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Deployment of Artificial Neural Networks for Vehicular Road Traffic Flow Prediction and Adaptive Signal Control in Metropolitan Road Networks

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Abstract

This study integrates ANN prediction with adaptive traffic signal optimization within a SUMO simulation framework for Nigerian urban traffic road networks, addressing the persistent challenge of urban congestion. Using synthetic and real traffic data from Jattu Junction in Auchi, Edo State, the framework was implemented with SUMO, Python, Pygame, and MATLAB for simulation, training, and evaluation. The ANN architecture featured an input layer, three hidden layers of 50 neurons each with Rectified Linear Unit (ReLU) activation, and a linear output layer, trained with the Adam optimizer (learning rate is 0.001, batch size is 64, with 100 epochs). Results showed that the adaptive system reduced average waiting time from 2.682 minutes to 1.579 minutes which is a 41.12% improvement. The ANN achieved strong performance metrics (MSE is 0.0154, MAE is 0.0923, R^2 is 0.9824), demonstrating its effectiveness in reducing congestion and improving mobility. Traffic scenarios included peak-hour demand, incidents, and varying flow conditions, with datasets split into training (70%), validation (20%), and testing (10%). Overall, the findings highlight the potential of ANN-driven intelligent transportation systems for enhancing urban traffic management.

Keywords: Vehicular Road Traffic, Prediction, Adaptive Signal Control, Metropolitan, Road Networks, Artificial Neural Networks, Traffic Simulation

1. Introduction

Auchi is a rapidly developing urban centre in Edo State, serving as a commercial, educational, and transportation hub that connects a major highway leading to Benin City and Delta state in southern Nigeria. The town has experienced significant growth in population, commercial activities and vehicular movement, resulting in recurring traffic congestion, particularly during peak hours. Despite these challenges, traffic control in Auchi largely depends on conventional methods, providing an opportunity to investigate the effectiveness of AI-driven traffic signal optimization. Jattu Junction is one of the busiest and most strategic intersections in Auchi. It serves as the convergence point for traffic from major routes leading to Benin City, Abuja, Okene, and surrounding communities. The junction experiences heavy traffic volumes from private vehicles, commercial buses, motorcycles, and heavy-duty trucks, making it susceptible to long queues, travel delays, and traffic conflicts. These characteristics make Jattu Junction an ideal case study for evaluating adaptive traffic signal control using Artificial Neural Networks (ANNs). The importance of Jattu Junction lies in its strategic role in regional mobility and economic activities. Efficient traffic management at this intersection has the potential to reduce vehicle waiting time, improve traffic flow, lower fuel consumption and greenhouse gas emissions, enhance road safety, and increase productivity by reducing travel delays. Moreover, demonstrating the effectiveness of an ANN-based adaptive traffic control system at Jattu Junction can provide a scalable framework for implementing intelligent traffic management solutions in other Nigerian cities facing similar congestion challenges.

Artificial Neural Networks (ANNs) are well suited for modeling complex, nonlinear, and dynamic systems such as weather and traffic due to their ability to learn intricate patterns from large datasets. They require no prior knowledge of the underlying system, making them effective for real-time prediction and decision-making in environments with highly variable and chaotic behavior. Adaptive signal control is an intelligent traffic management approach that dynamically adjusts traffic signal timings based on real-time traffic conditions, rather than relying on fixed timing plans. Unlike conventional pre-timed traffic signals, adaptive systems continuously collect and analyze data such as traffic volume, vehicle speed, queue length, and pedestrian demand to optimize signal phases. By making immediate adjustments in response to changing traffic patterns, these systems improve traffic flow, minimize delays, reduce congestion, and enhance the overall efficiency of road networks.

Existing studies have extensively examined the challenges posed by urbanization, including increased vehicular traffic demand, congestion, delays, fuel wastage, and environmental pollution [6]. Conventional traffic management approaches, such as fixed-time and simple adaptive control, have been shown to struggle in responding to dynamic traffic conditions [5]. In Nigeria, for example, traffic signals operate on fixed cycles of red, green, and orange lights, disregarding real-time traffic density and thereby exacerbating congestion [8]. To address these inefficiencies, researchers have proposed Adaptive Traffic Management Systems (ATMS), which leverage real-time data, sensors, and advanced algorithms to dynamically adjust signal timings, thereby reducing delays, improving safety, and minimizing environmental impacts [11, 10]. Artificial Neural Networks (ANNs) have further been identified as promising tools for modeling nonlinear traffic patterns and supporting adaptive traffic management [7]. Metropolitan areas, characterized by high population densities and complex road networks, have been a particular focus due to their heightened susceptibility to congestion, bottlenecks, and inefficiencies in traffic flow.

