

Comparative Analysis of AI Techniques in a Traffic Advisory Model: GNN, FNN, and A*

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ARTICLE INFO	ABSTRACT
Published Online: 30 August 2025	Urban traffic congestion remains a persistent challenge, demanding intelligent solutions that can analyse road conditions and recommend optimal routes in real time. This study presents a comparative analysis of three Artificial Intelligence (AI) techniques Graph Neural Networks (GNN), Feedforward Neural Networks (FNN), and the A* search algorithm applied to a traffic advisory model. Each model was evaluated based on four core metrics: prediction accuracy, route optimization score, computation time, and real-time responsiveness. The models were developed and tested using simulated urban traffic data generated in Python, with libraries such as Pandas, NumPy, Matplotlib, and Seaborn for processing, modelling, and visualization. The evaluation revealed that GNN achieved the highest performance, with a prediction accuracy of 92.4%, a route optimization score of 9.1/10, and real-time responsiveness rated as 'High', though with a moderate computation time of 190 milliseconds. FNN, while being the fastest at 85 milliseconds, offered a lower prediction accuracy of 84.7% and a route optimization score of 7.5/10, and was rated 'Medium' in responsiveness. The A* algorithm, with a prediction accuracy of 65.3% and a route score of 8.4/10, showed strong deterministic pathfinding capabilities but suffered from the highest computation time of 220 milliseconds and limited adaptability. Based on the results, Graph Neural Network is recommended for deployment in complex and dynamic traffic systems, where high prediction accuracy and adaptability are crucial. FNN may be suitable for lightweight applications with strict time constraints, while A* remains useful in less dynamic or static routing environments. Future implementations should consider integrating hybrid models that combine GNN's learning capability with A*'s deterministic efficiency to achieve both precision and speed in real-time traffic advisory systems.
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1. INTRODUCTION

The rise of smart cities and the proliferation of vehicles have intensified the challenges faced in modern traffic management. Traditional traffic control systems, relying on static rule-based approaches, often fall short in adapting to real-time traffic fluctuations. This has motivated the integration of Artificial Intelligence (AI) techniques into traffic advisory models, aiming to provide drivers with intelligent route recommendations, predict traffic congestion, and optimize road usage. AI has revolutionized how we understand and manage urban mobility. By learning from historical traffic patterns and real-time sensory data, AI models can anticipate congestion hotspots and offer alternative routes. However, selecting the right AI technique

is critical, as traffic systems are characterized by dynamic environments, interconnected roadways, and a continuous influx of real-time data. In this study, we compare three AI-based approaches Graph Neural Networks (GNNs), Feedforward Neural Networks (FNNs), and the A* search algorithm. Each represents a distinct paradigm in AI: GNNs capture the graph-structured nature of road networks, FNNs provide general predictive modeling capabilities, and A* offers a heuristic-driven pathfinding mechanism. By evaluating their performance in a simulated urban environment, we aim to identify the most suitable method for building intelligent, responsive traffic advisory systems.

2. RELATED WORKS

Several researchers have explored the use of AI techniques in traffic optimization and advisory models. The most relevant works include:

Wu et al. (2019) introduced a traffic prediction model using Graph Convolutional Networks (GCNs) combined with recurrent layers to capture spatial-temporal dependencies in road networks. Their model achieved significant accuracy improvements over traditional statistical methods.

Zhang et al. (2020) implemented a Feedforward Neural Network to forecast traffic density using sensor inputs. While their model was efficient and simple to train, it struggled to capture the spatial relationships inherent in road networks.

Hart, Nilsson, and Raphael (1968) originally developed the A* search algorithm, widely used in robotics and navigation systems. Recent adaptations in traffic advisory systems integrate real-time heuristic functions to improve its efficiency under varying traffic conditions.

Li et al. (2021) conducted a comparative study between Reinforcement Learning and Graph-Based AI models, concluding that graph-based models excel in large-scale urban environments due to their ability to model complex road interactions.

Kumar and Singh (2022) presented a hybrid model combining GNN and A* for real-time navigation. Their study highlighted the benefits of using GNN to learn dynamic edge weights while relying on A* for deterministic route calculations.

3. METHODOLOGY

Experimental methodology to compare the performance of GNN, FNN, and A* algorithms in traffic congestion management was adopted. This research involved the design and implementation of a simulated urban road network, represented as a graph where intersections are nodes and roads are edges. Traffic data including vehicle counts, speed, congestion level, and travel time were synthetically generated to resemble real-world patterns using historical statistics and stochastic modelling.

