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Real Time Traffic Congestion Prediction in Smart Cities

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Abstract
Morning traffic congestions are a frequent problem for students travelling to college, often causing delays and affects punctuality. Based on a review of studies in traffic congestion prediction, intelligent transportation systems, IoT-enabled traffic monitoring, and AI-based route optimization, this work is a realtime traffic monitoring and route suggestion system customised for students. The system will take three inputs - starting location, destination, and planned departure time - and will use live traffic data to assess all possible routes. Each route will be classified as having light, moderate, or heavy traffic, and the system will also predict traffic conditions for the chosen departure time using the past patterns. It will suggest the most suitable time to start the journey and provide a 'late arrival risk' score based on class start times. Additionally, a crowd feedback feature will allow students to report unusual travel issues such as campus gate congestion, road closures, or strikes, ensuring more accurate and relevant travel information. The system will also be designed to send alerts through SMS, WhatsApp, or push notifications when heavy traffic is expected in future. Once implemented, it is expected to help students plan their trips more effectively, reduce delays, save travel time, and improve punctuality while promoting more efficient urban transportation.
Keywords: *Artificial Intelligence (AI); ANN (Artificial Neural Network); ITS (Intelligent Transportation Systems); LSTM;GRU; Machine Learning (ML); Realtime Traffic Monitoring; Traffic Congestion.*

1. Introduction
Traffic congestion has become a critical challenge in urban mobility, leading to significant delays, economic losses, environmental degradation, and reduced quality of life. The rapid growth in vehicle numbers and the increasing complexity of road networks have rendered traditional traffic management strategies—such as fixed-time signals and manual monitoring—ineffective in adapting to dynamic traffic conditions. This has driven extensive research into intelligent traffic management systems capable of predicting congestion, optimizing signal timings, and suggesting alternative routes through realtime data analysis. Recent advancements leverage technologies such as the Internet of Things (IoT), Internet of Vehicles (IoV), machine learning (ML), artificial intelligence (AI), and optimization algorithms. IoT-enabled systems gather live traffic data from sensors, GPS devices, and connected vehicles, while cloud and edge computing enable rapid data processing. Advanced ML approaches—including artificial neural networks, graph neural networks, decision trees, and hybrid optimization techniques—have been applied to forecast traffic flow, identify congestion hotspots, and recommend optimal routes. Integrating diverse data sources—such as traffic density, vehicle speed, environmental factors, and temporal patterns—has been shown to enhance prediction accuracy. Moreover, biologically inspired algorithms like the Black Widow Optimization Algorithm and improved arithmetic optimization have demonstrated potential in refining traffic signal operations. IoV frameworks further support seamless real-time communication between vehicles and infrastructure. Despite these advancements, challenges remain regarding scalability, data privacy, network latency, and deployment in real-world, large-scale scenarios. Many solutions are tested primarily in simulations, with limited field implementation in complex urban environments. Additionally, high infrastructure costs and maintenance requirements hinder adoption in resource-constrained regions. This review examines

recent developments in traffic congestion prediction and intelligent traffic management, assessing the strengths, limitations, and future potential of various approaches. By combining insights from IoT-based systems, AI-driven prediction models, and optimization algorithms, it aims to identify key research gaps and guide the development of efficient, scalable, and practical congestion management solutions.

