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Predictive Analytics Framework for Traffic Congestion Using Artificial Intelligence (AI)Techniques

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ABSTRACT

Traffic congestion has continues to pose significant challenges in many urban centers globally, including Nigeria, undermining mobility, economic efficiency, and environmental sustainability. So far, conventional congestion management strategies in many developing countries is often focused on infrastructure expansion and manual traffic regulations, which have proven insufficient in addressing the complex, dynamic, and nonlinear behaviour of urban traffic systems. Therefore, this study examines traffic congestion control strategies across selected urban road networks in Nigeria, with a focus on operational traffic management, travel demand management, public transport prioritization, and developed an Intelligent Predictive Framework for Traffic Congestion using Artificial Intelligence to overcome these challenges. A multi-source and mixed method approach was employed; utilizing primary traffic data collected from major roads networks, signalized intersections during peak hours and historical traffic databases maintained by local transportation authorities. Congestion was assessed using indicators such as traffic volume, travel time, delay, speed, volume-to-capacity ratio, and level of service. The traffic dataset was partitioned chronologically into training (70%), validation (15%), and testing (15%) subsets. Experimental results demonstrated that the proposed AI-Based framework outperformed all other classifiers considered in this work achieving the lowest error values across all evaluation metrics with MAE (0.42), RMSE (0.58), and MAPE (6.9%), indicating superior predictive accuracy, robustness under peak-hour traffic conditions, and improved generalization to unseen data. Its performance gains are attributed to the hybrid integration of spatial and temporal learning, as well as optimized training and feature fusion strategies.

Keywords: Intelligent Predictive Framework, Artificial Intelligence, Congestion Control, Intelligent Transportation Systems, Traffic Congestion.

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1. INTRODUCTION

According to Litman (2021), the condition in which the demand for road usage exceeds the available roadway capacity, leading to reduced vehicle speeds, longer travel times, increased delays, and frequent stop-and-go traffic patterns is commonly referred to as traffic congestion.
It is a multifaceted and persistent problem that arises primarily from the imbalance between travel demand and the available capacity of roadway infrastructure (Rodrigue et al.,, 2020). This imbalance is shaped by a complex interplay of factors, including rapid urban growth, evolving travel behaviour, infrastructure limitations, and the interconnected nature of modern transportation networks (Downs, 2004). It is most noticeable during peak travel periods in urban areas, particularly at bottlenecks such as intersections, highway merges, work zones, and areas affected by traffic incidents or adverse weather conditions (Federal Highway Administration (Taylor et al.,2000; FHA, 2013). As cities continue to expand in size and population, mobility demands increase correspondingly, placing significant pressure on road systems that were often not designed to accommodate such volumes.

From a transportation engineering perspective, congestion occurs when traffic volume approaches or surpasses the designed capacity of a roadway or network, resulting in unstable traffic flow and a transition from free-flow to congested regimes (Garber & Hoel, 2015; HCM, 2022). Figure 1 depicts a typical traffic congestion flow in Lagos, Nigeria.

Figure 1: Typical Traffic Congestion Flow in Lagos, Nigeria

At this point, minor disturbances such as sudden braking and lane changes can trigger disproportionate reductions in speed and throughput, leading to cascading delays across the network. Rapid urbanization and increased vehicle ownership are major contributors to congestion pressures, especially in cities where public transport infrastructure has not kept pace with population growth (Eliasson, 2014). Rising incomes, combined with inadequate, unreliable, or inaccessible public transport options, encourage greater reliance on private vehicles.

In many developing countries, land-use patterns characterized by urban sprawl, mono-centric development and poor integration between residential, commercial, and industrial zones generate long commuting distances and peak-hour travel surges (Rodrigue et al.,2017). These patterns reinforce car dependency and exacerbate congestion, particularly along major roads and corridors. Poor coordination between land-use planning and transportation planning further amplifies these challenges, resulting in inefficient travel patterns that are difficult to manage using conventional traffic control measures. Institutional and operational factors also play a significant role in exacerbating congestion. According to Eliasson (2014), inefficient traffic signal timing, lack of coordination between adjacent intersections, weak enforcement of traffic regulations, and delayed responses to incidents and breakdowns can contribute to recurring bottlenecks and reduced network efficiency. Inadequate maintenance of road infrastructure, such as damaged pavements, faded lane markings, and malfunctioning traffic signals, further degrades traffic flow. Additionally, the absence of comprehensive real-time traffic monitoring systems limits the ability of traffic authorities to detect emerging congestion and respond proactively.

