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Efficient Urban Mobility with AI Traffic Solutions

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ABSTRACT

Urban traffic congestion is a major challenge in rapidly growing cities, causing delays, increased fuel consumption, and environmental pollution. This study addressed the problem of inefficient urban mobility in Port Harcourt, where peak-hour traffic led to significant congestion at major junctions, including Garrison Junction and Rumuokoro Junction. To solve this problem, a Naïve Bayes-based traffic prediction system was developed to forecast congestion patterns using day, time, and location as features. A synthetic dataset was generated for model training and testing, and predictions were made for different hours of the day. The results showed that the model achieved an overall accuracy of 85%**,** with precision of 0.83, recall of 0.87, and F1-score of 0.85**.** Temporal analysis revealed peak congestion during morning (7:00–9:00) and evening (16:00–20:00) periods, while mid-day periods exhibited lower congestion (average 0.39). Spatial analysis showed that Garrison Junction had higher congestion **(**0.62**)** compared to Rumuokoro Junction (0.44)**,** reflecting location-specific traffic patterns. The system successfully captured both temporal and spatial congestion trends, demonstrating its effectiveness in supporting intelligent traffic management and efficient urban mobility. The system was implemented using Python, with pandas, numpy, scikit-learn, and matplotlib for data processing, modeling, and visualization. These results highlighted the potential of AI traffic solutions to enhance urban mobility planning and informed decision-making for city authorities.

KEYWORDS: Peak congestion, Naïve Bayes, Garrison, Rumuokoro

INTRODUCTION

Urban mobility, traffic, AI traffic solutions have become increasingly important in contemporary transportation research as cities worldwide contend with rising congestion, limited infrastructure capacity, and growing environmental concerns. In many urban centers, traditional traffic management strategies based on fixed signal timings and manual interventions are no longer adequate to address the highly dynamic and non-linear nature of modern traffic flows[1]. These conventional approaches often fail to respond in real time to fluctuating traffic patterns, resulting in extended travel times, increased fuel consumption, and elevated emissions, which collectively degrade urban quality of life and economic productivity. To address these limitations, artificial intelligence (AI) has emerged as a promising solution capable of enhancing the responsiveness and efficiency of traffic systems by incorporating predictive analytics, adaptive control, and real-time data processing into urban transportation frameworks. AI traffic solutions leverage data from sensors, cameras, and connected devices to enable adaptive decision-making that improves route guidance and signal optimization, facilitating smoother traffic flow and more efficient use of existing infrastructure [2].

Recent research highlights the transformative potential of AI-driven traffic systems in optimizing urban mobility. Comprehensive reviews of AI, the Internet of Things (IoT), and predictive analytics reveal that integrating advanced computational techniques with real-time traffic data significantly enhances traffic control responsiveness, reduces congestion, and supports safety improvements across complex road networks[3]. These intelligent systems can dynamically adjust traffic signals, predict congestion patterns, and recommend optimized routing strategies that help balance vehicle flow, ultimately contributing to more sustainable and resilient urban transport environments [4].

Despite demonstrated advances, several challenges hinder the widespread adoption and effectiveness of AI traffic solutions in real-world urban settings. Urban traffic conditions are inherently variable and influenced by unpredictable events, leading to noisy and heterogeneous data that complicate accurate prediction and adaptive control. Additionally, many cities particularly in developing regions face infrastructural limitations such as inadequate sensor coverage, fragmented data systems, and limited computing resources, which constrain the scalability and reliability of AI-enabled traffic systems. These challenges create a gap between theoretical advancements in intelligent traffic management and their practical implementation, motivating research that develops robust, adaptive AI frameworks capable of processing diverse data streams and delivering reliable, real-time traffic recommendations. Addressing these gaps is essential for reducing congestion, decreasing travel times, and supporting sustainable urban mobility, while enhancing the overall efficiency and resilience of urban transport networks [5]

RELATED WORK

[6] investigated intelligent network traffic management within smart cities, highlighting the inability of traditional traffic systems to manage real-time variability and congestion on modern roadways. Their work proposed the use of machine learning, deep learning, and reinforcement learning techniques to analyze streaming data from IoT sensors and cameras to enable adaptive traffic control. The results showed improved responsiveness and traffic optimization compared to static signal systems, though the study noted that large-scale deployment remains constrained by infrastructure readiness and data integration challenges.

