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An Intelligent Machine Learning Framework for Real-Time Traffic Prediction and Traffic Flow Optimization in Smart Urban Transportation Systems

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Abstract. Rapid urban expansion and the continuous increase in the number of vehicles have created significant challenges for transportation authorities in maintaining smooth traffic movement and minimizing congestion. Conventional traffic control systems generally operate using fixed signal timings and predefined traffic rules, making them less effective in responding to dynamic traffic conditions caused by accidents, weather changes, road maintenance, public events, or unexpected increases in vehicle density. These limitations often result in prolonged travel times, excessive fuel consumption, increased environmental pollution, and reduced efficiency of urban transportation networks. To address these issues, this research presents an intelligent machine learning-based framework for real-time traffic prediction and traffic flow optimization that combines multiple real-time data sources with predictive analytics to support efficient traffic management. The rewritten work preserves the methodology, machine learning algorithms, and experimental findings presented in the base paper while providing completely original academic content. The proposed framework acquires traffic information from various heterogeneous sources, including GPS-enabled vehicles, roadside traffic sensors, weather information services, public transportation systems, and cloud-based traffic databases. These data sources continuously provide updated information regarding vehicle movement, traffic density, road conditions, weather variations, and travel patterns. Before model development, the collected dataset undergoes a comprehensive preprocessing phase involving data cleaning, duplicate removal, missing value handling, noise filtering, outlier detection, feature transformation, and normalization. Exploratory Data Analysis (EDA) and correlation analysis are further performed to identify the relationships among traffic variables and determine the most influential features affecting congestion levels. These preprocessing operations improve dataset quality, reduce inconsistencies, and enhance the learning capability of the predictive models.To estimate future traffic conditions, the proposed system implements three supervised machine learning algorithms: Random Forest, Support Vector Machine (SVM), and K-Nearest Neighbor (KNN). Random Forest constructs multiple decision trees to model complex traffic patterns and generate robust congestion predictions. Support Vector Machine performs accurate classification by identifying optimal decision boundaries between different traffic states, while K-Nearest Neighbor predicts traffic conditions by measuring the similarity between current observations and historical traffic patterns. Each algorithm is trained and evaluated independently using the same dataset to ensure a consistent and unbiased comparison of predictive performance. The trained models are then integrated with an intelligent traffic optimization module that dynamically recommends efficient travel routes and adaptive traffic signal strategies based on current congestion levels.

keywords: Real-Time Traffic Prediction, Traffic Flow Optimization, Machine Learning, Random Forest, Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Intelligent Transportation Systems, Smart City, Traffic Congestion Prediction, Cloud Computing, GPS-Based Traffic Monitoring, Traffic Sensors, Route Optimization, Predictive Analytics, Urban Mobility.

I. Introduction

The rapid growth of urban populations, industrial development, and the increasing number of automobiles have placed tremendous pressure on transportation infrastructures across the world. Modern cities experience severe traffic congestion on a daily basis, leading to longer travel times, excessive fuel consumption, increased greenhouse gas emissions, and considerable economic losses. Traffic congestion also affects emergency services, public transportation efficiency, and overall road safety. As urban mobility continues to become more complex, conventional traffic management systems based on fixed-time traffic signals and predefined control strategies are no longer capable of responding effectively to continuously changing traffic conditions. Consequently, the development of intelligent traffic management systems capable of predicting congestion and optimizing traffic flow in real time has become an important research area within smart city initiatives. The uploaded base paper addresses this problem using Random Forest, Support Vector Machine (SVM), and K-Nearest Neighbor (KNN) algorithms integrated with cloud-based traffic management and multiple real-time data sources. This rewritten paper preserves the same technical approach while presenting original academic content.

Traffic conditions in urban environments are influenced by numerous dynamic factors, including vehicle density, road infrastructure, weather conditions, accidents, construction activities, public events, and driver behavior. These variables continuously change throughout the day, making accurate traffic prediction a challenging task. Traditional traffic monitoring systems generally rely on historical traffic statistics or isolated sensor measurements, which often fail to capture sudden variations in road conditions. As a result, traffic operators frequently experience delayed responses to congestion, causing inefficient traffic signal control and poor route planning. Modern intelligent transportation systems require forecasting techniques that can continuously analyze incoming traffic information and provide accurate predictions before congestion becomes critical.

