Masters Thesis Information Showcase
Spring Semester-2026
Year 2026

Department: Mathematics
Programme: Masters of Science
Specialization: Applied Mathematics

1	**Title of the Thesis** Graph Neural Network Analysis of Traffic Networks
2	**Abstract** (min 300 to 500 words) Accurate traffic forecasting is essential for intelligent transportation systems, urban mobility management, congestion reduction, and sustainable smart-city development. However, road traffic exhibits complex spatial and temporal dependencies that conventional forecasting approaches may not adequately capture. This study proposes a Graph Spatio-Temporal Neural Network (GSTNN) framework for traffic network forecasting by integrating graph-based spatial learning with temporal sequence modeling. Real-world road networks are represented as graphs in which intersections or traffic locations correspond to nodes and roads represent edges, enabling the model to capture structural dependencies among interconnected locations. Graph Convolutional Neural Networks are employed to learn spatial relationships and traffic propagation across road networks, while Long Short-Term Memory networks model temporal variations and sequential traffic behavior. The proposed framework is evaluated using three large-scale real-world road networks from Texas, California, and Pennsylvania, providing diverse structural environments for assessing model robustness and generalizability. Performance is evaluated using AUC-ROC, coefficient of determination, Mean Absolute Error, Root Mean Square Error, and graph structural consistency. Comparative experiments demonstrate that the proposed GSTNN consistently outperforms the baseline GCN across all three datasets. The strongest performance is achieved on the California road network, where GSTNN obtains an AUC-ROC of 0.85, R^2 of 0.81, MAE of 0.24, RMSE of 0.35, and structural consistency score of 0.82. On the Texas and Pennsylvania networks, the proposed model similarly demonstrates improved predictive and structural performance. Experimental comparison further indicates that incorporating temporal information improves testing accuracy over spatial-only graph learning, demonstrating the importance of jointly modeling road connectivity and evolving traffic patterns. Overall, the findings demonstrate that integrating spatial graph representations with temporal sequence learning provides a robust approach for real-world traffic forecasting. The proposed GSTNN framework offers potential support for intelligent traffic management, congestion prediction, route optimization, smart signaling, and data-driven transportation planning, thereby contributing toward efficient, adaptive, and sustainable urban mobility systems.
3	**Impact on SDG#___"** (min 500 words) (Please mention the impact of the relevant attained SDG) The most relevant Sustainable Development Goal for this research is **United Nations SDG 11: Sustainable Cities and Communities**, particularly its emphasis on developing safe, resilient, inclusive, and sustainable urban environments. The research addresses a

fundamental smart-city challenge: accurately understanding and forecasting traffic conditions across complex road networks.

