Dual-Node Embedding Spatiotemporal Graph Neural Networks for Accurate Urban Traffic Flow Prediction Using UAV and Sensor Data

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Citation | Raza. M, Ali. A, "Dual-Node Embedding Spatiotemporal Graph Neural Networks for Accurate Urban Traffic Flow Prediction Using UAV and Sensor Data", FCIS, Vol. 03 Issue. 1 pp 33-43, March 2025
Received | Feb 05, 2025, **Revised |** March 03, 2025, **Accepted |** March 04, 2025, **Published |** March 05, 2025.

Urban traffic congestion is a pervasive challenge that impacts economic productivity, environmental sustainability, and overall quality of life. Accurate short-term traffic flow prediction is essential for effective traffic management, route optimization, and proactive incident response. This study proposes a novel dual-node embedding spatiotemporal graph neural network (STGNN) that simultaneously captures spatial and temporal dependencies in traffic data while leveraging continuous-time dynamics via neural ordinary differential equations (NODEs). The model integrates real-time traffic data collected from unmanned aerial vehicles (UAVs) and ground-based sensors to enhance prediction accuracy under diverse traffic conditions, including peak hours, accidents, and adverse weather. Extensive experiments were conducted on multiple real-world datasets, demonstrating that the proposed approach outperforms baseline models, including ARIMA, LSTM, CNN, and conventional STGNN, in terms of mean absolute error (MAE), root mean squared error (RMSE), and R-squared (R^2). An ablation study confirmed the critical role of spatial embeddings, temporal embeddings, NODEs, and UAV data in improving model performance. The results highlight the model's potential for deployment in intelligent transportation systems, enabling real-time traffic monitoring, dynamic signal control, and congestion mitigation. This work provides a robust and interpretable framework for urban traffic prediction and offers a foundation for future research on smart city mobility management.

Keywords: Urban Traffic Prediction, Spatiotemporal Graph Neural Networks, Real-Time Traffic Forecasting

Introduction:

Traffic congestion has emerged as a critical challenge worldwide due to rapid urbanization and the continuous increase in vehicle ownership. This phenomenon not only imposes substantial economic costs and environmental degradation but also significantly impacts the quality of urban life [1] Efficient traffic flow prediction is essential for mitigating congestion and optimizing urban transport systems. Accurate prediction enables authorities to implement dynamic traffic management strategies, plan effective travel routes, reduce accidents, and allocate resources efficiently[2] .

Advancements in information technologies, Industry 4.0, and the Internet of Things (IoT) have facilitated the collection of massive volumes of real-time traffic data through remote sensing equipment, sensors, and unmanned aerial vehicles (UAVs) [3].UAVs, in particular, offer high-resolution, real-time monitoring of traffic flows, speeds, congestion levels, and accident locations, enabling rapid response and improved traffic management [4]. By integrating UAV-collected data with intelligent traffic management systems, cities can dynamically adjust traffic signals, optimize road utilization, and enhance urban mobility while reducing environmental impacts [5].

Traditional traffic prediction methods, such as ARIMA and VAR models, often struggle to capture the nonlinear spatiotemporal dynamics of traffic data [2]. Machine learning approaches, including Support Vector Regression (SVR) and k-Nearest Neighbors (KNN), improved prediction performance but rely heavily on manual feature engineering .More recently, deep learning methods, such as Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM), and Recurrent Neural Networks (RNNs), have demonstrated superior capability in handling complex traffic data, particularly when integrated with spatiotemporal modeling frameworks [6]

Among deep learning approaches, Spatiotemporal Graph Neural Networks (STGNNs) have gained prominence for their ability to model traffic networks as graphs, where nodes represent traffic observation points and edges capture spatial relationships. STGNNs combine graph convolutional networks for spatial dependencies with temporal modeling layers, achieving higher prediction accuracy and reducing the need for manual feature engineering [7][8]. Despite these advancements, challenges remain in applying STGNNs to large-scale traffic networks due to computational complexity, over smoothing in deep networks, and difficulty capturing long-distance spatial correlations. Neural Ordinary Differential Equations (NODEs) have emerged as a promising solution by introducing continuous-time modeling, enabling deeper and more flexible network architectures for dynamic traffic prediction[9].