The consequences of traffic congestion extend far beyond inconvenience and mobility loss. Economically, congestion imposes substantial costs on individuals, businesses, and governments through wasted travel time, increased fuel consumption, reduced productivity, and higher vehicle operating costs (Downs, 2004). Delays in freight and logistics operations can disrupt supply chains, increase the cost of goods, and reduce the competitiveness of urban economies (Schrank et al., 2019). In many developing and rapidly urbanizing cities, congestion-related economic losses account for a significant share of gross domestic product, underscoring the urgency of effective congestion management strategies. These economic impacts are often compounded by inadequate transport infrastructure investment and inefficient traffic management practices, which limit the ability of cities to respond to growing mobility demands. Environmental impacts represent another critical dimension of traffic congestion. Vehicles operating under congested, stop-and-go conditions consume more fuel and emit higher levels of pollutants than those traveling at steady speeds (FHA, 2013). Congestion significantly increases emissions of carbon dioxide (CO_2), nitrogen oxides (NO_x), carbon monoxide (CO), and particulate matter, contributing to air pollution and climate change (Barth & Boriboonsomsin, 2008). In densely populated urban areas, these emissions pose serious public risks. Studies have linked prolonged exposure to traffic-related air pollutants to respiratory illnesses, cardiovascular diseases, and premature mortality (HEI, 2022).

From a social perspective, traffic congestion significantly reduces quality of life by increasing commuter stress, travel uncertainty, and time spent in traffic. Long and unreliable travel times can erode work life balance, reduce opportunities for leisure and social interaction, and contribute to mental fatigue and frustration. Congestion also limits access to essential services such as healthcare, education, and employment, particularly for individuals who rely on congested road networks or poorly integrated public transport systems HCM, 2022). These challenges raise important equity considerations, as low-income populations often bear a disproportionate share of congestion-related burdens while having fewer mobility alternatives. Addressing congestion, therefore, requires not only technical solutions but also inclusive policies that consider the social and distributive impacts of transportation systems. Historically, congestion mitigation strategies have focused primarily on increasing road capacity through infrastructure expansion, including road widening, construction of new highways, and addition of flyovers and bypasses.

While such measures may provide temporary relief, however, studies has shown that they often lead to induced demand, whereby improved road conditions encourage additional trips and greater private vehicle use, ultimately restoring or worsen congestion levels (Litman, 2021). Contemporary traffic research increasingly emphasizes that congestion is dynamic, nonlinear, and network-wide phenomenon rather than a localized problem (Saberi et al., 2020). Traffic systems exhibit complex interactions among vehicles, road segments, and control devices, meaning that disruptions in one location can rapidly propagate throughout the network. Empirical studies have demonstrated that congestion can spread from an initial bottleneck to upstream and downstream links, amplifying delays and affecting areas far removed from the original incident. Congestion propagation can be conceptualized as a contagion process, analogous to the spread of infectious diseases, where congestion states transmit through connected network elements (Papageorgiou et al.,, 2003). Recognizing congestion as a network-level phenomenon has important implications for traffic management and policy.

Effective congestion mitigation in this regards requires integrated strategies that consider interactions across the entire network, including arterial roads, highways, and local streets. Such strategies may involve coordinated signal control, corridor-level management, incident response coordination, and integration of public transport and non-motorized travel options. Advances in data availability and computational techniques have significantly enhanced the ability to understand, model, and manage traffic congestion. Intelligent Transportation Systems (ITS), can combine machine learning and predictive analytics, enabling proactive congestion management through real-time monitoring and early intervention (Lv et al., 2015). The deployment of Intelligent Transportation Systems (ITS), integrating cameras, connected vehicle technologies, GPS probe data, and mobile phone data, all these can enable real-time monitoring of traffic conditions at unprecedented spatial and temporal resolutions. Ultimately, these data-driven approaches offer a more sustainable and resilient pathway for addressing the complex and evolving challenge of urban traffic congestion.

2.LITERATURE REVIEW

2.1 Strategies for Effective Traffic Congestion Management

Congestion control refers to a comprehensive set of policies, techniques, and operational strategies designed to prevent, reduce, or manage traffic congestion within road transportation networks (Papageorgiou et al., 2003). As urban populations continue to grow and vehicle ownership rises steadily, congestion has become a persistent and complex challenge that undermines mobility efficiency, economic productivity, environmental sustainability, and overall quality of urban life. Unlike congestion mitigation, which traditionally emphasizes long-term infrastructure expansion such as road widening or the construction of new facilities, congestion control focuses on the efficient use and management of existing transportation infrastructure through operational, technological, and behavioural interventions (Federal Highway Administration (FHA, 2012). This shift reflects the growing recognition that expanding road capacity alone is neither economically sustainable nor effective in the long term, largely due to induced demand and spatial constraints in urban areas. See Figure 2, showing persistent challenges despite road widening.

Figure 2: Conventional Strategies (Road Widening)

From a transportation engineering perspective, congestion control strategies are designed not only to respond to congestion after it occurs but also to regulate traffic demand, optimize traffic flow, and prevent the onset of breakdown conditions that cause recurrent and non-recurrent congestion (Tang et al., 2025). This proactive orientation distinguishes congestion control from purely reactive traffic management approaches. One of the most widely adopted categories of congestion control strategies is traffic signal control, particularly in urban environments where intersections are critical points of conflict and frequent congestion formation. See Figure 3 depicting urban traffic signal control.