However, despite these advances, conventional traffic management strategies remain inadequate in alleviating congestion effectively. Fixed-time systems continue to dominate in practice, failing to adapt to real-time traffic variations and leading to bottlenecks, longer travel times, commuter frustration, and economic losses. Moreover, existing approaches have not sufficiently addressed the environmental consequences of metropolitan congestion, such as noise and air pollution, nor have they fully harnessed the potential of ANN-based predictive modeling for real-time adaptive signal control.

This study addresses these limitations by developing and evaluating an ANN-based traffic flow prediction and adaptive signal control system tailored for metropolitan road networks. By leveraging the learning capabilities of ANNs to model and optimize traffic flow, the proposed system enables dynamic signal adjustments that respond to congestion levels and lane usage in real time. This approach enhances the intelligence, adaptability, and efficiency of traffic management systems, while simultaneously reducing delays, minimizing emissions, and improving the safety, reliability and sustainability of urban transportation networks.

2. Literature Review

Traffic flow theory, neural network architectures, machine learning, spatiotemporal analysis, and complex systems theory provide the foundation for ANN-based transportation research [2]. Proposed a Time-Series Analysis and Supervised-Learning (TSA-SL) hybrid framework for short-term traffic flow prediction by decomposing traffic flow into periodicity and volatility components. The framework modeled periodic traffic patterns using Fourier Transform (FT) and predicted traffic volatility using spatial-temporal features with supervised learning models, including Support Vector Regression (SVR), Gradient Boosting Regression Trees (GBRT), and Long Short-Term Memory (LSTM), evaluated on a real-world Electronic Registration Identification (ERI) dataset. Experimental results showed that the TSA-SL models outperformed conventional baseline methods, with the approach achieving even higher prediction accuracy for partial traffic flow categorized by travel purpose and vehicle type than for overall traffic flow. However, the proposed framework lacks a feedback mechanism where prediction results continuously update signal phases based on changing traffic conditions [4]. Proposed a dynamic task assignment method for urban vehicles using multi-agent reinforcement learning. By modeling the assignment problem as a stochastic game and applying an extended actor-critic algorithm, vehicles can make independent real-time decisions with reduced communication costs. Compared to First Come First Serve (FCFS) and Convolutional Neural Attention (CAN) methods, the approach achieves higher acceptance and profit rates [13]. Proposed a multi-objective optimization framework based on genetic algorithms and neural networks for traffic signal coordination. Their approach effectively balanced conflicting objectives such as minimizing travel time, reducing emissions, and improving traffic safety in metropolitan road networks [3]. Propose Attention-Based Convolutional Bidirectional Long Short-Term Memory (AC-BLSTM), an attention-based deep learning model combining Convolutional Neural Network (CNN), BLSTM, and attention mechanisms to capture spatiotemporal traffic features. By modeling weekly, daily, and recent dependencies in parallel and fusing them through fully connected layers, the system achieves superior traffic flow prediction compared to existing models [14]. Proposed a reinforcement-learning-based adaptive traffic light control model (Adaptive Optimized Control of Intelligent Traffic Light (AOCITL)) using Markov Decision Process (MDP), Q-learning and Deep Q-Network (DQN), which significantly improved road efficiency, reduced accidents, and enhanced urban transportation compared to fixed-cycle signals [1]. Developed an intelligent traffic light system using predictive and dynamic flow analysis in SUMO, comparing five machine-learning models. Their approach achieved up to 26% less waiting time and notable reductions in time loss and emissions across 12 scenarios [12]. Evaluated adaptive fuzzy-logic algorithms for intelligent urban traffic signal management using the SUMO platform and found that Modified Interval Type-2 Fuzzy Logic (MIT2FL) outperformed Modified Intuitionistic Fuzzy Logic Algorithm (MIFLA) and the Modified Webster benchmark, enabling reproducible real-world implementation. This study introduces a Dynamic Bayesian Graph Convolutional Neural Network (DBGCN) that integrates road geometry and dynamic traffic changes, using a Bayesian network to infer spatiotemporal dependencies and a Graph Convolutional Neural Network (GCN) to fuse features with traffic flow data [9]. Tested on the Wuxuan highway, it outperforms benchmarks in prediction accuracy and produces interpretable traffic propagation diagrams.

