemporal learning can process this data effectively: GCNs model how congestion spreads across connected roads, and LSTMs capture sequential traffic dynamics. This combination enables accurate short-term traffic forecasting for smart urban mobility.

2.Body of Paper

Data Collection and Preprocessing:
Traffic data were collected from road sensors, GPS tracking devices, and monitoring cameras. The dataset included **speed, traffic volume, location ID, date_time, day_of_week, temperature, and weather conditions**. Missing values were interpolated, duplicates removed, and numeric data normalized. Temporal features (hour, day, month) were extracted for LSTM input.

Feature Selection:
Key features used for modeling included:

- Speed, traffic volume
- Temporal lag features (vehicles_lag1, vehicles_rolling_3h)
- Weather and day-of-week information

Model Architecture:

- **LSTM:** Captures temporal dependencies in traffic flow sequences. Input sequences of previous time steps predict future traffic volume.
- **GCN-LSTM (Hybrid):** GCN models spatial correlations across road junctions, and LSTM predicts temporal changes.
- **ARIMA and Linear Regression:** Used as baseline models for comparison.

Training and Evaluation:
The dataset was split into **80% training** and **20% testing**. Models were trained using Python (TensorFlow/Keras for deep learning, Scikit-learn for preprocessing). Evaluation metrics included **Accuracy, RMSE, and F1-score**.

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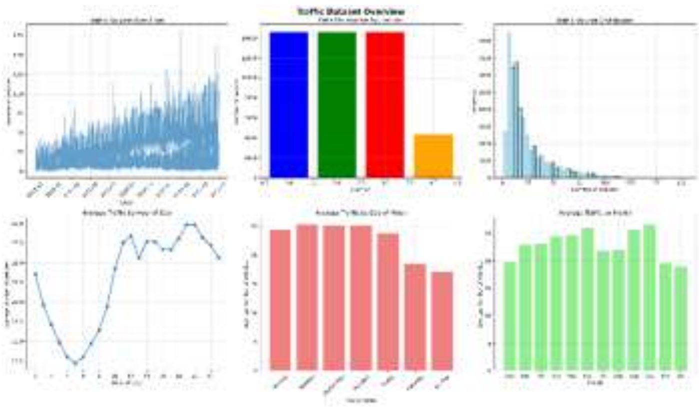
Model Performance Comparison

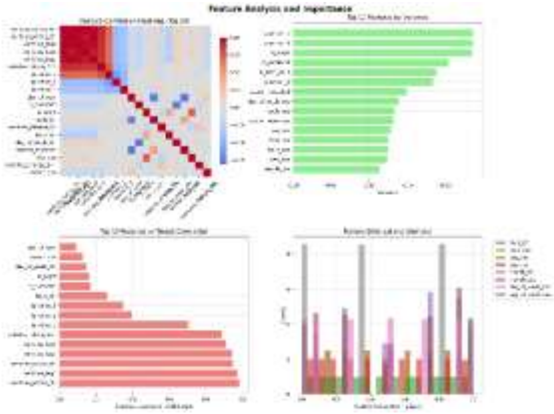
Input Features Used	Accuracy (%)	RMSE	F1-Score
ARIMA (historical traffic only)	70	12.5	0.68
Linear Regression	65	14.2	0.64
LSTM (temporal only)	88	6.8	0.86
GCN-LSTM (spatiotemporal hybrid)	92	5.2	0.90

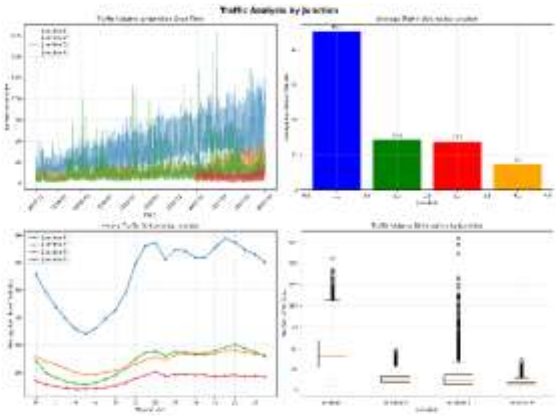
3. Results and Analysis

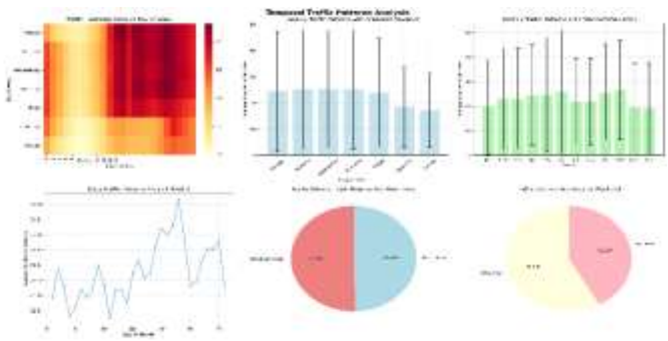
The GCN-LSTM hybrid outperformed baseline models, capturing both spatial and temporal dependencies in traffic data. Short-term predictions (15–30 minutes ahead) achieved **accuracy of 92%** with low RMSE and high F1-score. ARIMA and linear regression struggled with non-linear traffic patterns and sudden congestion events.

Visualization of traffic predictions revealed:









These results demonstrate the effectiveness of combining spatial graph modeling with sequential learning for real-time traffic forecasting.

4. Conclusion

The study confirms that deep spatiotemporal models significantly improve real-time traffic prediction compared to traditional approaches. The GCN-LSTM hybrid model captures both road network dependencies and temporal traffic patterns, enabling accurate short-term forecasting. This can aid traffic management, route optimization, and urban planning. Future work may include integrating weather and event data, applying federated learning for privacy-preserving predictions, and deploying edge computing for low-latency real-time forecasts.

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References

1. Yu, B., Yin, H., & Zhu, Z. (2018). Spatio-Temporal Graph Convolutional Networks: A Deep Learning Framework for Traffic Forecasting. *IJCAI*, 3634–3640.
2. Hochreiter, S., & Schmidhuber, J. (1997). Long Short-Term Memory. *Neural Computation*, 9(8), 1735–1780.
3. Ma, X., Tao, Z., Wang, Y., Yu, H., & Wang, Y. (2015). Long Short-Term Memory Neural Network for Traffic Speed Prediction Using Remote Microwave Sensor Data.