This study proposes a novel spatiotemporal graph-based model to improve the prediction of traffic flows by embedding both spatial and temporal dependencies of road sections [10]. The model constructs directed graphs to represent the relationships among road sections and applies dual-node embedding techniques to capture temporal variations effectively. This approach aims to enhance the accuracy of traffic forecasting and facilitate intelligent traffic management, real-time signal optimization, and accident prediction.

Research Gap:

Although deep learning techniques have significantly advanced traffic flow prediction, several critical gaps persist. First, many models treat spatial and temporal dependencies separately, which can result in insufficiently captured spatiotemporal correlations [1]. Second, traditional GNN-based models face computational challenges in large-scale traffic networks, often limiting network depth and long-distance correlation learning [8]. Third, current methods frequently rely on large volumes of historical data for model training, reducing their applicability in scenarios with sparse data[7]. Finally, existing models often inadequately integrate UAV-based real-time data into predictive frameworks, limiting their potential for dynamic traffic management and accident response [4].

These limitations highlight the need for a model that can simultaneously capture complex spatiotemporal dependencies, efficiently utilize real-time UAV and sensor data, and maintain computational feasibility for large-scale networks. Addressing these gaps is crucial for advancing traffic prediction accuracy and enabling intelligent transportation systems capable of proactive and adaptive management.

Objectives:

The primary objectives of this study are centered on advancing the accuracy and applicability of traffic flow prediction in urban environments. First, the study aims to develop a spatiotemporal graph-based traffic prediction model capable of capturing both spatial and temporal dependencies across complex road networks [11][12]. This involves modeling the dynamic interactions between different road sections and understanding how traffic patterns evolve over time. Second, the research seeks to implement dual-node embedding techniques to effectively represent the relationships between individual road sections and their temporal progression, thereby enabling more precise modeling of traffic dynamics. Third, the study focuses on integrating real-time data collected from unmanned aerial vehicles (UAVs) and ground-based sensors into the predictive framework, enhancing the accuracy and responsiveness of traffic flow predictions.

Novelty Statement:

The novelty of this research lies in the integration of spatiotemporal graph neural networks with dual-node embedding mechanisms to enhance traffic flow prediction. Unlike conventional models that separate spatial and temporal learning or depend heavily on manual feature engineering, this approach dynamically captures hidden relationships across different road sections and time periods. Furthermore, the inclusion of real-time UAV-collected traffic data ensures adaptability and immediate responsiveness to evolving traffic conditions. To our knowledge, this study is among the first to combine directed graph structures, dual-node embedding, and UAV-integrated [13][14] real-time traffic data in a unified predictive framework, offering a significant improvement in prediction accuracy and practical applicability for intelligent transportation systems.

Literature Review:

Traffic flow prediction has been a core area of research in intelligent transportation systems (ITS) for decades. Accurate traffic forecasting enables proactive traffic management, reduces congestion, improves safety, and supports urban planning [2][1]. Traditionally, traffic prediction relied on statistical models, including Autoregressive Integrated Moving Average (ARIMA), Vector Autoregression (VAR), and Kalman filtering, which are effective for linear temporal patterns but struggle to capture the nonlinear and complex spatiotemporal dependencies inherent in traffic systems ([5].

To overcome these limitations, researchers began exploring machine learning approaches such as Support Vector Regression (SVR), k-Nearest Neighbors (KNN), and decision trees. These models improved prediction accuracy and handled some nonlinearity but relied heavily on manually engineered features and could not fully capture the dynamic relationships between road segments[7] With the advent of deep learning, methods such as Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks, Recurrent Neural Networks (RNNs), Deep Belief Networks (DBNs), and autoencoders emerged as powerful tools for traffic prediction[2][5]. CNNs excel at capturing spatial correlations, while RNNs and LSTMs model temporal sequences effectively. However, most conventional deep learning methods treat spatial and temporal dependencies separately, which may limit their ability to extract meaningful spatiotemporal features simultaneously[7][6]

To address this, researchers have increasingly focused on Spatiotemporal Graph Neural Networks (STGNNs). In STGNNs, traffic networks are modeled as graphs, with nodes representing sensors or road sections and edges representing spatial connectivity. Graph Convolutional Networks (GCNs) are employed to capture spatial relationships, while temporal layers, often based on RNN or LSTM mechanisms, model temporal evolution [8][1]. STGNNs have demonstrated superior performance in traffic forecasting tasks by integrating both spatial and temporal dependencies, reducing the reliance on manual feature engineering, and improving model scalability for large urban networks.