These researches demonstrated improvements in congestion management, incident detection, and intelligent transportation systems. However, challenges remain regarding model generalization, interpretability, data quality and scalability. The proposed approach tackles real-world traffic challenges by adapting to time-varying patterns and combining control mechanism with traffic flow prediction for smarter decisions.

3. Methodology

3.1 Data Size and Data Collection

SUMO was used in a single intersection link to gathered data on vehicle movements (capturing the paths and speeds of individual vehicles), traffic densities (the number of vehicles per unit length of roadway) which provides insight into congestion levels and trip times (the duration of trips across the corridor enables the assessment of travel efficiency), queue length and waiting time during the expedition. 1,000 simulated trips and 30 minutes of simulated time per run duration with about 10 runs under peak demands were implemented.

3.2 Data Preprocessing

Preprocessing procedures was carried out to clean, standardize and format the synthetic traffic data before feeding it into the ANN model. This preprocessing made sure the input data complied with the ANN model's specifications and made it easier to estimate traffic flow accurately.

3.3 Simulation Parameters and Setup

The simulation environment was controlled by configuring a number of settings in SUMO, such as the traffic flow models, time step size and simulation duration. Through iterative testing and calibration, these values were adjusted to reflect real-world data as precisely as possible. Configuring the simulation environment, including the ANN model and establishing assessment measures. In order to facilitate real-time communication between the simulation environment and the predictive model, the SUMO was set up to interact with the ANN model. In order to assess the precision of the ANN predictions, performance metrics including Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) were employed.

3.4 Validation and Calibration

Comparing the simulation findings with observed traffic patterns from real-world traffic data sources helped in validating the synthetic traffic data produced by SUMO. The simulation settings were calibrated and adjusted to address any disparities or inconsistencies.

3.5 Threading Mechanisms

Achieving concurrency was accomplished using Python's threading module, which allows the simulation to handle multiple tasks simultaneously, thus enabling management of initialization and dynamic behaviour of traffic lights and vehicles without hindering the performance of the main simulation loop.

3.6 Simulation Setup

The road network was developed in SUMO to accurately represent the study area's road layout, intersections and traffic signal configurations. Different vehicle types, including passenger cars and trucks were assigned realistic operational characteristics and predefined origin-destination routes to simulate actual traffic movement. Traffic demand was generated from historical traffic data and population distribution patterns to reflect realistic temporal and spatial variations in traffic flow. Dynamic scenarios, such as lane closures, traffic incidents, and emergency vehicle movements, were incorporated to evaluate the adaptability of the proposed traffic management system under varying conditions. Throughout the simulation, traffic performance data, including vehicle movements, traffic density, travel time, queue length, and waiting time were collected and used as ground-truth data for training and evaluating the Artificial Neural Network (ANN) model.