Figure 3: Urban Traffic Signal Control

Traditional fixed-time signal control systems operate based on pre-determined timing plans derived from historical traffic data. While these systems are relatively simple and inexpensive to implement, they are often ineffective under fluctuating and unpredictable traffic conditions, such as those caused by incidents, weather variations, or special events (Jing et al.,2017). As a result, fixed-time control can lead to inefficient allocation of green time, increased queue lengths, and unnecessary delays.

To overcome these limitations, adaptive traffic signal control systems have been developed to adjust signal timings dynamically based on real-time traffic conditions. Systems such as the Split Cycle Offset Optimization Technique (SCOOT) and the Sydney Coordinated Adaptive Traffic System (SCATS) continuously monitor traffic flows using detectors and adjust cycle lengths, splits, and offsets accordingly. According to Gartner et al.,(1991), empirical studies have shown that these adaptive systems can significantly reduce intersection delays, queue lengths, fuel consumption, and travel times, thereby enhancing both local intersection performance and corridor-level efficiency. Beyond intersections, congestion control on freeways and major arterials is often addressed through Active Traffic Management (ATM) strategies. ATM focuses on real-time operational control to improve traffic flow, enhance safety, and maximize the effective capacity of existing roadways. Common ATM measures include ramp metering, variable speed limits, dynamic lane assignment, and hard-shoulder running. Ramp metering regulates the rate at which vehicles enter freeways, preventing sudden inflows that can overwhelm mainline traffic and trigger flow breakdowns (Aranuwa&Akinwumi, 2011). Numerous empirical studies demonstrate that ramp metering can increase freeway throughput, reduce travel time variability, and lower crash rates by smoothing traffic flow and minimizing shockwaves (Papageorgiou et al., 1991).

Variable speed limits complement ramp metering by adjusting speed limits in response to prevailing traffic and weather conditions, with the objective of harmonizing vehicle speeds and reducing abrupt braking and acceleration that contribute to stop-and-go traffic Smulders, 1990). Together, these ATM strategies enhance traffic stability and improve overall network performance under high-demand conditions. The deployment of Intelligent Transportation Systems (ITS) has further strengthened congestion control capabilities by enabling real-time traffic monitoring, analysis, and coordinated control (Papageorgiou et al., 1991).ITS integrates sensing technologies such as loop detectors, cameras, radar, and GPS-based probe data with communication networks and advanced data analytics. Traffic management centers use ITS data to detect incidents quickly, monitor congestion levels, optimize signal coordination, and implement rapid response strategies to minimize the duration and spatial extent of congestion (USDT, 2022).

Additionally, real-time traveler information systems delivered through variable message signs, mobile applications, and navigation platforms play a crucial role in congestion control by informing road users about current traffic conditions, incidents, and alternative routes. By enabling travelers to adjust their routes, departure times, or modes of transport, these systems help redistribute traffic demand more evenly across the network and reduce pressure on congested corridors (Ben-Akiva, 1991). In addition to operational and technological measures, traffic demand management (TDM) is a central component of effective congestion control (Litman, 2013). TDM strategies aim to reduce or redistribute travel demand, particularly during peak periods, by influencing traveler behavior and mode choice.

Common TDM approaches include congestion pricing, road space rationing, promotion of public transportation, telecommuting incentives, and the provision of high-occupancy vehicle (HOV) lanes. Congestion pricing has been successfully implemented in cities such as London, Singapore, and Stockholm, resulting in measurable reductions in traffic volumes and improved travel time reliability (WRI, 2026). These schemes have also delivered significant environmental benefits, including reduced emissions and improved air quality [Eliason, 2014). Road space rationing schemes, often based on vehicle registration numbers, have also been applied as temporary congestion control measures, particularly during severe pollution occurrence or major events, with evidence of short-term reductions in traffic volumes and emissions (Castro et al.,2025).

Recent advances in machine learning, artificial intelligence, and big data analytics have opened new frontiers in congestion control research and practice (Wei et al., 2019). Predictive congestion control models leverage large volumes of historical and real-time traffic data to forecast traffic conditions and proactively adjust control strategies before congestion fully develops. Reinforcement learning-based traffic signal controllers, for example, can learn optimal control policies through continuous interaction with the traffic environment, adapting to complex and highly dynamic conditions more effectively than traditional rule-based or optimization-based methods. Furthermore, the emergence of connected and automated vehicles (CAVs) presents significant opportunities for enhancing congestion control (Zhang, et al., 2023). Through vehicle-to-vehicle and vehicle-to-infrastructure communication, CAVs can share real-time information on speed, position, and traffic conditions, enabling more precise and coordinated traffic management. Even partial penetration of connected vehicles has been shown to improve traffic flow stability, reduce shockwaves, and increase effective roadway capacity (Talebpour & Mahmassan, 2016).