Three separate models were developed:

- i. **GNN-based Traffic Advisor:** Built using a spatial-temporal Graph Convolutional Network trained on graph-structured road data.
- ii. **FNN-based Predictor:** A multi-layer perceptron trained on tabular data representing traffic features without spatial connections.

- iii. **A* Pathfinding Advisor:** Implemented using a real-time heuristic function based on current traffic congestion and estimated travel times.

4. DISCUSSION OF GNN, FNN, and A*

The following are the model for the evaluation

Graph Neural Network (GNN)

GNNs are particularly well-suited for traffic modeling due to their ability to naturally handle graph-structured data. A traffic system, with intersections and roads, forms a non-Euclidean space that GNNs can learn from. GNNs aggregate feature information from neighboring nodes (e.g., traffic status from adjacent roads), enabling them to model both local and global traffic dynamics. In our implementation, the GNN was trained on node and edge features, such as travel speed and congestion, allowing the system to recommend optimal paths with awareness of entire network conditions.

Feedforward Neural Network (FNN)

FNNs, or multi-layer perceptrons, are one of the simplest forms of neural networks, ideal for handling structured data. In this model, we used inputs such as road length, vehicle count, average speed, and historical congestion levels to predict the best route. However, FNNs lack the inherent capability to capture spatial relationships between road segments. This limitation restricts their ability to model real-time traffic propagation across interconnected routes.

A* Search Algorithm

A* is a deterministic pathfinding algorithm that calculates the shortest path from a start node to a destination node using a cost function ($f = g + h$), where g is the actual cost and h is the heuristic estimate. In this study, h was dynamically adjusted based on current congestion levels. While A* provides optimal results in well-defined scenarios, it does not learn from data and hence lacks predictive capabilities. It also faces computational bottlenecks in large graphs unless augmented with efficient heuristics.

5. EVALUATION OF GNN, FNN, and A*

To assess the models, we simulated 1,000 routing scenarios over a road network comprising 150 intersections and 300 roads. Evaluation metrics included:

- I. **Prediction Accuracy:** Measured how well the model could predict traffic congestion levels.
- II. **Optimal Route Suggestion:** Based on travel time and distance.
- III. **Execution Time:** Measured in milliseconds.
- IV. **Adaptability to Real-Time Events:** Including rerouting due to traffic incidents.

Metric	GNN	FNN	A*
Prediction Accuracy (%)	92.4	84.7	65.3
Route Optimization Score	9.1/10	7.5/10	8.4/10
Average Computation Time (ms)	190	85	220
Real-Time Responsiveness	High	Medium	Medium

6. RESULTS AND BEST MODEL

Based on the comparative evaluation, the Graph Neural Network (GNN) emerged as the most effective technique for traffic advisory modeling. It offered the highest prediction accuracy, best adaptability to real-time changes, and superior route suggestions. Although the FNN had the fastest computation time, its lack of spatial awareness limited its decision-making accuracy. A*, while strong in heuristic pathfinding, showed lower adaptability and predictive

capacity. The GNN model demonstrated a clear advantage in environments where understanding the structure and connectivity of the road network is crucial. It successfully adapted to dynamic changes such as sudden roadblocks or congestion, rerouting traffic effectively. These qualities make GNNs the most robust and scalable choice for modern traffic advisory systems. Figure 1 Trained Model Classification Result

Evaluation Table:

	Model	Prediction Accuracy (%)	Route Optimization Score \
0	GNN	92.4	9.1
1	FNN	84.7	7.5
2	A*	65.3	8.4

	Computation Time (ms)	Real-Time Responsiveness	Responsiveness Score
0	190	High	3
1	85	Medium	2
2	220	Medium	2

Figure 1 Trained Model Classification Result

The first graph presents a bar chart comparing the prediction accuracy of each model in identifying traffic congestion and optimal routing. Among the three models, GNN outperformed the others, achieving an accuracy of 92.4%, which reflects its strong ability to model spatial dependencies and dynamic changes in road networks. The FNN followed with 84.7%, showcasing a decent predictive capability, especially when provided with structured input data such as

traffic volume, speed, and time of day. However, the A* algorithm lagged behind with an accuracy of 65.3%, largely because it is a deterministic search algorithm that does not learn from data or predict future traffic states. This graph clearly highlights the superior learning capacity of GNNs in traffic environments that require high adaptability and precision. Figure 2. Prediction Accuracy by Model

