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Future Traffic Prediction Using Deep Learning: A Hybrid Approach with LSTM and Graph Neural Networks

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Abstract

This paper presents a hybrid deep learning-based approach for future traffic prediction aimed at enhancing urban traffic management. With increasing urbanization and vehicular density, efficient traffic forecasting has become critical. The proposed model integrates Long Short-Term Memory (LSTM) networks and Graph Neural Networks (GNNs) to capture temporal and spatial dependencies within traffic data. Historical and real-time data from OpenStreetMap and Google Maps Distance Matrix API are utilized for training. A Flask-based web application offers real-time visualization and predictions. Results demonstrate the model's robustness in predicting traffic flow, thereby supporting data-driven urban planning.

Keywords: Traffic prediction, deep learning, LSTM, Graph Neural Networks (GNN), spatial-temporal modeling, smart cities.

1. Introduction

Urban traffic congestion is a growing problem as cities expand, leading to inefficiencies, delays, and environmental impacts. The ability to predict future traffic patterns is critical for city planners, traffic management authorities, and urban designers in managing congestion and improving mobility. This paper addresses the need for advanced traffic prediction systems by employing deep learning techniques Predict traffic flow. In particular, this study uses long-term networks (long-term memory) to record temporal dependencies and Graph Neural Networks (GNN) to analyze spatial patterns within road networks. The combination of these models provides a robust framework capable of predicting congestion hotspots and traffic trends across urban regions. By leveraging real-time and historical traffic data, The system is designed as follows to offer actionable insights For traffic management and urban planning. The project aims to enhance traffic prediction accuracy and provide valuable visualizations to support data-driven decision-making.

2. Related Work

Literature Survey

Medina-Salgado et al. (2022) reviewed Various computer technologies for predicting urban traffic flow and identified key challenges in mobility data analysis. Akhtar and Moridpour (2021) provided a comprehensive review of artificial intelligence-based traffic congestion prediction models, emphasizing real-time capabilities.

Kadiyala Ramana et al. (2023) introduced a Vision Transformer (VT) model integrated with CNN for improved urban traffic prediction. Their technique utilized tokenization and projection to surpass conventional approaches in accuracy and recall.

Kashyap et al. (2021) explored deep learning models like CNN, RNN, and LSTM, highlighting their effectiveness in capturing high-level traffic features from raw input data. Similarly, Binshaflout et al. (2023) focused on the application of GNNs for traffic pattern recognition, stressing their potential for enhancing traffic management systems.

Benarmas and Bey (2024) proposed a three-step deep learning framework using LSTM, generative models, and N-BEATS for accurate traffic prediction using real data from Beijing. Sahayaraj et al. (2024) presented a hybrid GNN and Gated-Attention GRU model, enhancing both spatial and temporal pattern recognition in traffic forecasting.

Ahmed et al. (2024) highlighted the benefits of multi-source data fusion via GNNs for improved prediction accuracy in dynamic urban conditions. Abduljabbar et al. (2021) tested an LSTM model on Melbourne traffic data, demonstrating superior performance over RNN and DLBP in short-term forecasting.

Finally, Deekshetha et al. (2022) applied regression-based machine learning models for 1-hour traffic prediction, identifying heavily congested roadways using past and current data.

SNo	Title	Author(s)	Year
1	Urban traffic flow prediction techniques: A review	Boris Medina-Salgado, Pilar Pozos-Parra, Javier E. Sierra	2022
2	A Review of Traffic Congestion Prediction Using Artificial Intelligence	Mahmuda Akhtar, Sara Moridpour	2021
3	A Vision Transformer Approach for Traffic Congestion Prediction in Urban Areas	Kadiyala Ramana, Gautam Srivastava, Madapuri Rudra Kumar, Thippa Reddy Gadekallu	2023
4	Traffic flow prediction models – A review of deep learning techniques	Anirudh Ameya Kashyap, Shravan Raviraj, Ananya Devarakonda	2021
5	Graph Neural Networks for Traffic Pattern Recognition: An Overview	Elham Binshaflout, Hakim Ghazzai, Yehia Massoud	2023
6	A deep learning-based framework for road traffic prediction	Redouane Benabdallah Benarmas, Kadda Beghdad Bey	2024
7	Optimizing Urban Traffic Flow Prediction: Integrating Spatial–Temporal Analysis with a Hybrid GNN and Gated-Attention GRU Model	K. Kishore Anthuvan Sahayaraj, Ayush Chodnekar, Ananya Mishra	2024
8	Enhancement of traffic forecasting through graph neural network-based information fusion techniques	Shams Forruque Ahmed, Sweety Angela Kuldeep, Amir H. Gandomi	2024
9	Short-Term Traffic Forecasting: An LSTM Network for Spatial-Temporal Speed Prediction	Rusul L. Abduljabbar, Hussein Dia, Sohani Liyanage	2021
10	Traffic Prediction Using Machine Learning	H. R. Deekshetha, A. V. Shreyas Madhav, Amit Kumar Tyagi	2022