As CAV technologies mature and adoption increases, they are expected to play a transformative role in congestion control by enabling cooperative driving strategies and more efficient use of existing infrastructure. Despite the availability of a wide range of congestion control strategies, effective implementation remains challenging and requires integrated planning, strong institutional coordination, and continuous system evaluation. Congestion is inherently a network-wide phenomenon, and isolated or uncoordinated control measures may simply shift congestion from one location or time period to another. Consequently, modern congestion control increasingly adopts a systems approach that combines adaptive traffic control, real-time management, demand regulation, and emerging technologies within a coherent policy framework (Vickrey, 1969). By optimizing existing infrastructure, managing demand intelligently, and leveraging advanced data-driven systems, congestion control measures can significantly improve traffic efficiency, reduce delays and emissions, and enhance the overall livability and sustainability of urban environments.

2.2 Advances in Predictive Congestion Management

Predictive congestion management has been described as the systematic application of traffic data analytics and computational modeling techniques to anticipate the formation and evolution of traffic congestion and to enable proactive traffic control actions before significant delays and network breakdowns occur (Wei et al.,,2019). Unlike reactive traffic management approaches, which respond only after congestion had already occurred. Predictive congestion management seeks to forecast future traffic states and support early, informed decision-making that optimizes overall network performance.

This paradigm shift is increasingly important in modern urban environments, where traffic conditions are highly dynamic, nonlinear, and influenced by complex interactions among infrastructure, travel behaviour, and external factors such as weather and incidents. Figure 4 depicts a congestion predictive framework for traffic congestion management.

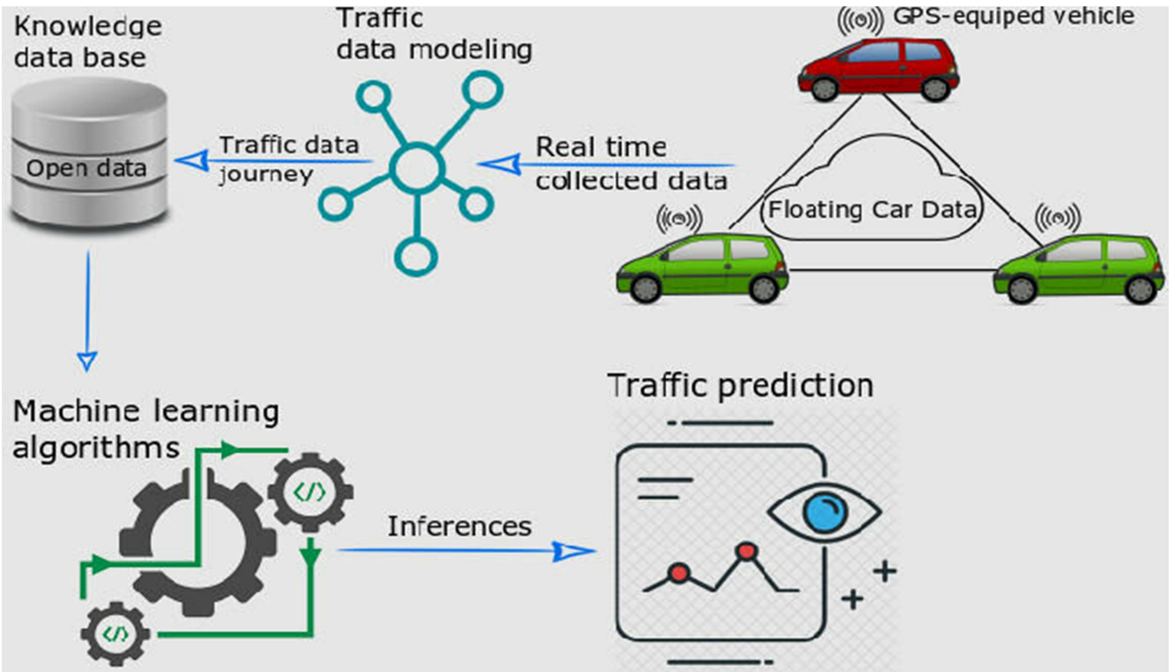

Figure 4: Typical Congestion Predictive Framework

Early efforts in predictive congestion modeling relied largely on classical statistical techniques, including autoregressive integrated moving average (ARIMA) models, Kalman filtering, and regression-based methods (Okutani & Stephanedes, 2017; Vasantha, 2017). These approaches capture temporal trends in traffic variables using historical observations and linear assumptions. However, real-world traffic systems rarely exhibit such stability due to abrupt changes, nonlinear interactions, recurrent peak-hour patterns, and strong spatial dependencies across interconnected road segments (Tiwari & Prasad, 2022; Zhou et al.,2023). The rapid advancement of machine learning (ML) and deep learning (DL) techniques has fundamentally transformed the field of predictive traffic modeling. Unlike classical statistical methods, ML and DL models are data-driven and capable of learning complex nonlinear relationships directly from large volumes of traffic data [Lv et al., 2015); Vlahogianni ,2004). This ability allows them to adapt to diverse traffic conditions and capture intricate patterns that are difficult to model analytically. With the increasing availability of high-resolution traffic data from loop detectors, GPS probes, connected vehicles, and mobile devices, ML and DL approaches have become particularly attractive for real-time and large-scale predictive congestion management. These models can be continuously updated as new data become available, enabling more accurate and responsive congestion prediction in rapidly changing urban environments.