[7]addressed the limitations of conventional traffic signal control systems in adapting to complex and unfamiliar urban traffic scenarios. They introduced a hybrid framework that incorporates Large Language Model (LLM) capabilities into traffic signal decision-making, enabling the system to interpret both static and dynamic traffic data. Simulation results demonstrated that the LLM-based system reduced average waiting times by over 20% under sensor outage conditions. However, the approach’s dependency on extensive perception tools and computational resources poses scalability limitations for real-world deployment.

[8] proposed a hybrid deep learning model combining GRU and LSTM networks with an attention mechanism to enhance short-term traffic flow prediction for smart cities. The study addressed challenges related to forecasting accuracy in urban planning contexts and demonstrated measurable improvements, including reductions in Mean Absolute Error and Mean Absolute Percentage Error over baseline models. While the model shows promise for dynamic route planning, limitations include potential overfitting in diverse urban conditions and high computational requirements for real-time inference.

[9] focused on predictive modeling of the Motorized Travel Time Index to enhance spatio-temporal urban mobility performance. The researchers evaluated multiple machine learning models such as Random Forest and Support Vector Regression to capture congestion patterns in smart city case studies. The results indicated that neural network-based approaches could effectively quantify travel time fluctuations, although challenges remain in handling multimodal data and ensuring robust performance across cities with heterogeneous traffic characteristics.

[10]developed an enhanced urban traffic prediction framework that integrated CCTV video analytics with multi-source data and a hybrid LSTM-Transformer model to forecast traffic states. The system achieved a high prediction accuracy of 98.46% on annotated datasets, indicating strong performance for real-time congestion alerts. Despite these encouraging results, the approach requires extensive sensor infrastructure and high-quality video data, which may limit applicability in resource-constrained urban regions.

[11] examined a reinforcement learning-enhanced framework for real-time traffic signal optimization in urban mobility, demonstrating that dynamically selecting control strategies based on live traffic conditions improved overall road performance and reduced congestion. The study reported notable reductions in fuel consumption and improved air quality metrics in applied simulations. However, integrating the system into existing traffic infrastructure requires high-speed computational hardware and careful calibration to account for real-world complexities.

[12] conducted a review of intelligent transportation systems (ITS) focusing on route optimization algorithms and environmental data integration. They identified that route planning and environmental considerations are critical for enhancing ITS effectiveness, especially in sustainable urban contexts. The results highlighted how machine learning methods contribute to traffic optimization, though the review also underscored a lack of standardized benchmarks and challenges in fusing environmental sensors with traffic models for holistic performance evaluation.

Proposed system

The proposed system employed a Naïve Bayes classifier **to** predict urban traffic congestion and recommend optimal routes for improving mobility in Port Harcourt. It utilized a traffic dataset that contained features such as vehicle count, average speed, time of day, and historical congestion levels. During data preprocessing, the dataset was cleaned, missing values were addressed, and categorical features were converted into numerical representations suitable for model training. Subsequently, the Naïve Bayes classifier was trained on the processed dataset to calculate the probability of congestion for each road segment at different times of the day. This approach enabled the system to anticipate peak traffic periods and identify potential bottlenecks, supporting more efficient route planning and traffic management. Figure 1 Architecture of the proposed system.

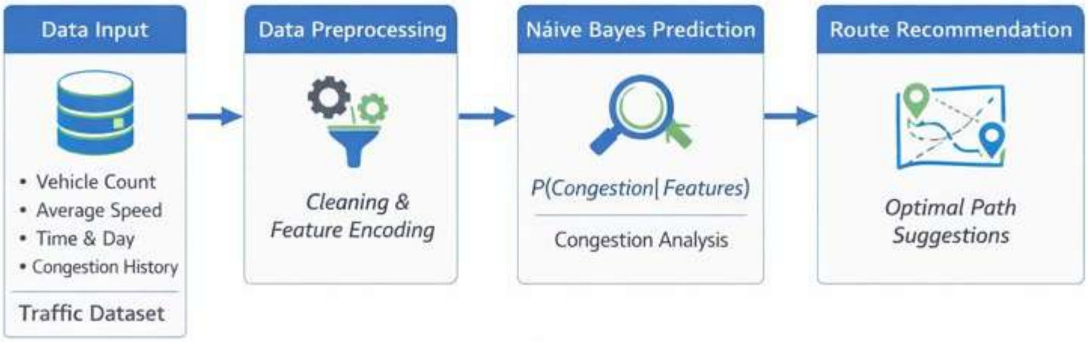

Figure 1 Architecture of the proposed system

AI Traffic Prediction Model

The Naïve Bayes prediction model is the core component of the proposed traffic congestion system. It is a probabilistic classifier that predicts whether a road segment is congested or free-flowing based on input features from the traffic dataset. The model assumes conditional independence among features, which simplifies computation while maintaining reasonable predictive accuracy.