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3. Proposed Work

The system aims to predict traffic patterns for future urban growth using a hybrid model combining Graph Neural Networks (GNN) and Long Short-Term Memory (LSTM). It collects road network data through OpenStreetMap and real-time traffic data via the Google Maps Distance Matrix API. Traffic data is stored in an SQLite database with separate tables for nodes, edges, and traffic information. GNN processes spatial relationships, while LSTM analyzes temporal data to forecast future traffic conditions. The model is trained using historical data and evaluated with metrics like MAE, MAPE, RMSE, and R^2. A Flask-based web application provides an interactive user interface with real-time and historical traffic data. The application visualizes traffic conditions on a map, with color-coded road segments for light, moderate, or heavy traffic. The system integrates data collection, analysis, and prediction components seamlessly. The goal is to support urban infrastructure development by predicting congestion.

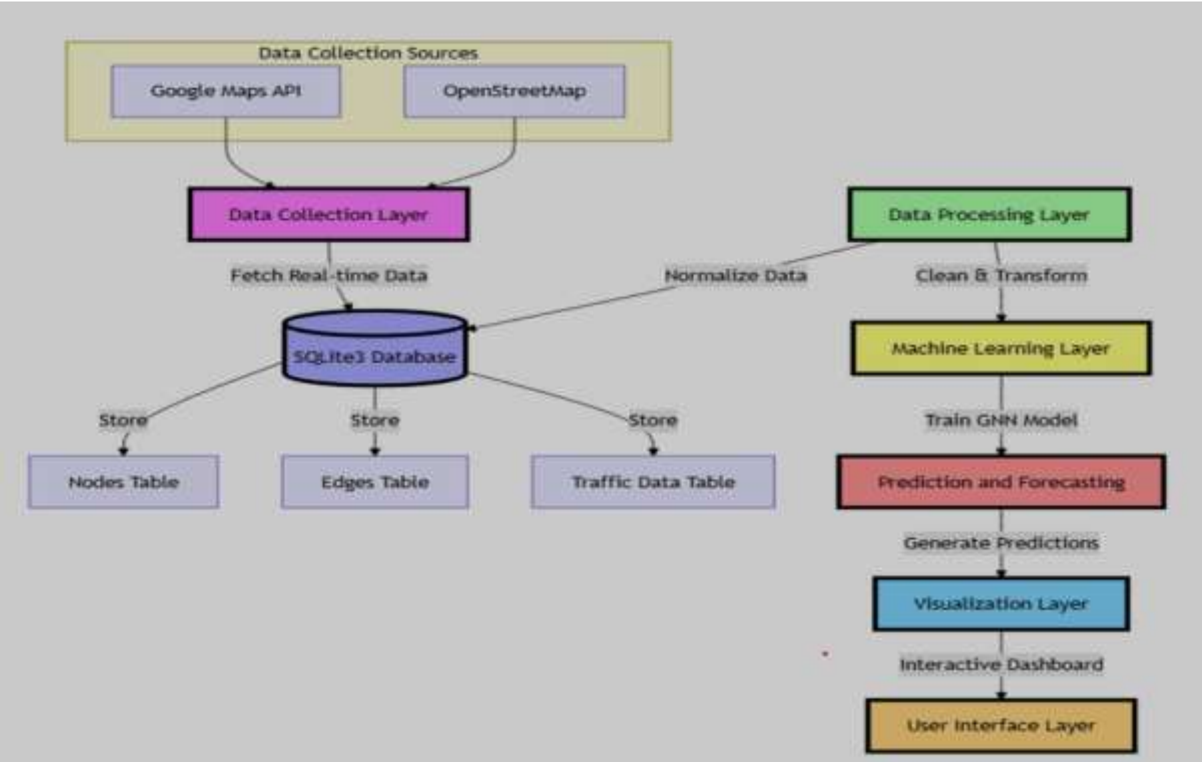

Fig1. Proposed Architecture

The architecture begins with data collection from Google Maps API and OpenStreetMap, which provide real-time and geographical traffic data. This data is gathered by the Data Collection Layer and stored in a SQLite3 database. The database maintains structured information across three tables: Nodes, Edges, and Traffic Data. These tables help represent the road network and traffic flow efficiently for further processing. The Data Processing Layer takes the raw data and performs normalization to prepare it for analysis. After transforming the data, it is passed to the Machine Learning Layer. The model is trained to understand spatial-temporal relationships within the data. The trained model is then used in the Prediction and Forecasting Layer to generate traffic predictions. Finally, these predictions are sent to the Visualization Layer, which creates an interactive dashboard. The User Interface Layer allows end-users to explore traffic forecasts.