Deep learning is a subset of machine learning in artificial intelligence (AI) that focuses on algorithms inspired by the structure and function of the brain, called artificial neural networks. Unlike traditional machine learning methods that rely on handcrafted features, deep learning models can automatically learn hierarchical representationsfrom raw data, making them especially powerful for complex tasks such as image recognition, natural language processing, speech recognition, and autonomous driving (Aranuwa & Fawehinmi, 2022). DL models are especially well suited for predictive congestion management because they can simultaneously capture temporal traffic evolution, spatial correlations among road segments, and the nonlinear dynamics inherent in traffic systems.

This multi-dimensional modeling capability is essential for urban-scale congestion prediction, where traffic conditions at one location are strongly influenced by upstream and downstream flows as well as by historical trends and periodic patterns. Among deep learning techniques, Recurrent Neural Networks (RNNs) and their variants have been widely adopted for traffic forecasting due to their ability to model sequential data. In particular, Long Short-Term Memory (LSTM) networks address the vanishing gradient problem associated with conventional RNNs by incorporating memory cells and gating mechanisms that regulate information flow. This design enables LSTMs to learn long-term temporal dependencies in traffic speed, volume, and density data, making them effective for short-term and medium-term congestion prediction (Vasantha, 2017). LSTM-based models have been successfully integrated into adaptive traffic signal control systems, where predicted traffic conditions are used to adjust signal timings proactively, reducing delays and improving intersection performance.

While LSTM and other temporal models excel at capturing time-dependent patterns, they do not explicitly account for the spatial structure of road networks. To address this limitation, Graph Neural Networks (GNNs) have emerged as a dominant paradigm in predictive congestion management. GNNs are designed to operate on graph-structured data, making them naturally suited to modeling transportation networks. In GNN-based traffic models, the road network is represented as a graph in which nodes correspond to sensors, intersections, or road segments and edges represent physical connectivity or traffic flow relationships.

This representation enables the model to capture how congestion propagates across adjacent and interconnected links. One of the most influential GNN-based architectures in traffic forecasting is the Diffusion Convolutional Recurrent Neural Network (DCRNN). DCRNN integrates diffusion-based graph convolutions with gated recurrent units (GRUs) to jointly model spatial diffusion processes and temporal traffic dynamics (Li et al., 2018)]. The diffusion convolution operation captures how traffic states spread through the network over time, while the recurrent component models temporal evolution. Another prominent GNN-based model is Graph WaveNet, which combines adaptive graph convolution with dilated temporal convolutions. Unlike models that rely on a fixed, predefined graph structure, Graph WaveNet learns an adaptive adjacency matrix directly from data, allowing it to capture dynamic and latent spatial relationships among road segments.

The use of dilated convolutions enables the model to capture multi-scale temporal patterns efficiently, making it well suited for short-term traffic forecasting. Empirical evaluations show that Graph WaveNet outperforms earlier GNN-based models, including DCRNN, in terms of prediction accuracy and robustness under varying traffic conditions. This adaptability is particularly valuable in urban networks where traffic patterns can change due to construction, incidents, or evolving travel behavior (Wu et al., 2019).

More recently, transformer and attention-based architectures have been introduced to address limitations in capturing long-range temporal dependencies. Transformers use self-attention mechanisms to model relationships across all time steps simultaneously, improving medium- and long-term traffic forecasting accuracy (Chang et al.,2025). To further enhance robustness, hybrid and ensemble approaches combine complementary architectures and aggregate predictions from multiple models, reducing sensitivity to noise and data irregularities Muhammadetl., 2025; Bhatele, 2025). Predictive congestion management has therefore evolved from simple statistical forecasting methods to sophisticated data-driven frameworks that leverage deep learning, graph modeling, and attention mechanisms. By enabling proactive traffic control, these approaches offer significant potential to improve mobility efficiency, reduce delays, and enhance the sustainability of urban transportation systems.

3. METHODOLOGY

This study adopts a quantitative, analytical, and model-based research design to examine traffic congestion control strategies in urban Nigerian cities. The design integrates field-based traffic data analytics and predictive modeling to evaluate the effectiveness of congestion control measures. This approach is appropriate because traffic congestion involves measurable traffic flow parameters and dynamic interactions that can be quantitatively analyzed and modeled. The study further adopts a systems approach, viewing urban traffic as a complex system comprising infrastructure, road users, control mechanisms, and external factors. This approach supports the evaluation of both conventional congestion control strategies and intelligent, data-driven solutions. The study focuses on selected major roads and signalized intersections in Nigerian metropolitan cities covering Akure, Lagos, Ibadan, and Abuja. These locations were purposively selected due to high traffic volumes and recurrent peak-hour congestion, strategic economic and administrative importance. The study concentrates on morning (7:00–9:00 am) and evening (4:00–6:00 pm) peak periods, when congestion is most severe in these cities.