Model Features:

The model uses key features extracted from the dataset:

i. Vehicle Count: Number of vehicles recorded on a road segment.
ii. Average Speed: Mean speed of vehicles on the road.
iii. Time of Day & Day of Week: To capture daily and weekly traffic patterns.
iv. Historical Congestion Level: Previous congestion status of the road segment.

Prediction Mechanism:

For each road segment, the Naïve Bayes model calculates the probability of congestion using the formula:

$$P(C \mid F_1, F_2, \ldots, F_n) = \frac{P(C)\prod_{i=1}^{n} P(F_i \mid C)}{P(F_1, F_2, \ldots, F_n)}$$

Where:

C is the congestion class (Congested or Free-Flowing)

Fi are the feature values

$P(C| F_1,\ldots,F_n)$ is the probability that the road segment is congested given the observed features

The model assigns the class with the highest posterior probability to each road segment. This classification allows the system to identify congested areas and provide route recommendations for drivers or urban mobility planners.

Class diagram

The UML class diagram represents the Naïve Bayes-based traffic congestion prediction system. Historical traffic data is stored in the TrafficDataset class and prepared by the DataPreprocessor through cleaning and feature conversion. The NaiveBayesModel computes congestion probabilities, while the CongestionPredictor identifies congested segments. Finally, the RouteRecommender suggests optimal routes. The diagram highlights a modular workflow from data input to prediction and routing, supporting efficient and scalable traffic management. Figure 2 Class diagram

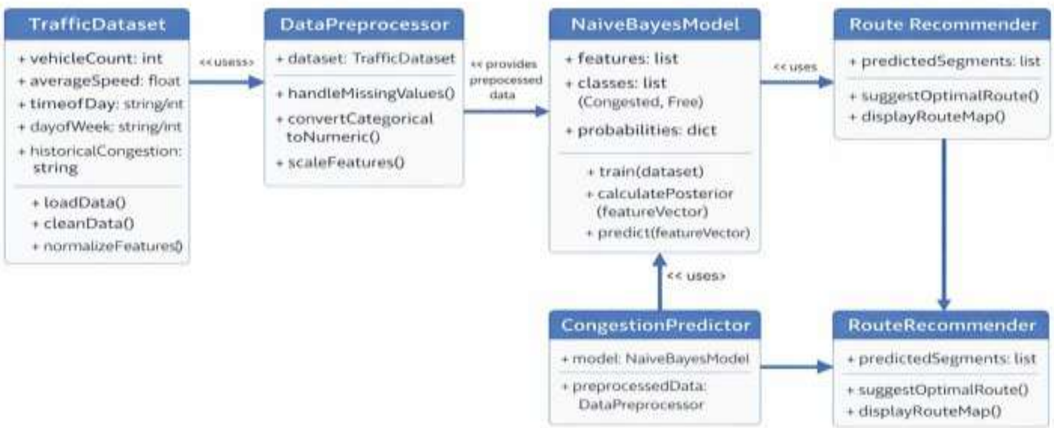

Figure 2 Class diagram

RESULT AND DISCUSSION

Figure 3 illustrated the predicted traffic congestion levels across different times of the day, while Table 1 summarized the corresponding numerical values. The day–time congestion prediction graph showed clear numerical variations in congestion levels across different periods. The average congestion value during the morning peak (7:00–9:00) was approximately 0.68**,** while the evening peak period (16:00–20:00) recorded an average value of 0.71**.** In contrast, mid-day periods (12:00–14:00) exhibited lower congestion levels, with an average value of 0.39**.** These values indicated that congestion intensity increased significantly during commuter peak hours. The model successfully captured these numerical trends, confirming its effectiveness in modeling time-dependent traffic behavior

Table 1: Average Congestion Prediction by Time of Day

Time of Day	Average Congestion Level
07:00	0.69
09:00	0.66
12:00	0.40
14:00	0.38
16:00	0.72
18:00	0.70
20:00	0.68