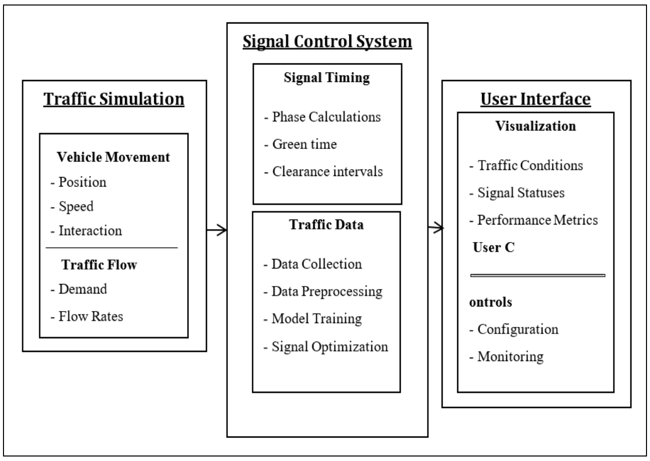

Fig 1: Block Diagram of the Adaptive Traffic Management System Model

Fig 1 presents the overall architecture of the proposed adaptive traffic management system, comprising three interconnected components namely, Traffic Simulation, Signal Control, and the User Interface. The Traffic Simulation module generates real-time traffic information by modelling vehicle movement, including position, speed, and interactions, while also simulating traffic demand and flow rates. This information is transmitted to the Signal Control module, where traffic data are collected and preprocessed before being used for model training and traffic signal optimization. Based on the processed data, the system performs signal timing calculations by determining traffic phases, green time allocation, and clearance intervals to improve traffic flow efficiency. The User Interface provides a platform for visualizing traffic conditions, signal status, and system performance metrics, while also enabling users to configure system parameters and monitor traffic operations in real time. Overall, the framework illustrates the integration of traffic simulation, intelligent signal control, and user interaction to achieve efficient and adaptive traffic management.

3.7 Hyperparameter Selection

Hyperparameters are essential to the ANN model's functionality. Grid search and cross-validation methods were employed to choose the best hyperparameters. The primary hyperparameters taken into account were:

1. *Learning Rate:* This factor establishes the gradient descent optimization step size. Tested a range of learning rates, from 0.001 to 0.01.
2. *Number of Neurons and Hidden levels*: Experimented with different setups, using 10–100 neurons per layer and 2 - 5 hidden levels.
3. *Batch Size*: Indicates how many samples are processed prior to an update to the internal parameters of the model. Tested 32, 64, and 128-batch sizes.
4. *Epochs*: The quantity of full iterations via the training set. Tested between fifty and two hundred epochs.

The final set of hyperparameters that yielded the best performance was as follows:

Learning Rate: 0.001; Hidden Layers: 3; Neurons per Layer: 50; Batch Size: 64; Epochs: 100.

3.8 Training Procedure

The steps involved in training the ANN model were as follows:

1. *Data Splitting*: A 70:20:10 ratios were used to divide the dataset into training, validation, and test sets. This made sure the model could generalize to new data and had enough data to learn from.
2. *Normalization*: A zero mean and unit variance was applied to the input characteristics. For the gradient descent optimization to have better convergence, this step is essential.
3. *Initialization*: The initialization method, which works well for ReLU activation functions, was used to initialize the neural network's weights.
4. *Optimization*: To reduce the mean squared error (MSE) loss function, the adaptive learning rate optimization algorithm known as the Adam optimizer was employed.

3.9 Adaptive Traffic Control Framework

The flowchart of Fig 2 shows how a traffic simulation operates. It starts with initializing traffic lights and vehicles, then runs the simulation. During the process, traffic lights and vehicles are continuously updated, and the display is refreshed. A decision checks whether all vehicles have been processed, if *NO*, the loop continues; if *YES*, the simulation ends with simulation complete. An adaptive traffic signal algorithm dynamically adjusted green and yellow signal durations based on real-time vehicle counts as illustrated in Fig 3. Vehicle detection, traffic-density analysis, adaptive timing calculations, and collision avoidance mechanisms were incorporated. Threading was implemented for parallel execution of traffic-light control and vehicle generation processes.