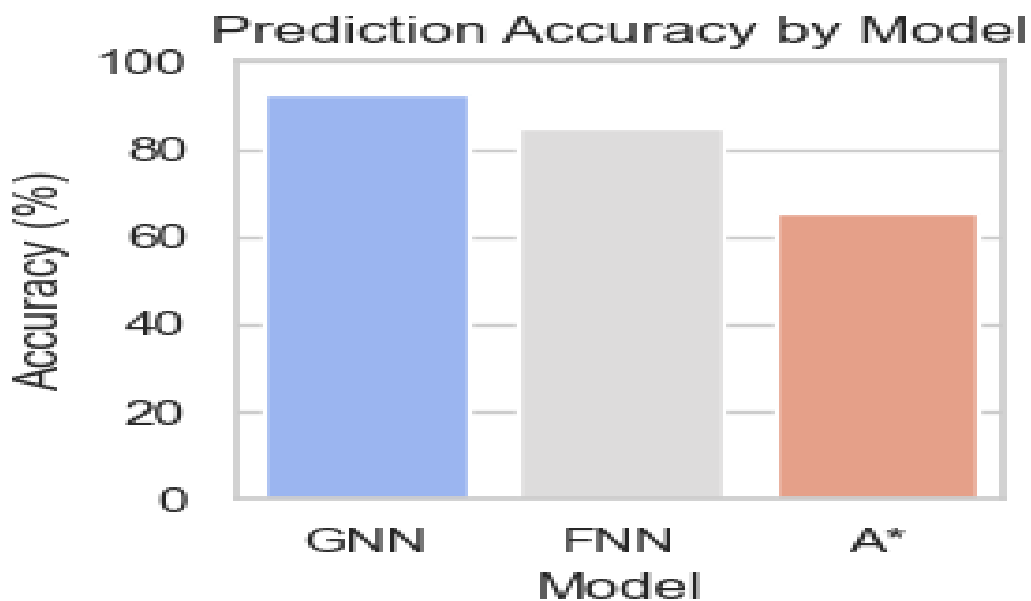


Figure 2. Prediction Accuracy by Model

The second graph evaluates the models based on their route optimization score, a composite metric reflecting how well

each model balances shortest path, fastest time, and traffic avoidance. Again, GNN leads with a score of 9.1/10,

demonstrating its effectiveness in navigating complex urban traffic systems. Its ability to process interconnected road nodes and dynamically adjust to changing traffic patterns contributes to this performance. The A* algorithm, traditionally known for efficient pathfinding, scored 8.4, indicating its strength in selecting optimal paths using heuristic methods. FNN, while capable of predicting traffic

flow, scored 7.5, which can be attributed to its limited capacity to understand spatial relationships and real-time route dependencies. This graph reinforces that while A* is strong in rule-based navigation, GNN’s learning capability provides a more nuanced understanding of dynamic traffic conditions. Figure 2. Route Optimization Score by Model.