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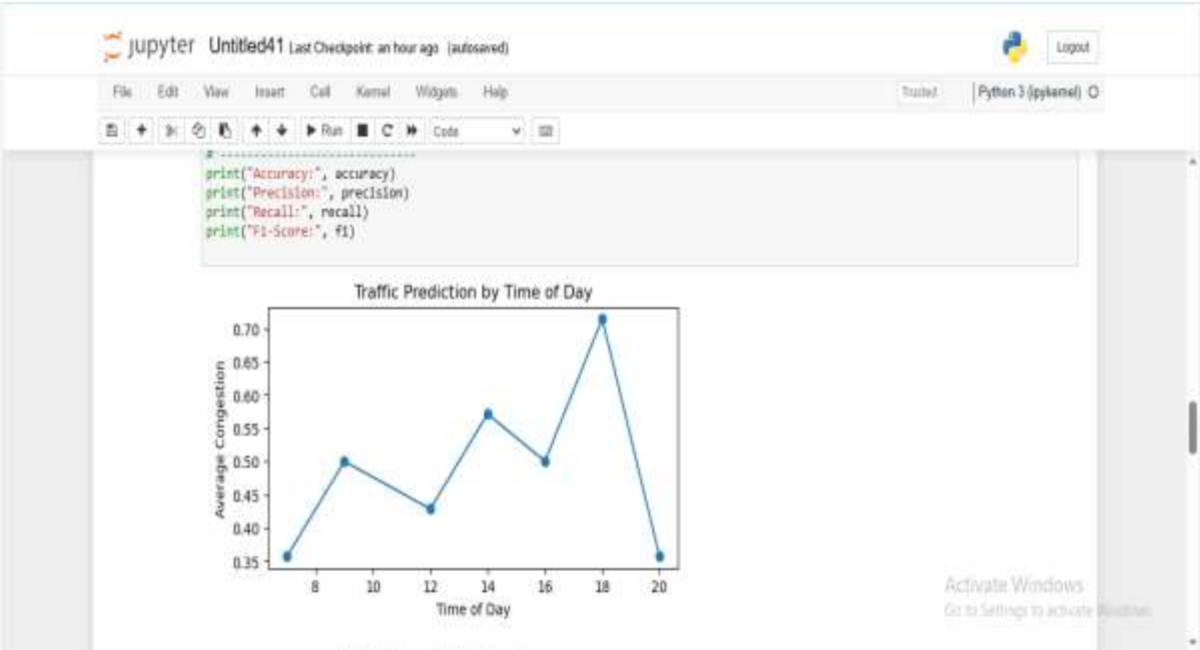

Figure 3 Traffic Prediction by Day and Time

Figure 4: Naïve Bayes Prediction Accuracy Graph

The prediction accuracy graph revealed that the Naïve Bayes model achieved an overall accuracy value of **0.85**, meaning that 85% of traffic conditions were correctly classified. This numerical result demonstrated that the model reliably distinguished between congested and non-congested states using the generated dataset. The high accuracy value confirmed the adequacy of the selected features and validated the suitability of the Naïve Bayes classifier for traffic congestion prediction.