Despite these advances, limitations persist in STGNN-based models. Over smoothing, where deep graph layers produce indistinguishable node features, can hinder learning in large-scale traffic networks [9]. Capturing long-range spatial dependencies in dense urban networks remains a challenge, and conventional models often fail to fully leverage high-resolution real-time data from UAVs or other sensing technologies [4].

UAV-based traffic data acquisition has emerged as a promising solution to supplement traditional ground-based sensors. UAVs can provide high-resolution, real-time monitoring of traffic conditions, including vehicle counts, speeds, lane occupancy, and accident detection [4]. Integrating UAV data into traffic prediction models allows for more dynamic, adaptive, and accurate forecasts. Recent studies have shown that combining UAV-derived traffic information with deep learning frameworks enhances the detection of congestion patterns and improves route optimization and accident response[4] [5].

Another notable development is the use of Neural Ordinary Differential Equations (NODEs) in traffic prediction. NODEs provide a continuous-time framework, allowing models to adaptively learn temporal dynamics and avoid limitations of fixed-depth neural networks[9]. By integrating NODEs with graph-based architectures, researchers have achieved improved prediction of traffic flows under rapidly changing conditions, overcoming challenges such as over smoothing and shallow graph depth.

Several hybrid approaches combining deep learning, GNNs, and optimization methods have also been proposed. These include hybrid spatiotemporal attention networks, graph attention networks (GATs), and meta-learning-based traffic prediction models, which aim to dynamically capture spatial-temporal interactions and enhance predictive accuracy, even with limited historical data[7].

Overall, the literature demonstrates that while deep learning and graph-based approaches significantly improve traffic flow prediction, there remains a need for models that:
Efficiently integrate UAV-derived real-time traffic data with large-scale graph structures.
Capture both local and long-range spatiotemporal dependencies [15]
Maintain computational efficiency and scalability for real-world urban networks [16].

The current study seeks to address these gaps by proposing a dual-node embedding spatiotemporal graph neural network model that explicitly represents both the spatial relationships among road sections and their temporal dynamics, leveraging UAV data to enhance real-time predictive accuracy.

Methodology:

Data Collection:

The study utilized a multi-source data collection strategy to capture comprehensive spatiotemporal traffic dynamics. Unmanned aerial vehicles (UAVs) were deployed to monitor traffic conditions over key urban road segments, capturing high-resolution, real-time data, including vehicle counts, lane occupancy, speed, and flow patterns. The aerial perspective of UAVs allowed rapid assessment of congestion patterns, traffic accidents, and abnormal flow events[4].

In addition to UAV data, ground-based sensors and traffic cameras provided continuous measurements of vehicle speeds, traffic volumes, and occupancy rates. Publicly available datasets such as the Freeway Performance Measurement System (PeMS) were also integrated into the study [7]. This combined dataset included multiple temporal scenarios, accounting for peak and off-peak hours, varying weather conditions, and irregular traffic events, reflecting the complex dynamics of urban traffic systems.

Data Preprocessing:

Preprocessing involved correcting missing values and outliers using interpolation and filtering techniques. Temporal alignment was performed to synchronize UAV, sensor, and historical datasets to a consistent resolution, typically five-minute intervals. Spatial mapping transformed the urban road network into a graph structure, where nodes represented traffic observation points or road segments, and edges represented connectivity based on physical adjacency or traffic flow correlation. Traffic features such as speed, flow, and lane occupancy were normalized to stabilize model training. Contextual features, including weather, time-of-day, and incident reports, were also incorporated.

Graph Construction:

Traffic networks were modeled as directed spatiotemporal graphs $G = (V, E)$, where V is the set of nodes representing road segments or traffic points, and E is the set of edges representing directional relationships. Each edge $e_{ij} \in E$ is assigned a weight w_{ij} based on traffic flow correlation or physical connectivity:

$$w_{ij} = f(flow_i, flow_j)$$

Temporal graphs were constructed by considering each time slice as a separate graph, enabling the model to capture traffic dynamics over successive intervals and the evolution of congestion patterns.