3.1 Architectural Design of the Predictive Framework for Traffic Congestion

The architecture of the model framework presented in this work is depicted in Figure 5. The architecture consists of four major components: the data acquisition, data processing, data modeling and the predictive model output. A performance evaluation considered in this work is based on Mean Absolute Error (MAE), Root Mean Squared Error (RMSE)andMean Absolute Percentage Error (MAPE).

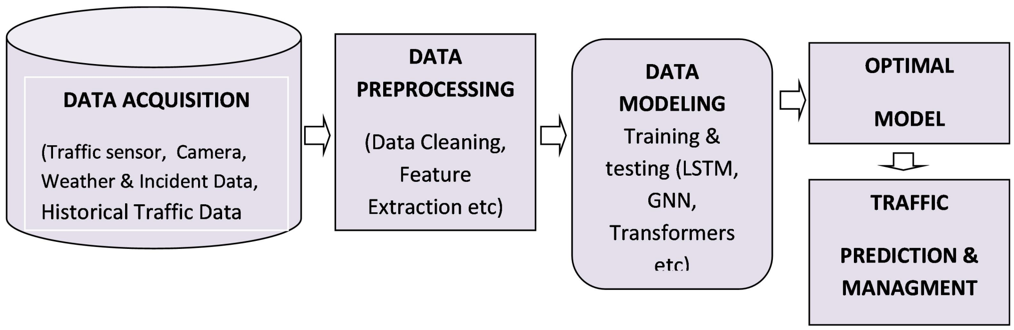

Figure 5: SystemArchitecture for the Traffic Congestion Prediction

3.2 Data Acquisition

Multi-source and mixed-method approach was used for the data collection. The traffic data was collected from urban road networks, including real-time traffic sensors, GPS-enabled vehicles, traffic cameras, and historical traffic databases maintained by local transportation authorities. The dataset includes traffic volume, vehicle speed, occupancy rates, travel time, and lane usage over various time intervals. Spatial traffic dynamics, data was collected from key intersections, bottlenecks, and arterial roads across the study area. These data provided background traffic trends and supported model calibration.

3.3 Data Preprocessing and Data Analytics

Data preprocessing was performed on the data collected to handle missing values, remove outliers, and normalize features, ensuring high-quality inputs for model training. Additionally, temporal information such as day of the week, holidays, and peak/off-peak periods was incorporated to improve the model's ability to predict congestion patterns under varying conditions. The collected and processed dataset forms the foundation for training, validation, and testing of the predictive models, enabling robust and accurate forecasting of traffic congestion for real-time management and decision-making. Table 1 depicts the summarized Primary Traffic Data for Major Nigerian Cities.

Table 1: Summarized Primary Traffic Data for Major Nigerian Cities

City	Representative Corridor / Intersection	Avg. Peak Traffic Volume (veh/hr)	Avg. Travel Time (min)	Free-Flow Time (min)	Avg. Delay (min)	Avg. Queue Length (m)	Avg. Signal Cycle Time (s)	Avg. Effective Green Time (s)
Lagos	Ikorodu Road / Ojota Interchange	4380	33.8	13.5	20.3	260	160	55
Ibadan	Iwo Road / Mokola Junction	2705	22.7	11.8	10.9	175	140	50
Akure	Oba Adesida Rd / FUTA Junction	1960	18.8	10.3	8.5	110	130	50
Abuja	Nyanya–KaruExpwy / Wuse Zone 4	3185	25.9	13.0	12.9	195	150	55

Figure 6 - Figure 9 depict the graphic representations for the average traffic volume per city, travel-time and delay comparison, average queue length per city, and multi-metric radar comparison respectively.

