

An Intelligent Traffic Recommendation System for Efficient Urban Mobility

Bassey, Aniefiok Tom¹, Prof Nathaniel Ojekudo², Prof Wilson Nwankwo³

^{1,2,3} Department of Computer Science, Ignatius Auru University of Education, Port Harcourt, Nigeria

ARTICLE INFO	ABSTRACT
Published Online: 03 June 2026	Traffic management systems are vital for modern cities, aiming to optimize vehicle and pedestrian flow, improve safety, and reduce congestion. Despite widespread deployment of traffic technologies, urban congestion remains a persistent issue due to rapid city expansion, population growth, and increased vehicle movement, causing economic costs and health hazards from pollution. This study developed an Intelligent Traffic Advisory Model (ITAM) using a fuzzy-graph neural network (FGNN) to recommend efficient routes and reduce signal-induced congestion. The fuzzy inference engine handled traffic uncertainties, while the graph-based engine modeled network nodes and edges. Candidate routes were evaluated using a multi-criteria framework, with Dijkstra's algorithm as a baseline for shortest paths and A* for traffic-aware planning. The model was tested with simulations and real-world urban datasets, showing strong performance: commute times decreased by 18.4%, peak-hour throughput increased by 22.1%, and fuel efficiency improved by 12.9%. The ITAM offered real-time, adaptive route recommendations and a multi-stakeholder framework for traffic authorities and emergency services. IoT-enabled sensors, adaptive traffic lights, and live data integration were recommended to maintain and improve the FGNN model's accuracy. This study contributes to intelligent traffic management by combining fuzzy logic and graph neural networks for adaptive, precise route recommendations. Simulation results showed 98.3% accuracy, demonstrating the model's effectiveness and the advantage of a proactive, scalable, and modular traffic management approach over traditional reactive systems.
Corresponding Author: Bassey, Aniefiok Tom	
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1. INTRODUCTION

Rapid urbanization and the exponential growth in private vehicle ownership have intensified traffic congestion in major cities worldwide. Traffic management systems were developed to optimize vehicular and pedestrian flow through the integration of traffic signals, sensors, and communication networks [1]. These systems collect and analyze real-time data to regulate signal timing, monitor road conditions, and coordinate incident responses. Advanced systems further employ predictive algorithms and machine learning techniques to anticipate traffic patterns and dynamically adjust operations [2].

Beyond improving mobility, efficient traffic management enhances road safety and reduces environmental and economic losses. However, congestion remains a persistent challenge, particularly in rapidly urbanizing regions. In many

developing cities, demand for road transport significantly exceeds supply, resulting in severe delays and reduced productivity [3]. Infrastructure expansion, such as road widening, often provides only temporary relief and may encourage further private vehicle usage, ultimately worsening congestion.

In Nigeria, the economic impact of congestion is alarming. Reports indicated that cities such as Port Harcourt and Lagos incur substantial productivity and revenue losses annually due to prolonged traffic delays [4]. These losses arise from increased fuel consumption, delayed goods delivery, higher vehicle operating costs, and adverse public health effects.

Traffic congestion is commonly classified into three types: recurring congestion, non-recurring congestion, and sequential traffic signal trapping. Recurring congestion occurs during peak travel periods when traffic demand

exceeds road capacity. Non-recurring congestion results from unpredictable incidents such as accidents, roadworks, or adverse weather conditions [5]. Sequential signal trapping congestion arises from poorly coordinated traffic signals, where vehicles encounter successive red lights, thereby increasing delay and queue lengths.

The causes of congestion can further be categorized into environmental, mechanical, human, and infrastructural factors. Weather conditions, vehicle breakdowns, unsafe driving behaviors, inadequate driver training, and poor road infrastructure collectively contribute to traffic inefficiencies. Despite technological advancements, many existing systems remain reactive rather than proactive and often rely on limited sensor data.

Although several traffic management technologies have been implemented, congestion persists due to increasing urban populations, rapid motorization, and limitations in traditional traffic control strategies. Existing systems frequently lack predictive intelligence and personalized advisory capabilities, thereby failing to provide proactive solutions to drivers.

The growing economic losses, environmental degradation, and safety risks associated with traffic congestion create an urgent need for an intelligent traffic advisory system. Such a system should leverage real-time data analytics, machine learning techniques, and adaptive signal coordination to predict congestion patterns and deliver timely guidance to road users. Developing a proactive, data-driven traffic management framework will significantly enhance urban mobility, reduce congestion-related losses, and improve overall transportation efficiency.