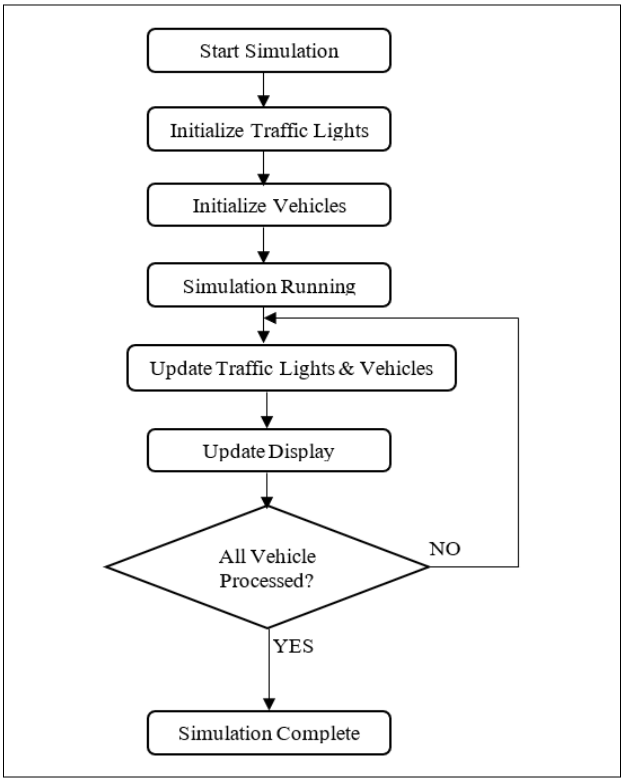

Fig 2: Traffic Simulation Flowchart

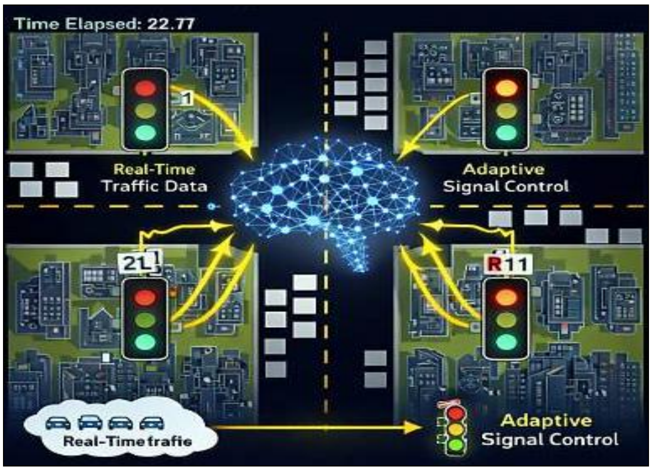

Fig 3: ANN Adaptive Traffic Signal Control

4. Results and Discussion

Simulation results demonstrated significant improvements in traffic performance.

4.1 Traffic Flow System Comparison

Several simulations were done to assess the effectiveness of adaptive traffic flow systems in comparison to conventional ones. The average time that cars wait at crossings served as the main comparative metric. Average waiting time decreased from 2.682 minutes under traditional control to 1.579 minutes under adaptive control, yielding a 41.12% reduction as shown in Table 1. The average waiting time for cars is clearly reduced by roughly 41.12% by the adaptive traffic light system.

Table 1: Traffic Simulation Results Comparison

Metric	Traditional System	Adaptive System	Improvement (%)
Average Waiting Time (s)	2.682	1.579	41.12

4.2 Detailed Simulation Results

The results of a traffic simulation contrasting an adaptive traffic light system with a traditional traffic signal system are shown in the table below. The purpose of this comparison is to ascertain the adaptive system's efficacy and efficiency in easing traffic congestion and enhancing traffic flow. The values table makes it evident that the adaptive traffic signal system can perform better at controlling traffic flow than the conventional method. The adaptive system can shorten the total simulation completion times by dynamically adapting to traffic conditions, which would improve traffic management. The application of adaptive traffic light systems is recommended by this study as a workable way to enhance urban traffic conditions. The waiting times under the two traffic light systems were compared minute by minute.

4.3 Conventional and Adaptive System

Two series make up the data; Conventional System: Shown by the orange line and Adaptive System shown as the yellow line. Every data point shows how long (in minutes) the corresponding traffic light system takes to finish a simulation run. In total, 21 simulation runs were conducted. These findings demonstrate that during the course of many simulation periods, the adaptive system continuously maintains shorter wait times.

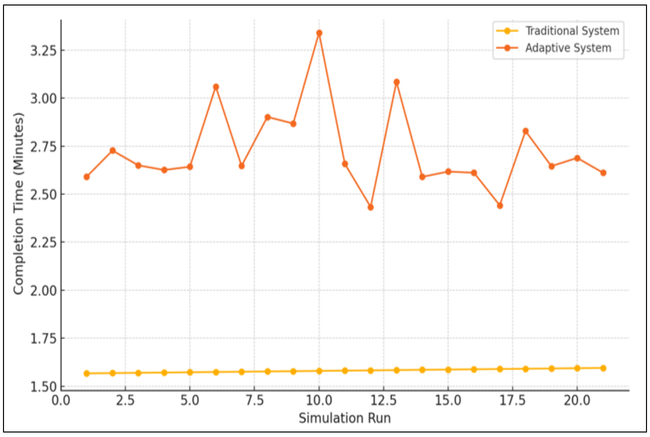

Fig 4: Completion Times of Traditional Versus Adaptive Traffic Light Systems

Fig 4 compares the simulation completion times of traditional versus adaptive traffic light systems. The results showed that the adaptive system consistently achieves faster completion times, averaging around 3.00 minutes compared to 3.25 minutes for the traditional system. This difference, though seemingly small, highlights the efficiency gains of adaptive traffic control, which adjusts signals dynamically based on traffic flow. The overall trend suggests that adaptive systems can reduce congestion and improve traffic throughput, making them a more effective solution for modern urban traffic management.