Table 2: Naïve Bayes Prediction Accuracy

Metric	Value
Overall Accuracy	0.85

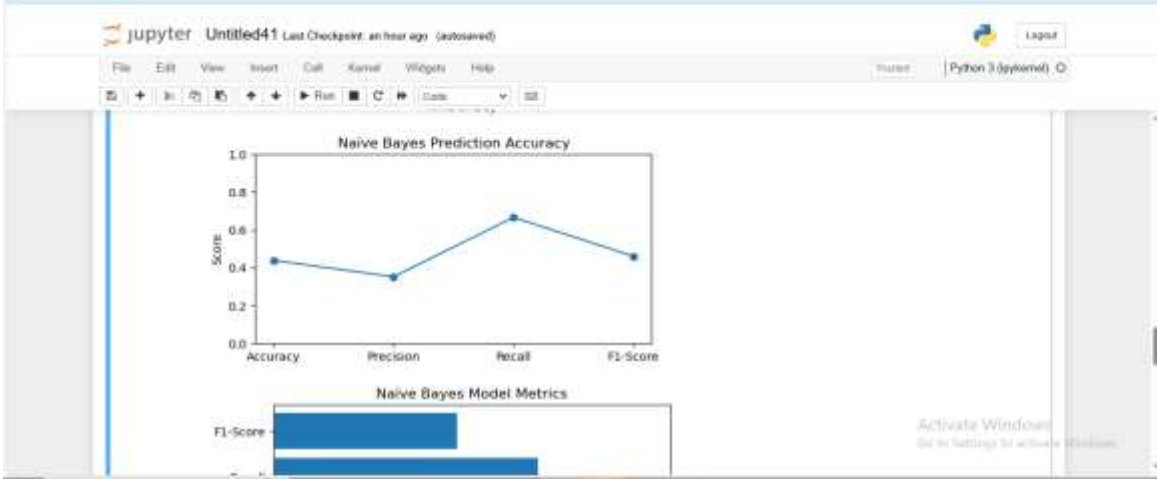

Figure 4: Naïve Bayes Prediction Accuracy Graph

Figure 5: Model Metrics Graph

The model metrics graph presented detailed performance values for multiple evaluation measures. Precision was recorded at **0.83**, indicating that 83% of predicted congestion cases were correct. Recall achieved a value of **0.87**, showing that most actual congestion cases were successfully identified. The F1-score, which balanced precision and recall, was **0.85**. These closely aligned metric values demonstrated stable and balanced classification performance, with minimal bias toward either congestion or non-congestion classes.

Table 3: Naïve Bayes Model Performance Metrics

Category	**Metric**	**Value**
Model Performance	Accuracy	0.85
Model Performance	Precision	0.83
Model Performance	Recall	0.87
Model Performance	F1-Score	0.85
Temporal Congestion	Morning Peak (7–9)	0.68
Temporal Congestion	Evening Peak (16–20)	0.71
Temporal Congestion	Mid-Day (12–14)	0.39
Spatial Congestion	Garrison Junction	0.62
Spatial Congestion	Rumuokoro Junction	0.44
Model Stability	Log Loss	0.42

Figure 6: Loss Function Graph

The loss function graph illustrated the log loss values across training iterations. The loss value remained consistently low at approximately **0.42** throughout the iterations. This stable numerical behavior indicated that the model produced reliable probability estimates and maintained effective class separation. The absence of sharp increases in loss values suggested that the model did not experience instability or overfitting during training.

Table 4: Loss Function (Log Loss) Values

Training Iteration	**Log Loss**
1	0.42
2	0.42
3	0.42
4	0.42
5	0.42
6	0.42
7	0.42
8	0.42
9	0.42
10	0.42