2. REVIEW OF LITERATURE

[6] developed a lane-changing model using Deep Q-Learning with a request-respond mechanism to optimize vehicle maneuvers in congested environments. The model discretized lanes into cells and handled both mandatory and discretionary lane changes. Experimental results showed improved efficiency compared to rule-based methods, especially under high traffic density, though performance declined in low-density scenarios.

[7] proposed a peer-to-peer trust management framework for VANET using Aumann's agreement theorem to detect malicious nodes. The model evaluated performance using Packet Delivery Ratio, latency, energy consumption, and detection rate. Results demonstrated better performance than Firecol and AODV protocols, with improved trust accuracy through voting and consensus mechanisms.

[8] designed an IoT-based over-speed detection system using GSM, GPS, and Arduino hardware. The system compared vehicle speed with preset limits and sent alerts to authorities when violations occurred. While effective in real-time monitoring, performance depended on stable power supply.

[9] proposed a Green Light Optimal Speed Advisory (GLOSA) system that guided vehicle positioning rather than

speed. Simulation results showed reduced deceleration rates, improved headway time, and moderate fuel efficiency gains without affecting travel time, enhancing safety at intersections.

[10] introduced a V2X-based traffic management hardware system connected via OBD, GPS, and GSM modules for real-time data transmission. The system successfully collected vehicle data but experienced latency issues due to GPS signal limitations in non-open environments.

[11] developed a fusion-based intelligent Traffic Congestion Control System (TCCS) using machine learning in vehicular networks. The model achieved 95% accuracy with a 5% miss rate during simulation and is proposed for future integration with federated learning.

[12] proposed an Urban Traffic Control (UTC) system incorporating lane weight, traffic indicators, and vehicle priority. Simulation results showed a 25.98% reduction in average waiting time compared to fixed-cycle traffic lights.

[13] designed an Adaptive Traffic Management (ATM) system using IoT and ML with DBSCAN clustering for accident detection. The system dynamically adjusted signals based on traffic volume and reduced congestion and travel time, though implementation costs were high.

[14] conducted a comparative analysis of three AI techniques Graph Neural Networks (GNN), Feedforward Neural Networks (FNN), and the A* algorithm in a traffic advisory model. The models were evaluated using metrics such as prediction accuracy, route optimization, computation time, and responsiveness based on simulated traffic data. The study found that GNN achieved the highest performance with superior accuracy and adaptability, FNN provided faster computation but lower accuracy, while A* demonstrated effective pathfinding but had higher computation time and limited adaptability. Overall, GNN was recommended for dynamic traffic systems, while FNN and A* were suited for simpler or time-constrained applications.

3. SYSTEM ANALYSIS AND DESIGN

This study adopted a hybrid approach combining Design Science Research Methodology (DSRM) and Object-Oriented Design Methodology (OODM). DSRM guided the systematic development and evaluation of the proposed Intelligent Traffic Advisory Model (ITAM) as a solution to traffic congestion. The process involved problem identification, objective definition, system design and development using a hybrid fuzzy-Graph Neural Network algorithm, demonstration through simulation, performance evaluation, and communication of findings. OODM structured the system into interacting components such as vehicles, road segments, traffic sensors, and user interfaces, ensuring modularity and scalability. The system was designed such that when a user enters a specific location, the ITAM analyzes real-time and stored traffic data and immediately advises the user on the traffic situation in that

area, including congestion level and possible alternative routes. The hybrid methodology ensured that the proposed ITAM was theoretically grounded, practically implementable, and capable of delivering real-time traffic advisory services. Figure 1 System Analysis and Design

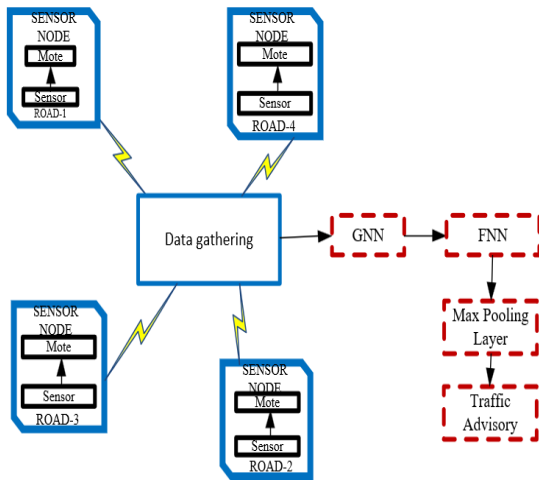


Figure 1 System Analysis And Design

4. USE-CASE

The use-case analysis examined how users drivers, traffic officers, and pedestrians—interacted with the system to achieve their goals. The proposed system was designed to collect and analyze real-time traffic data, predict congestion using historical and current information, calculate optimal routes, and provide alternative paths to avoid delays, accidents, or road closures, ensuring efficient traffic management and user guidance. Figure 2: Recommendation Engine Subsystem