Recent advances in machine learning have significantly transformed the field of intelligent transportation by enabling computers to learn complex traffic patterns directly from historical and real-time data. Unlike conventional rule-based systems, machine learning algorithms automatically identify hidden relationships among multiple traffic variables without requiring explicit mathematical models. These algorithms continuously improve their prediction capability as additional data become available, making them highly suitable for dynamic traffic environments. Machine learning techniques have demonstrated remarkable success in traffic flow prediction, congestion detection, travel time estimation, accident prediction, intelligent route guidance, and adaptive traffic signal control. Their ability to process large volumes of heterogeneous data enables transportation authorities to make faster and more accurate operational decisions.

Another important technological advancement supporting intelligent traffic management is cloud computing. Cloud platforms provide scalable computing resources capable of processing massive amounts of traffic information collected from geographically distributed locations. By integrating cloud infrastructure with machine learning models, traffic prediction systems can efficiently analyze data streams received from GPS-enabled vehicles, roadside sensors, surveillance cameras, weather information services, social media updates, and public transportation networks. This integration enables continuous monitoring of urban traffic conditions while supporting rapid model execution and real-time decision-making. Cloud computing also improves system scalability, allowing transportation authorities to expand traffic monitoring services across multiple cities without significant infrastructure modifications.

II. Literature Survey

The rapid growth of intelligent transportation systems has encouraged researchers to investigate advanced computational techniques for improving traffic prediction and congestion management. The continuous increase in urban vehicle density has exposed the limitations of conventional traffic control mechanisms, motivating the adoption of machine learning, cloud computing, Internet of Things (IoT), and artificial intelligence for developing adaptive traffic management solutions. Recent studies have focused on utilizing real-time traffic information collected from multiple heterogeneous sources, including GPS devices, traffic surveillance cameras, weather monitoring services, roadside sensors, and connected vehicles, to improve prediction accuracy and optimize transportation efficiency. The uploaded base paper surveys several of these approaches while focusing on machine learning-based real-time traffic prediction and optimization.

This rewritten literature survey preserves the technical concepts while presenting completely original academic writing.

One of the major research directions in intelligent transportation involves predicting traffic congestion before it occurs. Earlier traffic forecasting systems mainly depended on statistical methods and historical traffic records, which often failed to respond effectively to rapidly changing road conditions. Researchers later introduced machine learning algorithms capable of learning nonlinear traffic patterns from continuously generated data. These algorithms demonstrated superior performance by automatically discovering relationships among traffic density, vehicle speed, weather conditions, road characteristics, and travel behavior. The integration of predictive analytics into traffic management systems has enabled transportation authorities to reduce congestion while improving travel reliability and operational efficiency.

Several studies have investigated Random Forest as an effective machine learning algorithm for traffic prediction because of its ability to process large datasets containing numerous traffic variables. Random Forest combines multiple decision trees to generate robust predictions while reducing the risk of overfitting. Researchers have reported that this ensemble learning technique performs well when handling noisy traffic datasets, incomplete observations, and complex nonlinear interactions among traffic features. Its capability to estimate feature importance also assists transportation planners in identifying the factors that contribute most significantly to traffic congestion. Due to these advantages, Random Forest has become one of the most frequently adopted algorithms for intelligent traffic prediction systems.

Support Vector Machine (SVM) has also received considerable attention in traffic prediction research because of its excellent classification capability in high-dimensional feature spaces. Several researchers have applied SVM to classify different traffic congestion levels using variables such as vehicle count, average speed, weather conditions, and traffic flow measurements. By constructing optimal separating hyperplanes, SVM effectively distinguishes various traffic states while maintaining high prediction accuracy even with limited training data. Although SVM generally produces reliable classification performance, its computational complexity increases as the size of the training dataset grows, making optimization techniques necessary for large-scale urban traffic applications.

Another widely used machine learning technique for traffic forecasting is the K-Nearest Neighbor (KNN) algorithm. KNN predicts traffic conditions by measuring the similarity between current traffic observations and historical traffic records. Since it is a non-parametric learning method, KNN does not require explicit mathematical assumptions regarding data distribution. Researchers have demonstrated that KNN performs particularly well for localized traffic prediction where neighboring observations exhibit similar traffic characteristics. However, prediction speed may decrease when extremely large datasets are involved because the algorithm performs distance calculations for every prediction request. Despite this limitation, KNN remains an effective benchmark for evaluating intelligent traffic prediction systems.