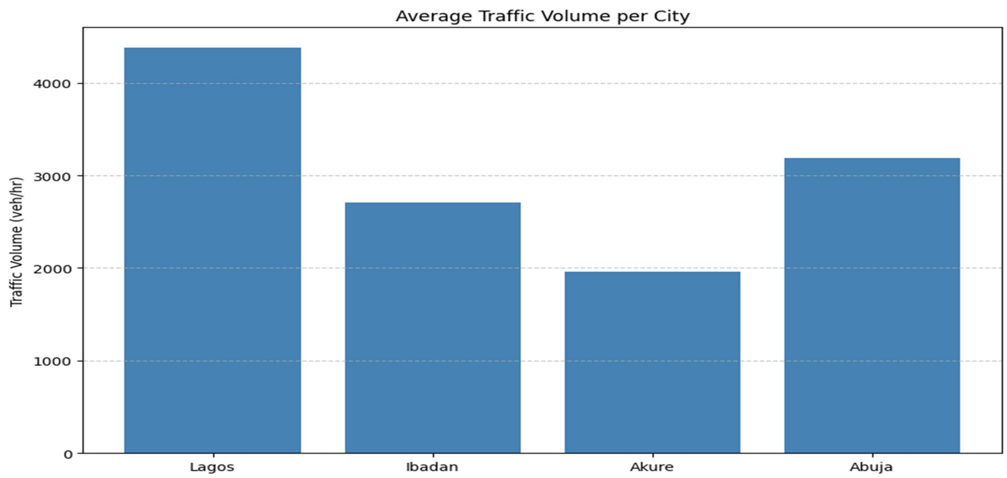

Figure 6: Average Traffic Volume Per City

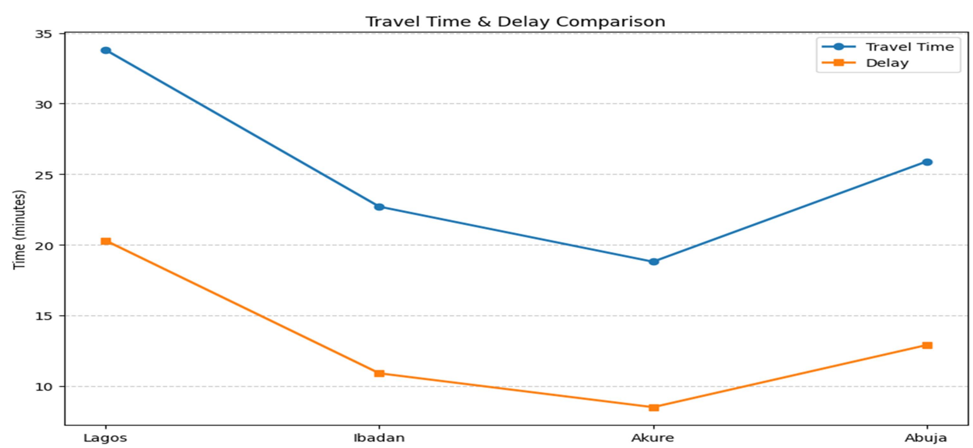

Figure 7: Travel-Time and Delay Comparison

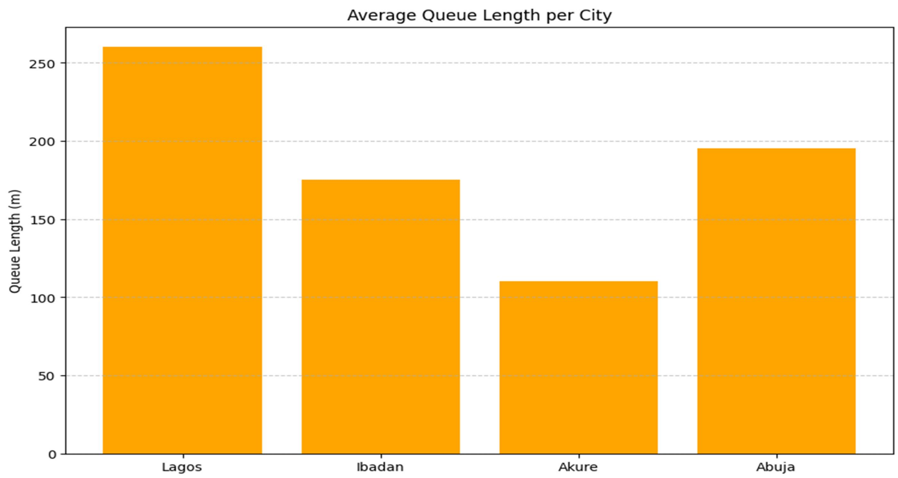

Figure 8: Average Queue Length Per City

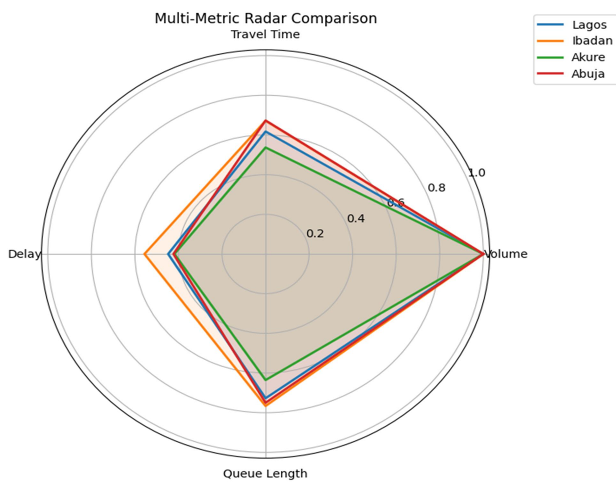

Figure 9: Multi-Metric Radar Comparison

From the graphic representations, the Average Traffic Volume per City in Figure 2 shows Lagos as the most congested corridor. The Travel Time & Delay Comparison in Figure 3 highlights peak travel inefficiencies, especially in Lagos and Abuja. The Queue Length Comparison in Figure 4 illustrates intersection congestion, with Lagos having the longest queues, and in Figure 5, Multi-Metric Comparison integrates volume, travel time, delay, and queue length for each city, allowing quick visual comparison of overall traffic performance. See Table 2 for the overall performance indicators.