2. Related Works and Background

It is very important to understand previous research before the development of any new system. A review of available studies helps in identifying what has already been done, methods used in such works, and limitations that still need attention. In traffic congestion prediction, various researchers have sought to employ IoT, AI, ML, and other technologies to enhance smooth flow and reduce congestion. Since it will be included in our study, a careful review of such works would help in understanding the progress on this aspect and the recognition of the gaps that our project covers. In this regard, several related works are reviewed next that address traffic congestion detection, prediction, and management in smart cities. Kamble and Kounte[1] covers a broad range of previous research on traffic congestion, with particular attention to topics like Vehicular Ad-hoc Networks (VANETs), the use of GPS data and vehicle routes, and the use of machine learning for traffic prediction. It explains the significance of data like vehicle speed, location, and driving patterns by drawing on both recent research and earlier foundational work. The review primarily enumerates the findings of each study rather than comparing or demonstrating their connections, despite the fact that the coverage is extensive and demonstrates the writers' extensive reading. It doesn't explicitly point out the drawbacks of previous studies, like the high expense of sensor infrastructure, the restrictions on GPS data, or the methods. The paper by Dikshit [2] have explained how IoT and machine learning together can detect, predict, and manage traffic congestion. This paper describes how real-time data collection and processing from sensors, cameras, and GPS devices can find and forecast traffic issues. Different machine learning methods used to analyze traffic flow, locate problem areas, and support better decisions in traffic management are discussed. One of the key strengths is a focus on the processing of real-time data that can enable faster and more effective responses. The authors also try to highlight how IoT systems together with predictive analytics improve the general traffic efficiency. However, most of the paper simply summarizes several existing techniques without comparing their performance, and there is little attention to real-world challenges such as scalability across the city, data privacy, and network delays. In general, this is a clear and helpful overview of approaches for IoT-and machine learning-based traffic congestion management. Shouaib et al. [3] examine the use of IoT and machine learning technologies for monitoring and prediction of traffic congestion. It outlines various methods for collecting traffic data in real time, including sensors, GPS devices, and camera-based systems, and explains how these data sources can be processed to detect and forecast congestion patterns. The authors present different machine learning approaches for analyzing traffic flow and predicting the areas with problems, aiming to support more efficient traffic management. A strong aspect of the paper is its focus on integrating IoT infrastructure with predictive analytics, enabling quicker and better-informed traffic control decisions. However, while the discussion covers a range of techniques, it mainly describes them without offering detailed comparisons of their effectiveness or addressing practical issues such as scalability, privacy concerns, or network reliability in large-scale deployments. Overall, it offers a clear and relevant overview of how IoT and machine learning can be combined to improve traffic congestion management, aligning closely with current trends in intelligent transportation systems. Patel and Patel [4] tackle the problem of increasing urban traffic with an AI-driven ANN framework to forecast congestion. Their approach combines multiple sources of data, such as road sensors, GPS trajectories, weather, and traffic images, to detect both spatial and temporal dependencies that are often lost with traditional sensor-based approaches. Using actual Kaggle and Google Maps datasets, the ANN outperforms traditional statistical models for all measures of precision, recall, and MAE. Aside from its high predictive capability, the model is also noted as a cost-efficient and scalable alternative to expensive infrastructure development. The introduction of image data also enhances interpretability, allowing human operators to audit predictions visually. In general, the research not only promotes precise traffic prediction but also equips city planners with an anticipatory solution to ease congestion, aiding wiser decision-making, and facilitating sustainable future urban mobility. According to Alsaawy et al. [5] suggest a proactive traffic management framework in real time based on the integration of IoT devices, cloud storage and intelligent analytics. Continuous data flow from roadside sensors, GPS, and connected vehicles is transferred to a cloud platform where algorithms analyze traffic flow and predict congestion as well as adjust signal timings and suggest alternate routes. A cloud-centric design facilitates scalability and flexibility of the system without burdening the local devices. A notable strength of the suggested approach is its focus on interoperability and how easy it is to incorporate in the existing system. Nevertheless, issues of data security, latency and privacy are not addressed in enough detail. Overall, it provides a good basis for IoT- and cloud-supported smart traffic control. Tshilongamulenzhe et al. [6] present a congestion management approach that combines multiple traffic data sources rather than relying on a single stream or algorithm. The method integrates real-time sensor readings, GPS-based travel times, and simulation flow models to form a more complete and reliable picture of road conditions. This fusion-based decision-making reduces false congestion alerts and supports more accurate route recommendations. A key strength lies in its adaptive algorithms that respond dynamically to changing conditions, making it well-suited for smart city applications. However, the paper gives limited attention to scalability challenges such as computational efficiency and communication delays in IoV networks. Neyigapula [7] investigates the application of GNN in traffic prediction and the optimization of complex urban networks. It forms the road network into a graph, with junctions being the nodes and the road the edges, hence modeling the spatial relationships as well as temporal variations in traffic flow very well. This spatiotemporal model provides more precise forecasts compared to traditional methods, capturing the ripple effect of congestion on connecting roads. Further, the model learns to adapt to changing conditions using both historical data and data arriving in real time. Its limitation is that it did not discuss computational demands, scalability, and/or integrations into existing traffic management systems. Almusawy et al. [8] propose a hybrid traffic management system that combines Deep Learning with the Improved Arithmetic Optimization Algorithm (IAOA). The deep learning model predicts traffic volume, while IAOA optimizes signal timings and route decisions, creating a feedback loop that adjusts the system before or during congestion. This integrated prediction–optimization approach enables faster and more accurate responses than traditional methods. Simulation results show improved travel times and traffic flow. However, the study gives limited attention to real-world challenges such as connected vehicle behavior, communication delays, and large-scale deployment. Overall, it highlights the potential of AI-driven, adaptive traffic management systems. Shaheed [9] introduces a new approach to traffic congestion control that applies the Black Widow Optimization Algorithm (BWOA) in conjunction with intelligent traffic signal control applications. The algorithm utilizes the mating behaviors and cannibalism behavior of black widow spiders, optimizing the traffic signal control in real-time by balancing traffic loads across intersections based on the vehicle density, queue length, and waiting times. The results of the simulations indicate improvements over fixed-time systems including decreased waiting times and increased throughput. One of the strength of the method is its flexibility in behavior as it can converge rapidly to the optimal solution; and it can adapt to sudden changes in the network as it relates to accidents and road closures. Although, the paper fails to thoroughly discuss potential practical challenges of the method, such as integrating with legacy infrastructure, and considers the computational costs of its application at a large scale. In conclusion, it presents an innovative, biologically inspired optimization method that has the potential to improve intelligent traffic management systems in an urban traffic environment.