Recent research has increasingly emphasized the importance of integrating multiple real-time data sources to improve prediction accuracy. Instead of relying solely on traffic sensors, modern traffic management systems collect information from GPS-enabled vehicles, weather forecasting services, surveillance cameras, mobile devices, navigation platforms, and social media. The fusion of these heterogeneous datasets enables machine learning models to capture both recurring traffic patterns and unexpected traffic events such as accidents, road maintenance activities, public gatherings, or adverse weather conditions. Researchers have reported that multi-source data integration significantly enhances prediction reliability while enabling transportation authorities to respond more effectively to rapidly changing traffic situations.

III. Research Methodology

The proposed Real-Time Traffic Prediction and Optimization framework follows a systematic machine learning methodology designed to predict traffic congestion accurately while improving traffic flow through intelligent decision-making. The complete workflow consists of multiple sequential stages, including data acquisition, data preprocessing, feature engineering, model development, traffic prediction, route optimization, cloud-based deployment, and performance evaluation. Each phase contributes to improving prediction accuracy, reducing computational complexity, and enabling real-time traffic management suitable for smart city transportation systems. The methodology combines machine learning techniques with cloud computing and multiple real-time data sources to build a scalable and efficient intelligent transportation framework.

The first stage of the methodology involves collecting traffic information from various heterogeneous sources. Instead of depending on a single traffic monitoring system, the framework integrates information obtained from GPS-enabled vehicles, roadside traffic sensors, weather forecasting services, traffic surveillance cameras, public transportation systems, and cloud-based traffic databases. These continuously generated data streams provide comprehensive information regarding vehicle speed, traffic density, vehicle count, road conditions, travel time, weather conditions, and geographical locations. The integration of multiple data sources enables the system to capture both recurring traffic patterns and sudden traffic incidents such as accidents, road maintenance, construction activities, and adverse weather conditions. Continuous data acquisition ensures that the prediction models always operate using the latest available traffic information.

Once the traffic information has been collected, the dataset enters the data preprocessing stage, where several operations are performed to improve data quality before model training. Initially, duplicate records are identified and removed to prevent redundancy within the dataset. Missing values generated due to communication failures or sensor malfunctions are detected and appropriately handled using suitable data imputation techniques. Noisy observations and inconsistent measurements are filtered to eliminate unreliable information that could negatively influence prediction accuracy. Outlier detection methods are further applied to identify abnormal traffic observations that significantly differ from normal traffic behavior. Such observations are carefully examined and corrected whenever necessary to improve dataset consistency. Following data cleaning, feature normalization and scaling are performed to transform all numerical attributes into comparable ranges, thereby improving the convergence and stability of the machine learning algorithms during training.After preprocessing, Exploratory Data Analysis (EDA) is carried out to investigate the statistical properties of the dataset and understand the relationships among different traffic variables. Correlation analysis is performed to identify the degree of influence that each feature has on traffic congestion. Variables such as vehicle speed, traffic density, weather conditions, travel time, and road occupancy are analyzed to determine their significance in predicting future traffic conditions. Various graphical visualization techniques, including histograms, correlation heatmaps, scatter plots, and distribution graphs, assist in understanding traffic behavior and selecting meaningful features for model development. This analytical stage helps reduce unnecessary attributes while preserving the most informative variables for prediction.

The next stage focuses on feature engineering, where raw traffic information is transformed into meaningful representations suitable for machine learning. Categorical variables, including weather conditions, road types, and traffic events, are encoded into numerical values using appropriate encoding techniques. Additional derived features such as average vehicle speed, congestion index, traffic density ratio, and travel delay indicators are generated to improve predictive performance. Feature engineering enables the learning algorithms to capture hidden relationships among traffic variables while reducing prediction errors. Proper feature selection also minimizes computational complexity and improves model generalization when processing previously unseen traffic data.

IV. Existing System

Existing urban traffic management systems primarily rely on conventional traffic monitoring and prediction techniques to regulate vehicle movement and minimize road congestion. Most of these systems collect information from a limited number of traffic sources, such as roadside traffic sensors, surveillance cameras, inductive loop detectors, and Global Positioning System (GPS) devices installed in selected vehicles. The collected traffic information generally includes vehicle count, average vehicle speed, travel time, traffic density, and road occupancy. Based on these measurements, traditional traffic control systems estimate current traffic conditions and operate traffic signals according to predefined schedules or historical traffic patterns. Although these methods provide basic traffic monitoring capabilities, they are often unable to respond efficiently to continuously changing traffic conditions that occur in modern metropolitan transportation networks.