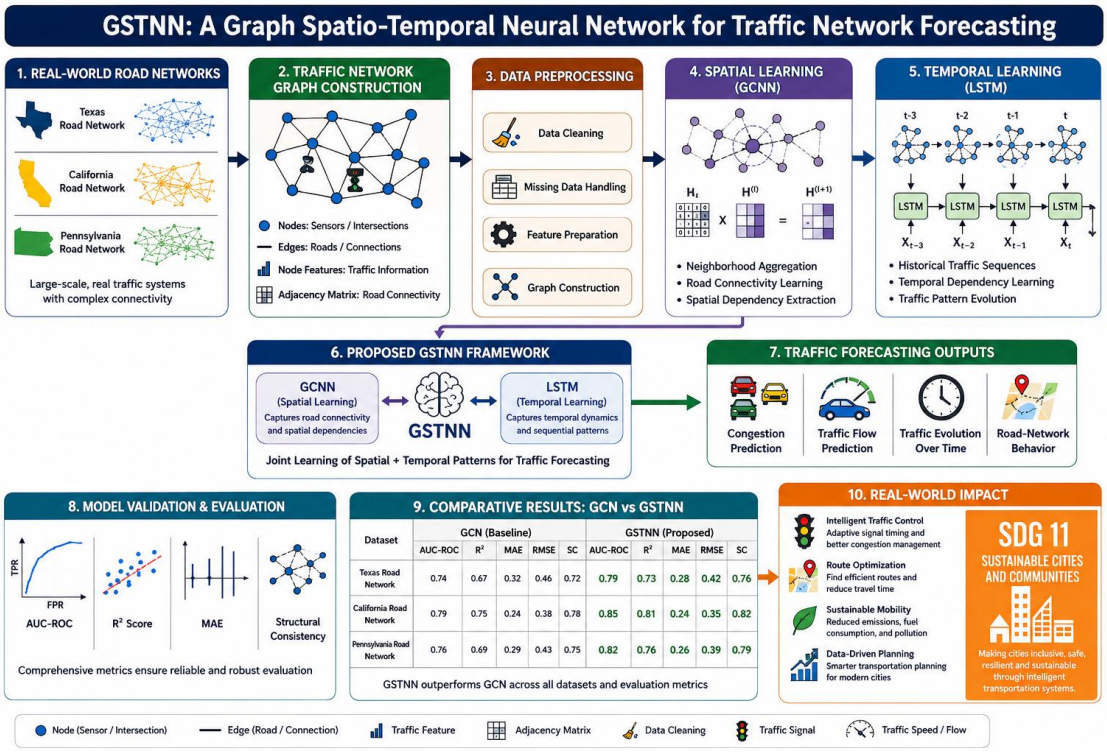
Rapid urbanization and increasing transportation demand create significant challenges, including traffic congestion, longer travel times, inefficient route utilization, and pressure on existing transportation infrastructure. The paper specifically identifies the need for improved traffic-management solutions in rapidly growing cities and proposes Graph Neural Networks as a mechanism for understanding traffic behavior across interconnected locations.

The proposed **Graph Spatio-Temporal Neural Network (GSTNN)** contributes to sustainable urban transportation by simultaneously modeling the spatial and temporal characteristics of traffic. Road systems are naturally represented as graphs, where intersections or traffic sensors constitute nodes and roads form edges. Graph-based learning enables the framework to identify how traffic conditions at one location influence connected locations, while temporal learning captures how those conditions evolve over time. The paper implements this through the integration of graph-based spatial learning and LSTM-based temporal modeling.

A major contribution of the research is its application to **large-scale real-world road networks**. The framework considers road-network datasets from Texas, California, and Pennsylvania. These datasets contain complex connectivity structures and provide geographically distinct environments for evaluating whether the proposed methodology can operate beyond a single network configuration. For example, the Texas network contains approximately 1.39 million nodes, while the California network contains approximately 1.96 million nodes.

The experimental findings further support the potential of GSTNN for intelligent transportation applications. Across all three datasets, GSTNN achieves higher AUC-ROC and R^2 values, lower MAE and RMSE, and higher structural consistency than the baseline GCN. These improvements indicate that incorporating both spatial connectivity and temporal traffic behavior can provide more effective traffic-network prediction than spatial graph modeling alone.

The framework can consequently support smart-city applications such as **traffic congestion forecasting, intelligent signal management, route optimization, transportation planning, and adaptive traffic control**. By anticipating changing traffic conditions, intelligent transportation systems can potentially improve road utilization and reduce unnecessary travel delays.

From the sustainability perspective, improved traffic forecasting may also indirectly contribute to reduced fuel consumption and transportation-related emissions by helping vehicles avoid prolonged congestion and enabling transportation authorities to manage road infrastructure more efficiently. This environmental effect is a reasonable application of the framework, although the present paper does **not directly measure emissions or fuel**

	consumption, so it should be presented as potential impact rather than an experimentally demonstrated result. Overall, the research contributes to **SDG 11** by advancing an AI-driven framework for smarter and more adaptive transportation systems. Its integration of graph neural networks, temporal modeling, real-world road-network analysis, and predictive traffic analytics provides a computational foundation for developing more efficient, connected, and sustainable urban mobility infrastructure.
4	**Scholar Name** (along with contact details) Sadaqat Ali sadaqatalitunio770@gmail.com
5	**Supervisor & Co-supervisor Name** (along with contact details) Dr. Ubaida Fatima
6	**Graphical Abstract**