4. Implementation

The system is designed to collect and process real-time traffic data using the Google Maps API. The data collection begins with road network information gathered from OpenStreetMap, including details on roads, intersections, and geographical coordinates. This data is used to analyze traffic patterns and make future predictions using a hybrid model of Graph Neural Networks (GNN) and Long Short-Term Memory (LSTM) networks. The GNN captures spatial dependencies within the road network, while the LSTM identifies temporal trends in traffic data. Both components are combined to provide accurate traffic speed predictions across different road segments. A Flask-based web application serves as the user interface, allowing users to interact with the traffic data and predictions. The web application integrates features such as map visualization with color-coded road segments, displaying real-time traffic conditions. The system's performance is assessed using metrics such as Mean Absolute Error (MAE) and Root Mean Square Error (RMSE), and integration testing ensures that all components function smoothly

5. Results

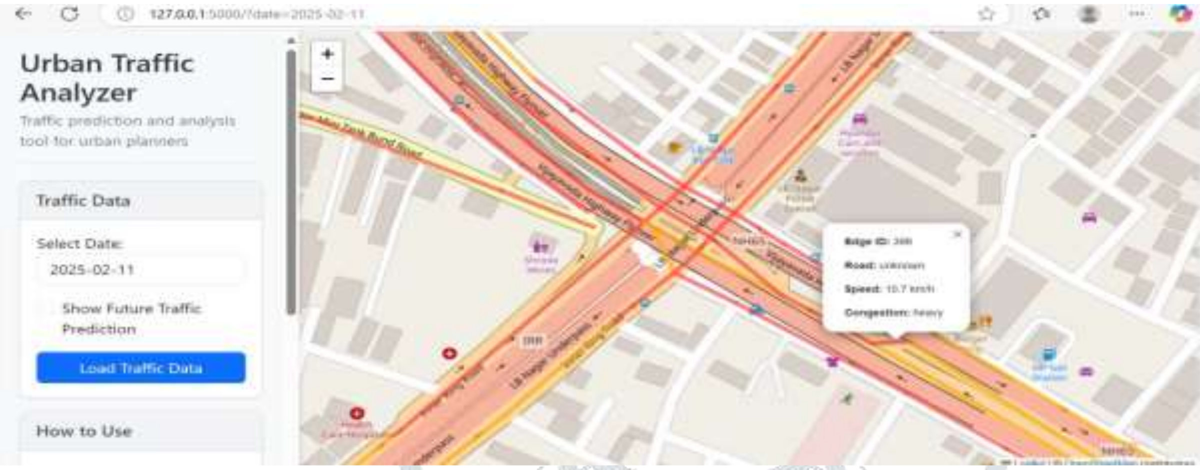

Figure 1: Visualization of Historical Traffic Data with Congestion Indicators

Figure1 displays actual traffic data for a past date, with a map showing congestion levels on different road segments. Selecting a road segment shows details like vehicle speed, edge ID, road name, and congestion status, highlighting a congested area.

Figure 2: Forecasted Traffic Congestion Visualization

Figure 2 shows the predictive functionality of the system, where traffic congestion is forecasted based on past data. A pop-up includes predicted values, helping to anticipate future traffic issues

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=== Final Training Loss ===
Initial Loss: 87.9134
Final Loss: 11.3140
Improvement: 87.13%

Starting evaluation with 353 test samples

=== Accuracy Metrics ===
Mean Absolute Error (MAE): 1.19 km/h
Mean Absolute Percentage Error (MAPE): 6.34%
Root Mean Square Error (RMSE): 2.01 km/h
R-squared: 0.9296
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Figure 3: Model Evaluation Metrics for Traffic Prediction

Figure3 presents the model's evaluation after training, showing key metrics such as MAE, MAPE, RMSE, and R^2 Score, which demonstrate the accuracy and reliability of the model in predicting traffic patterns.

6. Conclusion

The Urban Traffic Analysis and Prediction System is a significant advancement in traffic management, combining machine learning with urban planning. The system uses a hybrid approach of Graph Neural Networks (GNN) and Long Short-Term Memory (LSTM) networks. GNNs are used to capture the spatial relationships between different road segments in the traffic network, while LSTMs model the temporal patterns of traffic flow over time. This combination allows for accurate predictions of traffic patterns. The system provides valuable insights for dynamic routing and infrastructure planning, using an SQLite database for efficient data storage and a Flask web application for easy visualization of results. Overall, it demonstrates the effectiveness of machine learning in addressing real-world urban traffic challenges.

References

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