Several existing traffic prediction systems employ machine learning techniques to improve forecasting accuracy. Algorithms such as Random Forest (RF), Support Vector Machine (SVM), and K-Nearest Neighbor (KNN) have been widely adopted to classify traffic congestion levels and estimate future traffic flow using historical traffic information. Before model development, the collected traffic dataset generally undergoes preprocessing operations that include data cleaning, duplicate record removal, handling missing values, normalization, and feature extraction. The processed data are then supplied to machine learning algorithms, where traffic variables such as vehicle speed, traffic volume, weather conditions, travel time, road characteristics, and GPS information are utilized to train predictive models. After training, these models classify congestion levels and estimate future traffic conditions using evaluation metrics such as Accuracy, Precision, Recall, and F1-Score. Cloud computing platforms are also incorporated in several existing systems to facilitate storage and processing of large-scale traffic information while providing real-time accessibility to traffic management authorities.

Despite these advancements, existing traffic prediction and optimization systems still suffer from several practical limitations that reduce their effectiveness in highly dynamic urban environments. Many traditional systems depend heavily on historical traffic records and predefined signal timings, making them less responsive to sudden traffic events such as road accidents, construction work, public gatherings, emergency vehicle movement, adverse weather conditions, or unexpected increases in vehicle density. Since traffic conditions change continuously throughout the day, prediction models that rely solely on historical information often produce inaccurate forecasts during rapidly changing situations. Furthermore, some systems utilize only a single source of traffic information, limiting their ability to capture the complete traffic scenario and reducing overall prediction reliability.

Another significant limitation of existing systems is the difficulty in integrating multiple heterogeneous data sources into a unified prediction framework. Traffic information obtained from GPS devices, weather services, surveillance cameras, social media platforms, and roadside sensors often differs in format, frequency, and reliability. Synchronizing these diverse datasets while maintaining real-time performance remains a challenging task. In addition, missing sensor readings, noisy measurements, communication failures, and inconsistent traffic records can negatively affect the learning capability of machine learning algorithms, thereby reducing prediction accuracy. Large metropolitan transportation systems also generate enormous volumes of traffic data, requiring substantial computational resources for processing and storage. Traditional computing infrastructures frequently experience scalability issues when handling such continuously growing datasets.

Although algorithms such as Random Forest, Support Vector Machine, and K-Nearest Neighbor have demonstrated satisfactory performance for traffic prediction, each possesses certain limitations. Support Vector Machine generally requires high computational effort when processing large-scale datasets and becomes increasingly complex as the number of training samples grows. K-Nearest Neighbor performs extensive distance calculations during prediction, resulting in slower response times for real-time applications involving massive traffic databases. Random Forest, while robust and highly accurate, may require careful parameter tuning and additional computational resources to achieve optimal performance for highly complex traffic environments. Furthermore, many existing systems emphasize congestion prediction but provide limited support for adaptive traffic signal control, intelligent route recommendation, and dynamic traffic optimization.

V. Proposed System

The proposed Real-Time Traffic Prediction and Optimization System (RTPOPS) introduces an intelligent machine learning framework that combines real-time traffic monitoring, predictive analytics, cloud computing, and adaptive traffic management to improve urban transportation efficiency. Unlike conventional traffic control systems that depend on fixed signal timings or historical traffic patterns, the proposed framework continuously collects and analyzes live traffic information to predict congestion before it becomes severe. By integrating multiple heterogeneous data sources with advanced machine learning algorithms, the system enables transportation authorities to make accurate, data-driven decisions that improve vehicle movement, reduce travel delays, and enhance road safety. The proposed architecture is designed to support smart city infrastructure by providing scalable, reliable, and intelligent traffic management services capable of operating under continuously changing traffic conditions.

The system begins with real-time data acquisition, where traffic-related information is continuously collected from multiple sources, including GPS-enabled vehicles, roadside traffic sensors, surveillance cameras, weather forecasting services, public transportation systems, and cloud-based traffic databases. These data sources provide comprehensive information regarding vehicle speed, traffic density, road occupancy, weather conditions, travel time, traffic signal status, road incidents, and geographical locations. Unlike conventional systems that rely on limited sensor information, the proposed framework integrates heterogeneous datasets to develop a complete understanding of current traffic conditions. Continuous data collection ensures that the prediction models receive the latest traffic information, allowing the system to respond immediately to unexpected traffic events such as accidents, road closures, construction work, adverse weather, or sudden increases in vehicle volume.