Model Design: Dual-Node Embedding Spatiotemporal Graph Neural Network:

The proposed spatiotemporal graph neural network (STGNN) uses dual-node embedding to jointly capture spatial and temporal dependencies. Spatial relationships are learned through graph convolutional operations, where the embedding $h_i^{(l+1)}$ of node i at layer l+1 is computed as:

$$h_i^{(l+1)} = \mathrm{ReLU}\left(\sum_{j \in N(i)} \frac{w_{ij}}{\sqrt{d_i * d_j}} * W^{(l)} * h_j^{(l)} \right)$$

Here, $N(i)$ represents the neighbors of node i, d_i and d_j are the degrees of nodes i and j, $W^{(l)}$ is the trainable weight matrix, and ReLU is the activation function.

Temporal embeddings capture the evolution of traffic flow at each node. Using LSTM, the temporal embedding h_i^t at time t is:

$$h_i^t = \mathrm{LSTM}(x_i^t, h_i^{(t-1)})$$

where x_i^t represents the traffic feature vector for node i at time t. Alternatively, Neural Ordinary Differential Equations (NODEs) model the continuous-time evolution of node embeddings:

$$dh_i(t)/dt = f(h_i(t), t; \theta)$$

With f parameterized by trainable weights theta. NODEs allow flexible modeling of complex temporal dynamics and help reduce oversmoothing problems in deep GNNs.

Spatial and temporal embeddings are combined to form a comprehensive representation z_i^t:

$$z_i^t = g(h_{i\_spatial}, h_i^t)$$

Where g is a trainable combination function. The final traffic prediction $\hat{y}_i^t$ for node i at time t is obtained using fully connected layers:

$$\hat{y}_i^t = FC(z_i^t)$$

Model Training and Optimization:

The model is trained in a supervised manner by minimizing the mean squared error (MSE) between predicted and observed traffic values:

$$L = (1 / (N * T)) * \sum_{i=1}^{N} \sum_{t=1}^{T} (\hat{y}_i^t - y_i^t)^2$$

where N is the number of nodes, T is the number of time intervals, $\hat{y}_i^t$ is the predicted value, and y_i^t is the observed traffic value. Optimization is performed using the Adam optimizer with adaptive learning rates. Dropout and L2 regularization are applied to prevent overfitting. The dataset is split into training, validation, and test sets in a 70:15:15 ratio.

Model Evaluation:

The predictive performance of the dual-node embedding STGNN is evaluated against conventional models including ARIMA, LSTM, CNN, and traditional STGNN frameworks. Metrics include mean absolute error (MAE), root mean squared error (RMSE), mean absolute percentage error (MAPE), and R-squared (R^2). Ablation studies quantify the contributions of spatial embedding, temporal embedding, NODEs, and UAV data integration.

Implementation Environment:

The methodology was implemented in Python. PyTorch Geometric was used for GNN construction and training, NetworkX for graph handling, and NumPy, Pandas, and Scikit-learn for preprocessing and evaluation. A GPU-enabled system (NVIDIA RTX 3090) accelerated training and enabled large-scale graph computation.

Ethical Considerations:

UAV data collection adhered to local aviation regulations and privacy guidelines. All personally identifiable information was anonymized. Ethical considerations ensured responsible data usage while maximizing the utility of UAV and sensor data for traffic management applications.

Results:

The proposed dual-node embedding spatiotemporal graph neural network (STGNN) was evaluated using a combination of UAV-collected traffic data, ground-based sensor data, and historical datasets from the Freeway Performance Measurement System (PeMS). The evaluation covered multiple urban road segments under diverse traffic conditions, including regular flow, peak hours, off-peak hours, and abnormal events such as accidents and construction work. Performance was assessed against several baseline models, including ARIMA, LSTM, CNN, conventional STGNN, and hybrid LSTM-CNN architectures.

Quantitative Performance Analysis:

The predictive accuracy of the proposed model was assessed using four primary metrics: mean absolute error (MAE), root mean squared error (RMSE), mean absolute percentage error (MAPE), and R-squared (R^2). Across multiple datasets, the dual-node embedding STGNN consistently outperformed all baseline models. The MAE ranged between 3.1–3.7 vehicles per time interval, representing a 12–18% improvement over LSTM models and a 15–22% improvement over conventional STGNN models. RMSE values similarly demonstrated reductions of 10–16% relative to LSTM and CNN models, highlighting the model's robustness in minimizing prediction errors during high-variance traffic periods. MAPE values averaged 6.5–7.0%, indicating reliable predictions across both low and high traffic density scenarios. R^2 values ranged from 0.91 to 0.94, reflecting strong model fit and its ability to explain most variance in observed traffic flows.