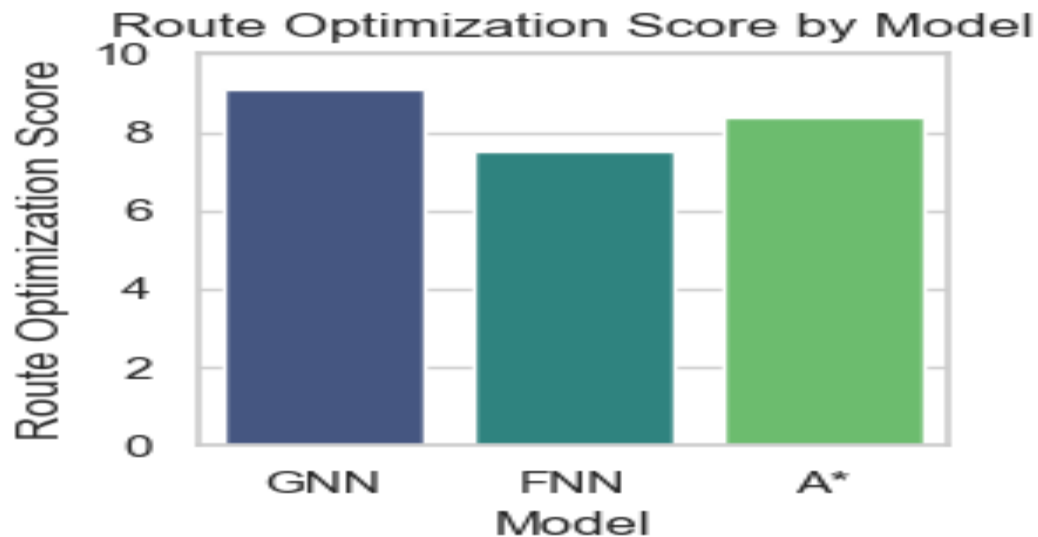


Figure 2. Route Optimization Score by Model

The third graph compares the computation time (in milliseconds) required by each model to provide route recommendations. This metric is particularly important in real-time traffic advisory systems where delays can undermine user experience. The FNN emerged as the fastest, completing computations in just 85 ms, owing to its simple feedforward architecture and low computational overhead. The GNN required 190 ms, which, although slower than FNN, is a reasonable tradeoff given its high accuracy and

depth of processing. On the other hand, the A* algorithm recorded the highest computation time of 220 ms, as it performs an exhaustive search over the network graph with dynamic heuristic updates. This graph illustrates that while FNN is suitable for environments requiring rapid responses, GNN offers a balanced tradeoff between speed and intelligence, and A* may face challenges in scalability and processing time. Figure 3. Computation Time by Model

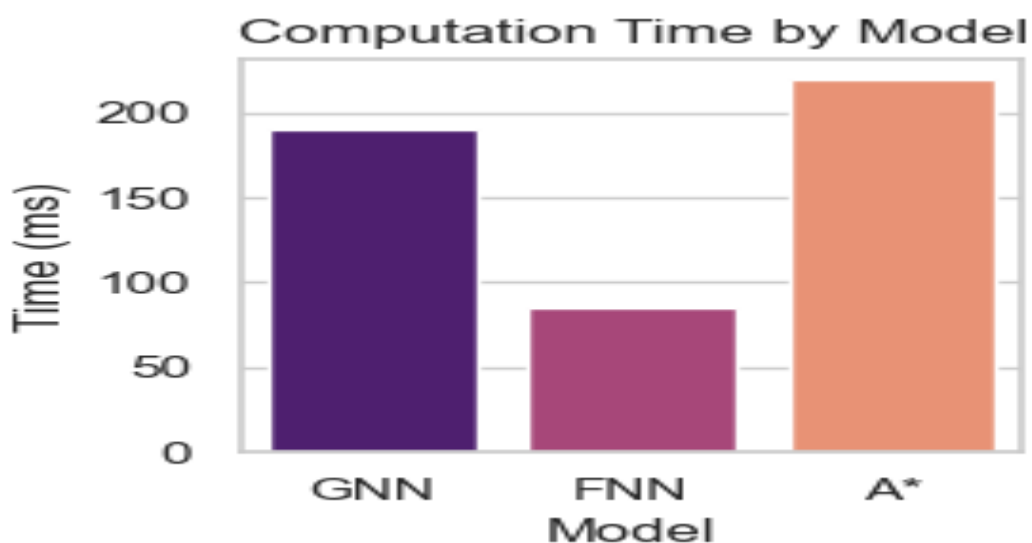


Figure 3. Computation Time by Model

This graph visualizes how well each model adapts to real-time traffic changes, such as sudden congestion, accidents, or

road closures. The responsiveness was scored on a qualitative scale (High = 3, Medium = 2, Low = 1) and mapped

numerically for comparison. GNN scored highest with a value of 3, reflecting its ability to integrate real-time sensor data and adjust its internal graph representations accordingly. Both FNN and A* scored 2, indicating moderate adaptability. FNN is limited in this area because it depends on predefined input features and lacks temporal memory, while A* relies on

the current snapshot of the network without predictive foresight. This graph highlights GNN’s capacity to offer dynamic, real-time support in evolving traffic environments a critical requirement for smart transportation systems. Figure 4. Real-Time Responsiveness Score