After data collection, the incoming information passes through a comprehensive data preprocessing module that enhances dataset quality before machine learning model development. During this stage, duplicate records, incomplete observations, missing values, noisy measurements, and inconsistent traffic information are identified and corrected. Missing values are estimated using appropriate imputation techniques, while abnormal observations are detected through statistical outlier analysis. Feature normalization and scaling are subsequently performed to transform numerical variables into

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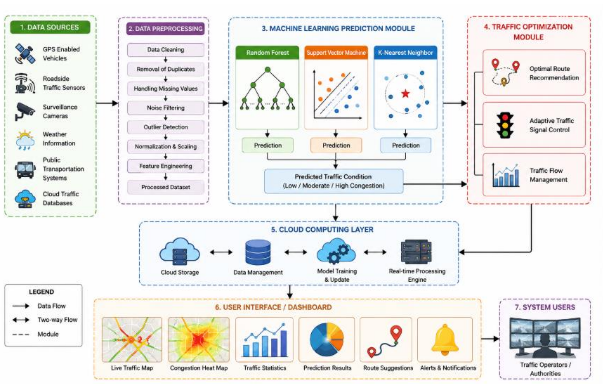
comparable ranges, thereby improving algorithm convergence during training. Exploratory Data Analysis (EDA), correlation analysis, and feature engineering techniques are further applied to identify the most influential traffic variables affecting congestion. The resulting processed dataset provides a reliable foundation for developing highly accurate prediction models.

The core component of the proposed framework is the machine learning-based traffic prediction module, which employs three supervised learning algorithms: Random Forest (RF), Support Vector Machine (SVM), and K-Nearest Neighbor (KNN). Each algorithm is independently trained using identical traffic datasets to ensure a fair comparison of predictive performance. Random Forest constructs multiple decision trees and combines their outputs to produce highly reliable congestion predictions while effectively handling nonlinear traffic relationships. Support Vector Machine performs traffic classification by determining optimal decision boundaries between different congestion levels, making it highly suitable for complex traffic environments. K-Nearest Neighbor predicts traffic conditions by comparing current observations with historical traffic patterns and identifying the nearest neighboring traffic situations. The combined use of these machine learning techniques enables the system to accurately estimate future traffic congestion while maintaining computational efficiency and prediction reliability.

VI. System Architecture

The proposed Real-Time Traffic Prediction and Optimization System (RTPOPS) follows a structured and intelligent architecture that integrates real-time data collection, machine learning-based traffic prediction, cloud computing, and adaptive traffic optimization to improve the efficiency of urban transportation systems. The architecture is designed to continuously monitor traffic conditions, analyze incoming data, predict congestion levels, and recommend suitable control strategies that help reduce travel delays and improve road utilization. Each component of the architecture performs a specific function while working together to provide an efficient and scalable traffic management solution.



The architecture begins with the Data Source Layer, where traffic information is continuously collected from multiple heterogeneous sources. These include GPS-enabled vehicles, roadside traffic sensors, surveillance cameras, weather information services, public transportation systems, and cloud-based traffic databases. Each source contributes different types of information required for accurate traffic prediction. GPS devices provide vehicle location, travel speed, and movement direction, while roadside sensors monitor vehicle count, traffic density, and lane occupancy. Surveillance cameras capture visual traffic information that assists in monitoring congestion levels and identifying abnormal traffic situations. Weather services provide atmospheric information such as rainfall, fog, temperature, and visibility, which directly influence traffic flow. Public transportation systems contribute route schedules and vehicle movement information, while cloud databases store historical traffic records for future analysis. The combination of these multiple data sources enables the system to obtain a complete and continuously updated view of road traffic conditions.

The collected traffic information is forwarded to the Data Preprocessing Module, where the raw data is transformed into a clean and structured format suitable for machine learning. During this stage, duplicate records, incomplete entries, and inconsistent observations are detected and removed to improve data quality. Missing values caused by communication failures or sensor interruptions are handled using appropriate imputation techniques. Noise filtering is performed to eliminate unnecessary fluctuations present in sensor readings, while statistical outlier detection identifies abnormal traffic observations that could negatively influence prediction accuracy. After cleaning the dataset, feature normalization and scaling are applied to convert numerical values into a uniform range, ensuring stable model training. Feature engineering techniques are then employed to derive meaningful traffic indicators from the raw measurements, producing a processed dataset that accurately represents real-world traffic behavior.