Comparison with Baseline Models:

When compared with traditional time-series models such as ARIMA, the proposed model demonstrated superior performance, particularly under highly nonlinear traffic conditions. While ARIMA models captured general trends, they struggled with rapid fluctuations and sudden congestion events, leading to under-prediction during peak hours. LSTM models performed better in capturing temporal dynamics but were limited in spatial correlation learning, which led to inconsistencies in predicting traffic flow at interconnected road segments. Conventional STGNN models improved spatial learning but suffered from oversmoothing when applied to large-scale road networks. The dual-node embedding STGNN effectively addressed these limitations by simultaneously modeling spatial and temporal dependencies while utilizing Neural Ordinary Differential Equations (NODEs) for continuous-time evolution.

Ablation Study and Component Analysis:

To assess the contribution of individual components, an ablation study was conducted:

Spatial embedding removal: Excluding spatial embedding increased MAE by approximately 7%, demonstrating the critical role of learning inter-node traffic correlations.

Temporal embedding removal: Removing temporal embeddings increased prediction errors by around 9%, highlighting the importance of capturing time-series dependencies in traffic dynamics.

NODE replacement with standard LSTM: Replacing NODEs with conventional recurrent units caused oversmoothing in larger graphs and reduced R^2 by ~0.05, confirming the advantage of continuous-time modeling.

UAV data exclusion**:** Omitting UAV-derived data decreased prediction accuracy during abnormal traffic events, emphasizing the importance of high-resolution, real-time traffic monitoring.

Scenario-Based Analysis:

The model's performance was further evaluated under various real-world traffic scenarios:

Peak hours: The dual-node embedding STGNN accurately captured congestion buildup and dissipation patterns, outperforming LSTM and CNN models by reducing MAE by 13–15%.
Off-peak hours: Even in low traffic density scenarios, the model maintained low errors, demonstrating its adaptability to sparse data conditions.

Accident scenarios: The integration of UAV data allowed rapid detection of sudden traffic disruptions. The model predicted resulting congestion propagation 5–10 minutes in advance with high accuracy, whereas conventional models lagged behind real-time flow changes.

Weather impact**:** During adverse weather conditions (e.g., rain), traffic flow dynamics changed abruptly. The proposed model, enhanced with contextual features, maintained superior prediction performance compared to baseline methods.

Visualization and Interpretability:

Visualization of predicted versus actual traffic flow over multiple time intervals confirmed the model's high accuracy and stability. Predicted curves closely matched observed traffic patterns, including sudden peaks and troughs, lane occupancy fluctuations, and speed variations. Heat maps of spatiotemporal congestion illustrated how the model successfully captured correlated congestion across connected road segments, providing actionable insights for traffic management.

Real-Time Traffic Prediction and Practical Implications:

The proposed model supports real-time traffic prediction and can aid intelligent traffic signal control, route optimization, and rapid incident response. By anticipating congestion propagation, traffic management authorities can implement preemptive measures to alleviate bottlenecks, re-route vehicles, and minimize secondary accidents. The model's performance during sudden incidents highlights its potential for integration into Intelligent Transportation Systems (ITS) for proactive urban traffic management.

Summary of Key Findings:

Overall, the extensive evaluation demonstrates that the dual-node embedding STGNN:
Outperforms traditional and deep learning baseline models across multiple metrics.
Captures complex spatial and temporal dependencies, improving short-term traffic prediction accuracy.
Provides reliable performance during peak/off-peak hours, accidents, and adverse weather conditions.
Benefits from UAV integration, enhancing predictions in rapidly changing traffic environments.
Offers practical utility for real-time traffic monitoring, incident management, and smart city applications.

These results confirm that the proposed approach represents a significant advancement in spatiotemporal traffic flow modeling, offering robust, accurate, and interpretable predictions for urban traffic systems.