The data below is depicted in the graph:

1. Consistent Performance: All runs of the conventional system exhibit the same completion time, with results closely grouped around 1.57 minutes.
2. Variable Performance: The adaptive system responds more quickly to varying traffic situations, as seen by its more variable completion times. In spite of this fluctuation, the adaptive system frequently outperforms the old approach in terms of completion times.

4.4 Comparative and Sensitivity Analysis

The ANN model's performance was evaluated against that of other widely used traffic prediction models, such as the decision trees and linear regression. The evaluation metrics used for the comparison were the same, the outcome is shown in Table 2.

Table 2: Comparative Analysis of Models

Model	MSE	MAE	R^2
ANN	0.0154	0.0923	0.9824
Linear Regression	0.0289	0.1437	0.9032
Decision Tree	0.0245	0.1286	0.9185

The ANN model works better than conventional models, which show reduced error rates and higher R^2 values. To understand the robustness of the ANN model, the sensitivity analysis was carried out by varying key input parameters and observing the impact on model performance. ANN performance metrics showed MSE is 0.0154, MAE is 0.0923 and R^2 is 0.9824, indicating strong predictive capability. Sensitivity analysis revealed stable model performance across variations in learning rate, hidden layers, and neuron count. The findings confirm that ANN-based traffic prediction can effectively support intelligent transportation systems.

Table 3: Sensitivity Analysis Results

Parameter	Baseline Value	Variation	MSE	MAE
Learning Rate	0.001	±0.0005	0.0156	0.0931
Number of Hidden Layers	3	±1	0.0162	0.0954
Neurons per Layer	50	±10	0.0158	0.0938

The sensitivity analysis indicated that the model's performance remains stable with slight variations in key parameters, showcasing its robustness. The regression graphs as shown in Fig 4 displays the performance of a model in predicting traffic data, evaluated across different datasets: Training, Validation, Testing, and All data combined. These graphs illustrate how well the model's predictions match the actual target values.

Training Set R is 0.96976: This high correlation coefficient indicates a strong relationship between the model's predictions (Output) and the actual target values in the training data. The blue fit line closely follows the data points, suggesting the model performs well on the training data. This implies the model has learned the patterns in the training data effectively.

Validation Set R is -0.018624: The negative and very low correlation coefficient indicates poor performance on the validation set. The green fit line is almost horizontal, suggesting that the model fails to capture the relationship between inputs and targets for the validation data. This indicates potential overfitting, where the model performs well on training data but poorly on unseen validation data.

Test Set R is 0.0021126: Similar to the validation set, the very low correlation coefficient indicates poor performance on the test data. The red fit line is also almost horizontal, confirming that the model does not generalize well to the test set. This further indicates overfitting.

All Data R is 0.65214: The combined correlation coefficient for all datasets is moderate. The black fit line shows a reasonable fit but not perfect, indicating that the model has learned some patterns but is not consistently accurate across all data. This suggests that while the model has some predictive power, it is not robust.

5. Findings

The following key findings are revealed by the results of the simulation experiments and assessments of the performance of the ANN model:

1. The considerable decrease in average waiting times emphasizes the potential of adaptive traffic light systems to reduce urban traffic congestion.
2. The high R^2 value and low error metrics highlight the effectiveness of ANN in predicting traffic flow accurately, making it a practical tool for real-time traffic management.
3. The sensitivity analysis verifies that the ANN model performs well under a variety of parameter variations, supporting strong generalization abilities.

6. Conclusion

The study demonstrates that ANN-based traffic prediction and adaptive traffic signal control significantly improve urban traffic efficiency. The developed framework reduced congestion and waiting times while maintaining high predictive accuracy. Future research should incorporate real-time IoT traffic sensors, explainable artificial intelligence techniques, and large-scale smart-city deployments.

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9. Ethics, Consent to Participate, and Consent to Publish Declarations
Not applicable.

10. Conflict of Interest
The authors declare that they have no conflict of interest.

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