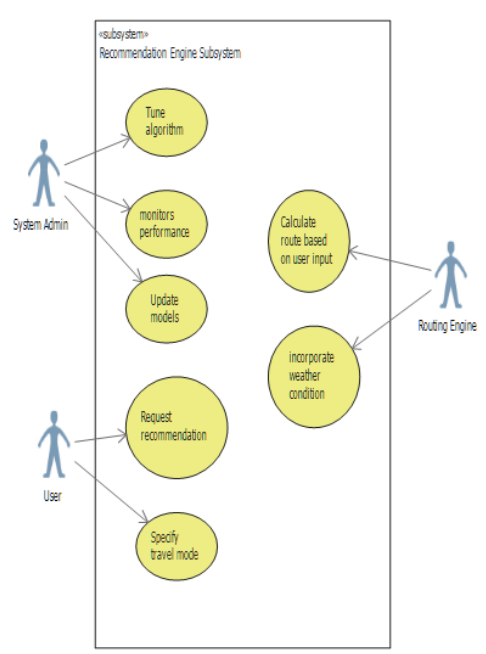


Figure 2: Recommendation Subsystem

5. ACTIVITY ANALYSIS

Activity analysis breaks down tasks to understand how actions are performed, identify bottlenecks, and optimize processes. It considers tasks, actors, workflow, inputs and outputs, and decision points. In this study, the activity diagram maps processes for collecting traffic data, analyzing it, generating route recommendations, and providing real-time updates to users. Figure 3: Registration Subsystem Activity diagram of the System

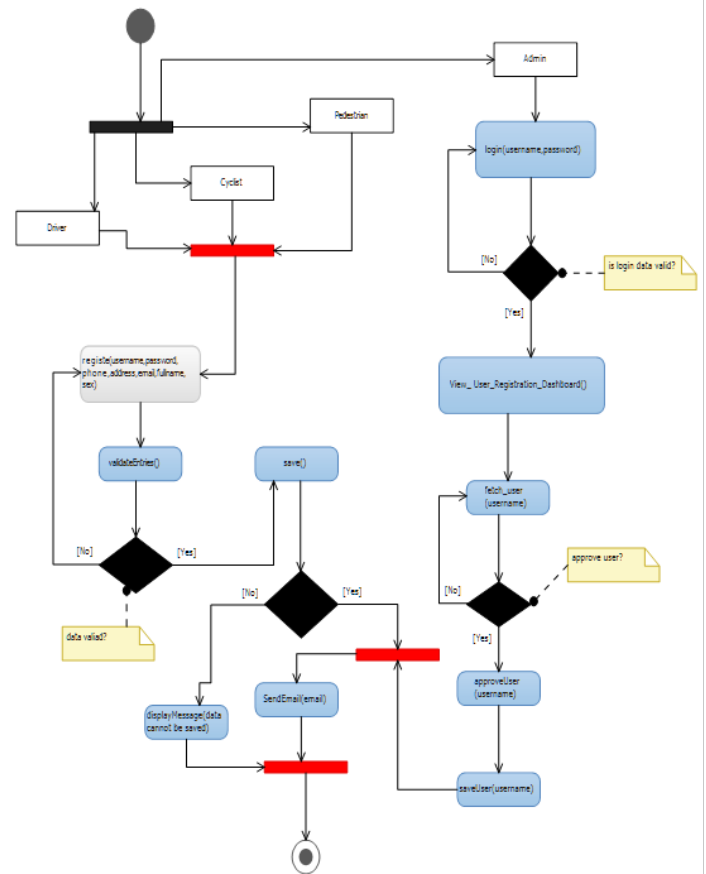


Figure 3: Activity diagram of the System

6. SYSTEM IMPLEMENTATION

In this study, Python (v3.6) was used to implement the Intelligent Traffic Advisory Model due to its rich libraries for machine learning and data processing, including TensorFlow, PyTorch, OpenCV, scikit-learn, NumPy, pandas, SciPy, PIL, pickle, and matplotlib. The models were developed in the Spyder environment by Anaconda. The FGNN model generated route recommendations based on the user's start and end locations. For a journey from Garrison to Eleme Junction, the model analyzed real-time and historical traffic, environmental conditions, and driver behavior using fuzzy logic and graph-based learning, providing three alternative routes with estimated travel times Table 1