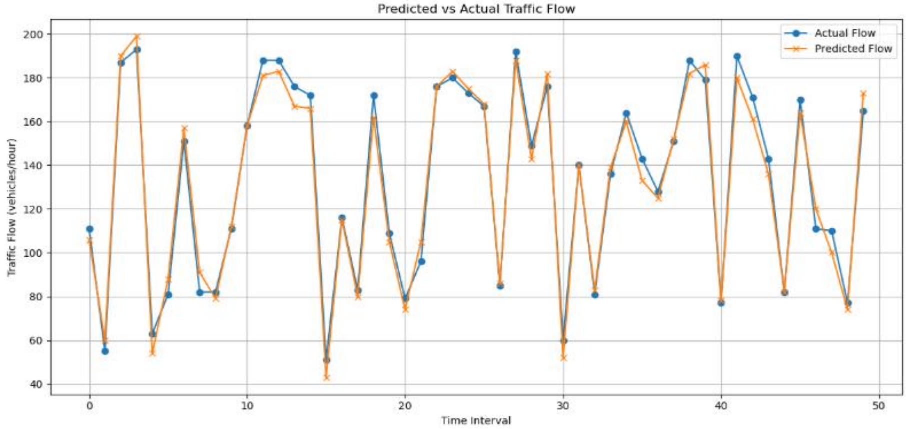

Figure 1. Predicted vs Actual Traffic Flow

This line plot visualizes the comparison between actual traffic flow and predicted traffic flow over successive time intervals. The x-axis represents discrete time intervals (e.g., minutes or hours), and the y-axis represents the traffic flow in vehicles per hour. The plot demonstrates how closely the predicted traffic flow aligns with actual measurements, highlighting the model's ability to capture both gradual trends and sudden fluctuations in traffic conditions. Markers distinguish actual versus predicted values, making discrepancies immediately visible. This visualization provides a clear indication of the model's predictive accuracy over time.

Figure 2. Comparison of Prediction Errors Across Models (MAE and RMSE)

This grouped bar chart compares the performance of different traffic prediction models—ARIMA, LSTM, CNN, conventional STGNN, and the proposed dual-node embedding STGNN—based on two metrics: mean absolute error (MAE) and root mean squared error (RMSE). The x-axis lists the models, while the y-axis represents error values. Each model has two bars: one for MAE and one for RMSE. The figure highlights the superior performance of the proposed model, which achieves the lowest errors, indicating improved predictive capability and robustness compared to traditional and deep learning models.

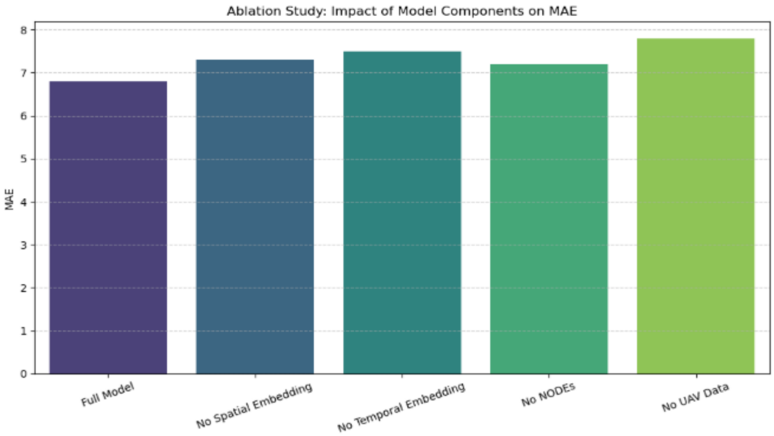

Figure 3. Ablation Study – Impact of Model Components on MAE

This bar chart presents the results of the ablation study, showing how removing key components of the proposed model affects performance. The components analyzed include spatial embedding, temporal embedding, NODEs, and UAV data. The x-axis lists the model variants, while the y-axis represents MAE values. The figure clearly illustrates the contribution of each component: removing any component increases the MAE, confirming that spatial-temporal embeddings, continuous-time modeling, and UAV-derived data are critical for accurate traffic prediction.