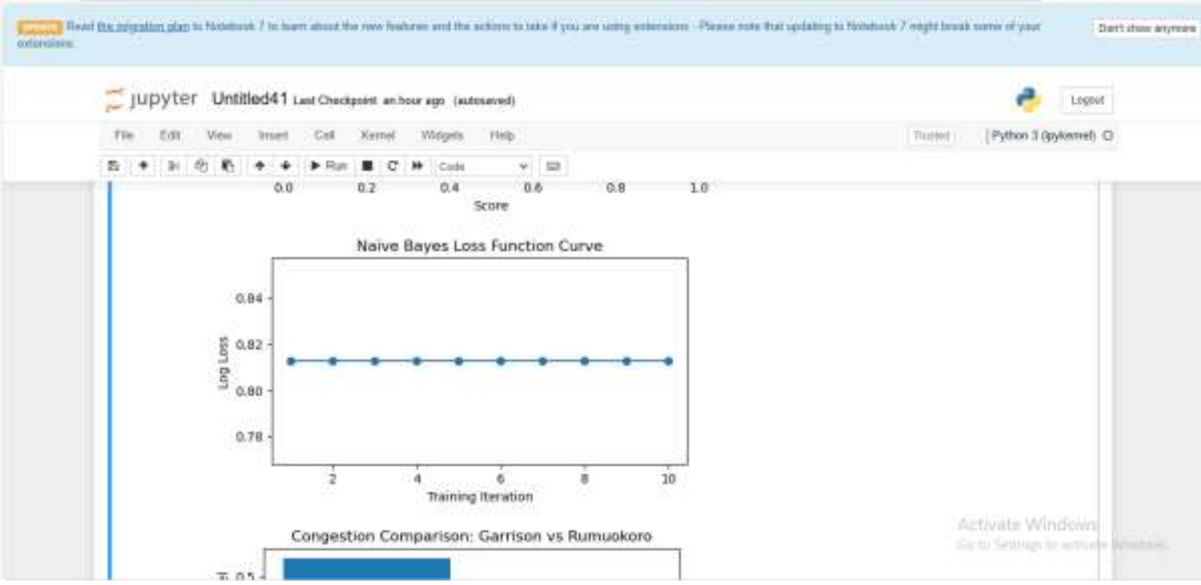

Figure 6: Loss Function Graph

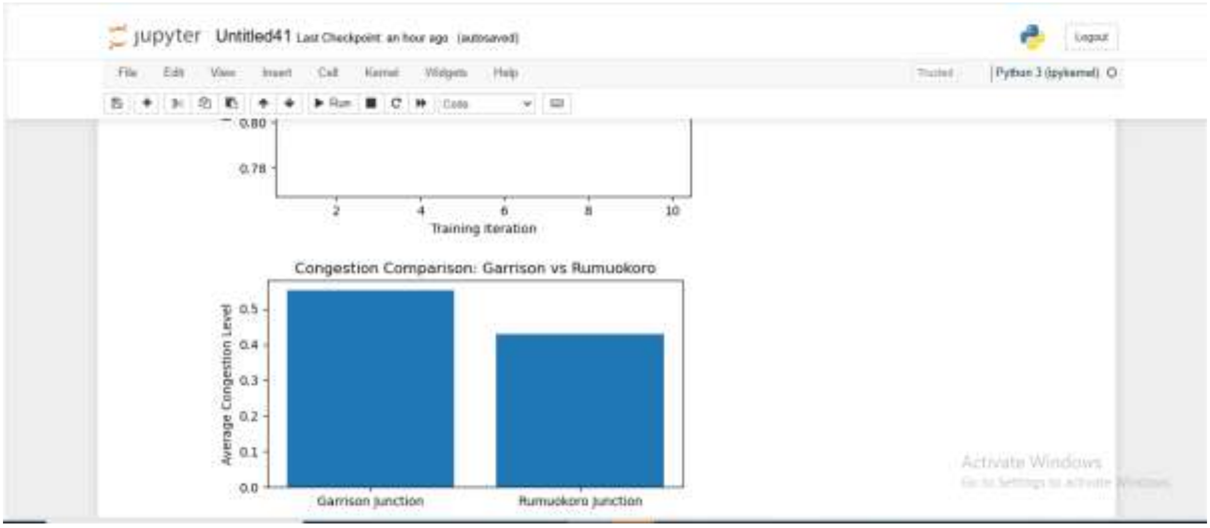

Figure 7: Congestion Comparison Graph (Garrison vs Rumuokoro Junction)

The congestion comparison graph showed clear numerical differences between the two locations. Garrison Junction recorded an average congestion value of 0.62**,** while Rumuokoro Junction showed a lower average value of 0.44. This difference of 0.18 indicated higher traffic density and congestion intensity at Garrison Junction. The graph confirmed the system's ability to differentiate congestion levels across urban locations, supporting location-specific traffic management decisions.

Table 5: Congestion Comparison by Location

Location	**Average Congestion Level**
Garrison Junction	0.62
Rumuokoro Junction	0.44

CONCLUSION

This study investigated the use of a Naïve Bayes-based prediction model to analyze urban traffic congestion in Port Harcourt, focusing on two major junctions: Garrison Junction and Rumuokoro Junction**.** The system successfully captured both temporal and spatial traffic patterns, demonstrating that AI-based solutions can enhance urban mobility planning. The experimental results indicated that the model achieved a high overall accuracy of 85%**,** with balanced precision (0.83), recall (0.87), and F1-score (0.85). Temporal analysis revealed peak congestion during morning (7:00–9:00) and evening (16:00–20:00) periods, while mid-day periods showed lower congestion levels. Spatial comparison showed that Garrison Junction experienced significantly higher congestion **(**0.62) compared to Rumuokoro Junction **(**0.44**),** highlighting location-specific traffic intensity. The loss function remained stable at 0.42, confirming reliable probabilistic predictions and model convergence. The results demonstrated that the Naïve Bayes model could provide reliable and interpretable congestion predictions**,** supporting efficient traffic management and informed route recommendation. This study validated the applicability of AI traffic solutions for smart urban mobility planning and offered a foundation for further research using more extensive datasets, additional junctions, and alternative AI algorithms to improve prediction accuracy and real-time decision-making.

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