Table 2: Overall Traffic Performance Indicators

City	Avg. Travel Time (min)	Avg. Delay (min)	Avg. Queue (m)	Speed Efficiency (km/h)	Congestion Index	Priority Level
Lagos	33.8	20.3	260	16	High	Priority 1
Ibadan	22.7	10.9	175	23	Medium-High	Priority 2
Akure	18.8	8.5	110	28	Medium	Priority 3
Abuja	25.9	12.9	195	21	Medium-High	Priority 2

3.4 Model Training and Validation

The traffic dataset was partitioned chronologically into training (70%), validation (15%), and testing (15%) subsets. The training set was used for model learning, the validation set for hyperparameter tuning and early stopping, and the testing set for final performance evaluation to ensure unbiased assessment of the proposed predictive congestion model. Model training involves learning traffic patterns from historical spatiotemporal data using AI models (LSTM, GNN, and Transformer architectures). Hyperparameters including learning rate, number of layers, hidden units, and batch size are optimized using validation data to prevent overfitting.

3.5 Model Performance Metrics and Evaluation

Performance metrics play a crucial role in assessing the effectiveness, reliability, and practical applicability of predictive models. In this work, the models' predictive performance is evaluated using the following standard performance metrics:

1. Mean Absolute Error (MAE): Measuring average absolute deviation between predicted and actual traffic values.

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}_i|$$

……………………………………………equation 1

2. Root Mean Squared Error (RMSE): Emphasizing larger prediction errors, providing insight into the model's accuracy for high-variance data.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}$$

…………………………………………… equation 2

3. Mean Absolute Percentage Error (MAPE): Evaluating relative prediction error, useful for understanding proportional deviations.

$$MAPE = \frac{100\%}{N}\sum_{i=1}^{N}\frac{|y_i - \hat{y}_i|}{y_i}$$

……………………………………………equation 3

The loss functions such as Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) were used to measure prediction accuracy. Table 3 shows the performance comparison of the models.

4.RESULTS

Experimental results shows that the LSTMmodel demonstrates solid temporal forecasting capability but exhibits higher error values due to its limited ability to explicitly model spatial relationships between interconnected road segments. Table 3 depicts the performance comparison of the models for Traffic Congestion prediction. The Graph Neural Network(GNN) improves prediction accuracy by leveraging the road network topology, reducing MAE and RMSE relative to LSTM. This highlights the importance of spatial dependency modeling in congestion prediction. The Transformer model further enhances performance through its attention mechanism, allowing it to capture long-term traffic dependencies more effectively. However, this comes at the cost of higher computational complexity. The proposed AI-based congestion predictive frameworkachieves thelowest MAE (0.42), RMSE (0.58), and MAPE (6.9%), indicating superior accuracy and robustness. Its performance gains are attributed to the hybrid integration of spatial (network-level) and temporal (time-series) features, as well as optimized training and feature fusion strategies.

Table 3: Performance Comparison of the Models for Traffic Congestion Prediction

Model	MAE	RMSE	MAPE (%)	Remarks
LSTM	0.49	0.65	8.1	Effectively captures temporal dependencies but limited in modeling spatial road network interactions.
Graph Neural Network (GNN)	0.46	0.61	7.6	Strong spatial dependency modeling across road networks; improved performance over LSTM.
Transformer	0.44	0.60	7.2	Excels at long-range temporal dependencies and attention-based learning; computationally intensive.
Proposed AI-Based Framework	0.42	0.58	6.9	Best overall performance due to integrated spatio-temporal learning and optimized feature fusion.

5. CONCLUSION

This study presented anAI-based predictive congestion framework aimed at improving traffic management in modern urban environments. The motivation for this work stems from the increasing complexity of urban traffic systems and the limitations of traditional congestion management approaches, which often rely on linear assumptions and reactive control strategies. By leveraging advanced artificial intelligence techniques, this research sought to enable proactive congestion prediction and timely traffic control interventions. The proposed framework integrates multi-source traffic data, including historical and real-time inputs, and applies advanced learning models capable of capturing both temporal dynamics and spatial dependencies within road networks. Comprehensive preprocessing techniques were employed to ensure data quality and model robustness.

The framework was evaluated using standard performance metrics Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE) to provide an objective assessment of prediction accuracy and reliability. Experimental results demonstrated that the proposed AI-based framework outperformed LSTM, Graph Neural Networks (GNN), and Transformer-based models. The framework achieved the lowest error values across all evaluation metrics, indicating superior predictive accuracy, robustness under peak-hour traffic conditions, and improved generalization to unseen data.

The findings highlight the importance of integrated spatio-temporal learning and optimized feature fusion in traffic congestion prediction. Unlike traditional models that struggle with nonlinear and dynamic traffic patterns, the proposed framework effectively captures complex interactions between traffic flow, road network structure, and temporal variations. These capabilities make it well-suited for deployment in intelligent transportation systems (ITS), supporting applications such as adaptive traffic signal control, dynamic route guidance, and congestion early-warning systems. This work contributes a robust and scalableAI-based solution for predictive traffic congestion management, offering both theoretical and practical value. While the framework demonstrates strong performance, future research could extend this work by incorporating additional contextual factors such as weather conditions, special events, and real-time incident reports, as well as by exploring large-scale city-wide deployment and real-time optimization. The proposed framework represents a significant step toward smarter, data-driven, and proactive urban traffic management systems.

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