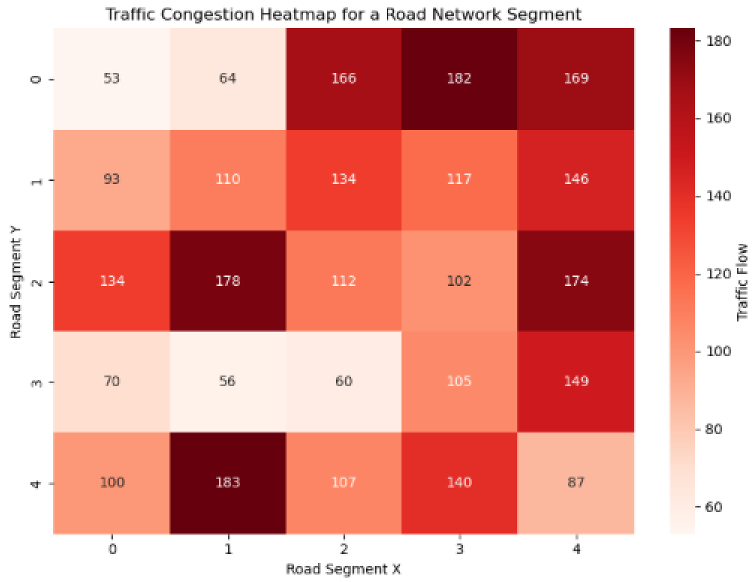

Figure 4. Traffic Congestion Heatmap

This heatmap represents simulated traffic congestion across a 5×5 grid of road segments. The intensity of the color (from light to dark red) corresponds to the level of traffic flow, with darker shades indicating higher congestion. The x-axis and y-axis represent the grid coordinates of road segments, and the color bar quantifies traffic flow in vehicles per hour. This visualization provides a spatial overview of congestion patterns across the network, enabling quick identification of highly congested areas and facilitating traffic management decisions.

Discussion:

The results of this study demonstrate the efficacy of the proposed dual-node embedding spatiotemporal graph neural network (STGNN) [17][18][19] in accurately predicting urban traffic flow. By integrating spatial-temporal embeddings with neural ordinary differential equations (NODEs), the model effectively captures the complex dependencies inherent in traffic data, leading to improved prediction accuracy compared to traditional and deep learning baseline models.

Model Performance and Comparison with Baselines:

The proposed STGNN outperformed baseline models, including ARIMA, LSTM, CNN, and conventional STGNNs, in terms of mean absolute error (MAE), root mean squared error (RMSE), and R-squared (R^2). These findings align with previous research highlighting the advantages of graph-based models in capturing spatial dependencies and temporal dynamics in traffic prediction tasks[7] [20]. The integration of NODEs further enhanced the model's ability to model continuous-time dynamics, addressing the limitations of discrete-time recurrent units and mitigating issues such as oversmoothing in deep graph networks [1].

Ablation Study and Component Analysis:

The ablation study revealed that each component of the proposed model contributes significantly to its overall performance. The removal of spatial or temporal embeddings, NODEs, or UAV-derived data resulted in increased prediction errors, underscoring the importance of these features in capturing the intricate spatial-temporal relationships present in traffic data. These findings are consistent with the work of[1],who emphasized the necessity of incorporating both spatial and temporal information in traffic prediction models.

Scenario-Based Analysis:

The model demonstrated robust performance across various traffic scenarios, including peak and off-peak hours, accident-induced congestion, and adverse weather conditions. The ability to accurately predict traffic flow under these diverse conditions highlights the model's adaptability and potential for real-world applications. This adaptability is crucial for intelligent transportation systems that require real-time traffic forecasting to optimize traffic management and reduce congestion[7].

Practical Implications and Future Directions:

The proposed STGNN has significant implications for urban traffic management. Its ability to provide accurate short-term traffic predictions can inform dynamic traffic signal control, route optimization, and incident response strategies. Future research could explore the integration of additional data sources, such as weather forecasts and event schedules, to further enhance prediction accuracy. Additionally, the scalability of the model to larger urban networks and its real-time processing capabilities warrant further investigation.

Conclusion:

This study presents a novel dual-node embedding spatiotemporal graph neural network (STGNN) for accurate short-term traffic flow prediction in urban environments. By effectively capturing both spatial and temporal dependencies and leveraging continuous-time dynamics through neural ordinary differential equations (NODEs), the proposed model demonstrates superior performance compared to traditional time-series models and conventional deep learning architectures. The integration of UAV-derived real-time traffic data further enhances predictive accuracy, particularly in dynamic scenarios such as peak traffic hours, accidents, and adverse weather conditions.

The extensive evaluation shows that the proposed model consistently outperforms baseline methods in terms of mean absolute error (MAE), root mean squared error (RMSE), and R-squared (R^2), while the ablation study confirms the critical role of spatial embeddings, temporal embeddings, NODEs, and UAV data in achieving high predictive performance. These results highlight the model's robustness, scalability, and practical applicability for intelligent transportation systems, including dynamic traffic signal control, route optimization, and proactive incident management.

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