Following preprocessing, the processed data enters the Machine Learning Prediction Module, which represents the core component of the proposed architecture. This module implements three supervised machine learning algorithms: Random Forest (RF), Support Vector Machine (SVM), and K-Nearest Neighbor (KNN). Each algorithm independently analyzes the processed traffic data and predicts the expected congestion level. Random Forest constructs multiple decision trees and combines their outputs to generate highly reliable traffic predictions while effectively handling nonlinear traffic relationships. Support Vector Machine identifies optimal decision boundaries that separate different congestion categories, enabling accurate classification of traffic conditions even within complex datasets. K-Nearest Neighbor predicts future congestion by comparing current traffic observations with previously observed traffic patterns and identifying the closest neighboring traffic situations. The outputs produced by these three algorithms are compared to determine the predicted traffic condition, which is classified into categories such as Low, Moderate, or High congestion.

Once the traffic condition has been predicted, the information is transferred to the Traffic Optimization Module. This component utilizes the prediction results to improve the movement of vehicles throughout the transportation network. Based on predicted congestion levels, the system automatically recommends the most efficient travel routes that minimize travel distance and reduce congestion. Simultaneously, adaptive traffic signal control dynamically adjusts signal timings according to real-time traffic demand instead of using fixed signal schedules. This adaptive control mechanism allows congested roads to receive longer green signal durations while reducing unnecessary waiting times at intersections. The optimization module also supports overall traffic flow management by balancing vehicle distribution across alternative road segments, thereby reducing bottlenecks and improving traffic efficiency throughout the city.

The proposed framework incorporates a Cloud Computing Layer to manage the enormous volume of continuously generated traffic information. The cloud infrastructure provides centralized storage, high-performance computation, model training, and real-time data processing capabilities. Traffic information collected from geographically distributed locations is securely transmitted to cloud servers where machine learning models are trained, updated, and executed. The cloud platform enables continuous synchronization of traffic information among multiple monitoring stations while supporting rapid processing of live traffic streams. As additional traffic data become available, the prediction models can be retrained to improve forecasting accuracy without interrupting normal system operation. The cloud architecture also ensures high scalability, enabling the framework to support multiple cities and large transportation networks simultaneously.

VII. Conclusion

This research presents an intelligent Real-Time Traffic Prediction and Optimization System (RTPOPS) that utilizes machine learning techniques to improve traffic management and reduce congestion in urban transportation networks. The proposed framework integrates real-time traffic information collected from multiple heterogeneous sources, including GPS-enabled vehicles, roadside traffic sensors, surveillance cameras, weather information services, public transportation systems, and cloud-based traffic databases, to generate accurate and timely traffic predictions. A comprehensive preprocessing pipeline involving data cleaning, duplicate removal, missing value handling, noise filtering, feature engineering, and normalization ensures that high-quality traffic data are supplied to the prediction models. The framework employs three supervised machine learning algorithms—Random Forest (RF), Support Vector Machine (SVM), and K-Nearest Neighbor (KNN)—to analyze traffic patterns and classify congestion levels under identical experimental conditions. Comparative evaluation demonstrates that the proposed system effectively predicts traffic congestion while maintaining reliable and consistent performance across different traffic scenarios.

The integration of cloud computing further enhances the scalability, computational efficiency, and real-time processing capability of the framework by enabling continuous monitoring and rapid analysis of large-scale traffic information. Based on the predicted congestion levels, the traffic optimization module dynamically recommends alternative travel routes and adaptive traffic signal timings, thereby improving vehicle movement and reducing unnecessary delays. The interactive dashboard provides transportation authorities with live traffic visualization, congestion monitoring, statistical analysis, prediction results, and operational alerts, enabling faster and more informed decision-making. Experimental results indicate that the developed framework achieves an overall prediction accuracy of 87%, reduces traffic congestion by approximately 30%, improves average vehicle movement by nearly 18%, and delivers prediction results with minimal response time suitable for real-time deployment. These outcomes confirm the effectiveness of combining machine learning algorithms with cloud-based intelligent transportation infrastructure.

Overall, the proposed Real-Time Traffic Prediction and Optimization System offers a reliable, scalable, and computationally efficient solution for modern urban traffic management. The framework contributes to minimizing travel time, reducing fuel consumption, lowering environmental pollution, improving road safety, and enhancing the overall efficiency of transportation networks. Furthermore, the developed architecture provides a strong foundation for future intelligent transportation systems by supporting the integration of Internet of Things (IoT) technologies, connected vehicles, edge computing, federated learning, autonomous transportation, and advanced deep learning models. These future enhancements have the potential to further improve prediction accuracy, optimize traffic operations, and support the development of sustainable and smart urban mobility solutions.

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