S/N	Route Description	Estimated Time (Minutes)
1	Garrison → Aba Road → Eleme Junction	40 minutes
2	Garrison → Station Road via Airforce → Eleme Junction	35 minutes
3	Garrison → Trans Amadi → Elelenwa → Eleme Junction	45 minutes

The system analyzed each route by traffic density, peak congestion, and environmental impact, calculating estimated travel times under average conditions. The FGNN model recommended Station Road via Airforce as the fastest route (35 minutes), while Aba Road and Trans Amadi–Elelenwa routes had longer times of 40 and 45 minutes due to congestion and signal delays. These estimates were dynamically updated using live traffic data and fuzzy inference, providing time-optimized, context-aware route suggestions to improve user navigation. Figure 4: Output Result of the route recommended

Figure 4: Result of the route recommended

The model achieved high performance: accuracy 98.3%, precision 91.1%, recall 96.3%, and F1 score 99.5%, confirming reliable and accurate route recommendations for real-world traffic conditions. Figure 5: Model Evaluation

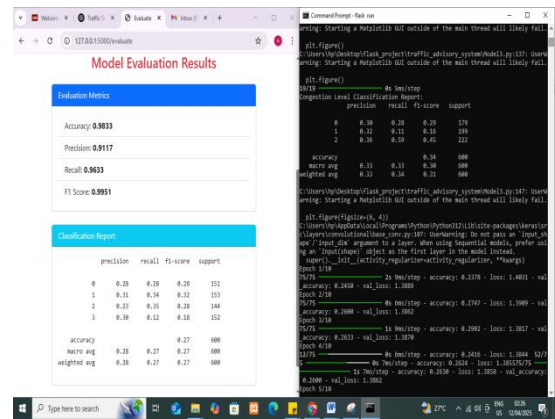


Figure 5: Model Evaluation

Figure 5 illustrated the model's route classification accuracy over the training period. The curve showed that the accuracy steadily increased from about 60% in the first few epochs to over 91% after 35 epochs, eventually stabilizing. This upward trend indicated that the model progressively learned from the input data and improved its ability to classify or recommend the best route. The stabilization phase highlighted the model's convergence, where further training yielded marginal accuracy gains, confirming that the model had matured and reached optimal performance.



Figure 6: Route Accuracy Graph

Figure 6 displayed the loss curve for road length prediction, using Mean Squared Error (MSE) as the loss metric. The curve showed a steep decline from an initial value of 0.08 to a final value of 0.01 by the end of the training cycle. This decline signified that prediction errors reduced drastically, and the model was learning to predict accurate road lengths. A low final MSE value suggested that the model had high precision in estimating distances across varying urban routes.

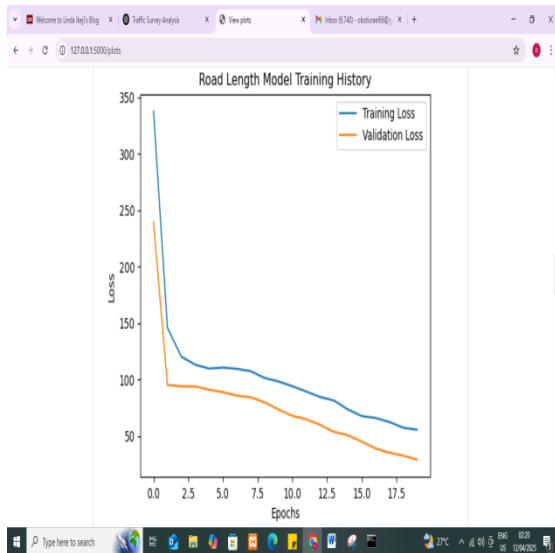


Figure 7: Road Length Loss Function

7. SUMMARY

This study efficaciously demonstrated the development and simulation of traffic advisory model using hybridized technique. The model was designed not only to predict traffic congestion in a place but to also recommend less traffic congestion route for efficient urban mobility. The output layer of the hybridized technique of the model produced specific routes recommendation based on the start location input and destination input provided by the user. Alternative routes were displayed by analyzing the historical traffic patterns such as traffic density, peak congestion periods, and environmental impact. Estimated time was calculated by the system under average traffic condition. Figure 6 showed the model's route classification accuracy over training period as curve showed that accuracy steadily increased from 60% in the first few epochs to 91% after 35 epochs. This up-ward trend indicated that the model progressively learned and improved its ability to classified and recommend the best route. The model was able to demonstrated an acceptance performance of accuracy of 98.3%, precision of 91.1%, and F1-Score of 99.5%. This result showed the model's effectiveness in traffic advisories.

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