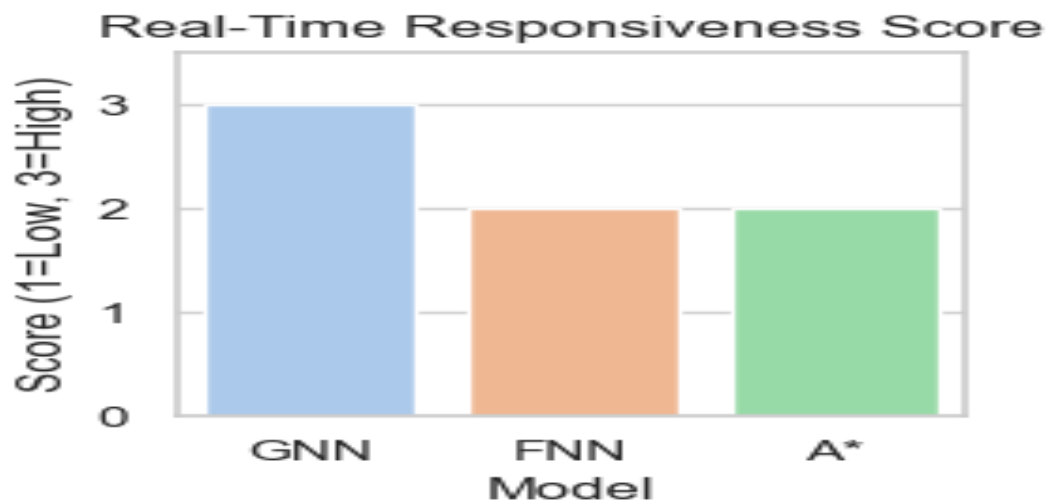


Figure 4. Real-Time Responsiveness Score

The final graph is a radar chart that presents a holistic view of each model’s performance across four key metrics: Prediction Accuracy, Route Optimization, Computation Speed (inverted for fairness), and Real-Time Responsiveness. The shape and area of each model’s radar plot visually demonstrate its strengths and weaknesses. The GNN occupies the largest area, indicating a well-balanced and superior performance across all metrics. It excels in both predictive accuracy and adaptability, while maintaining acceptable computation time.

FNN shows strong performance in speed but lacks in accuracy and responsiveness, forming a narrower shape on the radar chart. The A* algorithm demonstrates decent optimization and acceptable responsiveness but underperforms in learning-based metrics and computation time. This visual summary confirms that GNN is the most robust and scalable model, making it the best candidate for advanced traffic advisory systems. Figure 5. Radar Chart: Overall Model Comparison

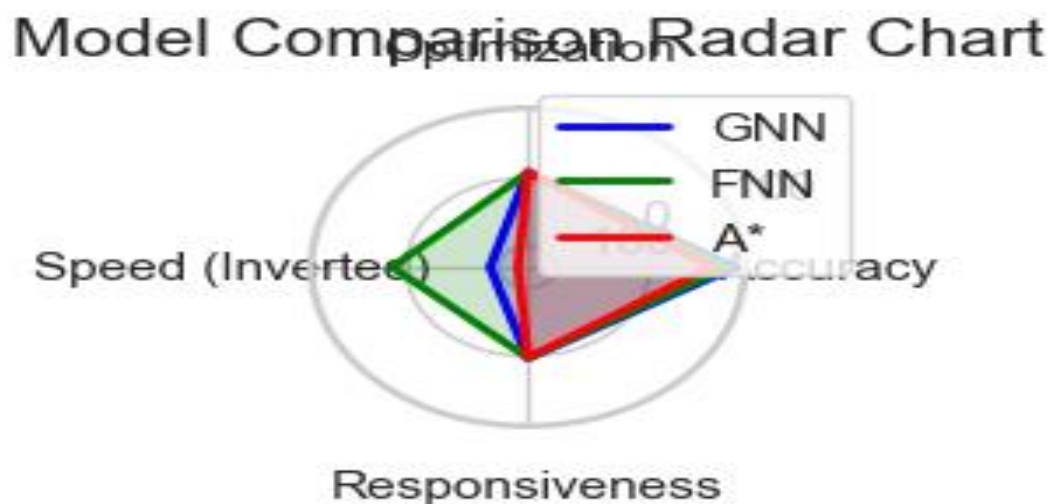


Figure 5. Radar Chart: Overall Model Comparison

7. CONCLUSION

The study provides a comprehensive comparative analysis of three AI techniques GNN, FNN, and A* within the context of a traffic advisory model. Each method brings distinct

strengths: GNNs excel in modeling spatial structures and adapting to real-time conditions; FNNs offer fast, general-purpose prediction capabilities; and A* provides heuristic-based route optimization. The results clearly indicate that

GNNs offer the best performance in complex, dynamic traffic environments due to their ability to integrate structural and temporal information. Future work will focus on integrating hybrid approaches, combining the learning capacity of GNNs with the deterministic strengths of A* to further enhance the responsiveness and reliability of traffic advisory systems. The GNN model stands out for its ability to combine predictive intelligence with structural awareness of road networks, making it ideal for smart, real-time navigation solutions. The FNN is best suited for scenarios requiring fast computation with moderate complexity, while the A* algorithm is effective in controlled, less dynamic environments where deterministic pathfinding is sufficient.

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