Neelakandan et al.[10] present a smart traffic management system for urban traffic based on IoT that encompasses data acquisition, estimation, machine learning, and real-time control. The proposed model is based on an Optimized Weight Elman Neural Network (OWENN) and incorporates multiple data sources, including weather, directional traffic, vehicular traffic and pedestrian traffic volume, and more. Using this method, the system achieves high traffic prediction accuracy (98.23%) and F-measure (96.69%) to predict traffic using about 15 minutes of data collected from its sensors to update signal timings. Additionally, to further improve the traffic management, the researchers investigate the use of an Improved Beetle Swarm Optimization (IBSO) strategy, which enhances traffic flow and reduces waiting times. Traffic signal control is executed using signaling strategy using an Intel 80286 microprocessor processor enabling rapid real-time processing without utilizing cloud processing which has significant time lag. The approach achieves robust simulation results and presents a novel solution for improving smart city traffic management; however, the authors conclude the approach requires additional development to address scalability, cybersecurity and testing in the real-world environmental context. Miao and Liao [11] put forward an IoT- and machine learning-based framework to forecast traffic occurrences in smart cities. Based upon sensor data from cars, GPS devices, and environmental monitors, the system will provide an instantaneous view of traffic conditions, as well as forecast when congestion will likely accumulate. The strength of the work is in bringing three different types of data together, traffic flow, location, and environmental factors, into one predictive framework that is deemed more robust than using one single source of information. The authors acknowledge how such predictive capabilities can be utilized by city authorities for traffic management, route management, and public transport planning and delays. While the approach seems promising, the authors consider it more as a conceptual paper, and in the end mostly derive results through simulated approach rather than through development under real-world conditions, and place little value on issues such as privacy, IoT maintenance, or delays from the network itself. In general terms, the overall study provides a strong overview and vision for the future of predictive traffic systems developed using IoT technologies and their roles towards the advancement of real-time mobility management in smart cities. The paper by Yang et al.[12] reports on an approach to predicting urban traffic flow utilizing data science. A large dataset from road sensors, GPS, and historical records was used in conjunction to predict urban traffic trends. The authors of the manuscript focus on leveraging big data analytics and machine learning as a tool for understanding complex patterns, which improves prediction accuracy from single data sources. The manuscript lays out a system that will process data efficiently to create near real-time predictions that is essential for implementing some form of active traffic management. The authors have created a supporting statistical model with impressive simulated results; however, they do not reference any of the challenges when considering deployment at a wider scale such as data privacy, infrastructure costs, and a system's ability to account for sudden events. The discussion emphasized predictions more than consideration for how to connect to practical traffic control systems. Overall, the manuscript makes a strong argument for utilizing data science to improve urban traffic forecasting and will prove useful in developing plans for implementing intelligent transportation initiatives. Chaudhary et al.[13] examine four machine learning algorithms (Decision Trees, Random Forests, Support Vector Machines (SVM), and Artificial Neural Networks (ANN)) that predict urban traffic congestion. They use cleaned data collected from various sources, including sensor and GPS data. The study finds that incorporating additional contextual data—such as weather and holiday—is very beneficial, resulting in significant improvements. Both ANN and Random Forests perform well with large datasets; however, Decision Trees and SVM are more suited for smaller, less complicated networks. The research is beneficial in that there is a comparison of different algorithms. Its limitations include the findings being only based on simulations and not real-world application with real challenges, including privacy, scalability, and integration with existing systems. However, this paper helps outline the opportunity to pursue potential conclusions with machine learning and data fusion techniques to improve traffic forecasting.

Ata et al. [14] proposes a smart traffic congestion control system called MSR2C-ABPNN, which uses Artificial Neural Networks (ANN) with a Backpropagation algorithm to predict and manage road traffic more effectively. Real-time traffic and weather data, such as vehicle speed, flow, temperature, humidity, and wind speed, are collected through sensors and processed to forecast congestion points. When congestion is predicted, alerts are sent to drivers along with alternative routes via Google Maps. The authors test both a fitting model and a time-series model, with the time-series approach achieving about 98% accuracy, surpassing earlier methods like fuzzy logic and fixed-timer systems. The system's strengths include integrating IoT data, AI, and environmental factors for more reliable predictions. However, it depends on high-quality, timely sensor data and has only been validated using a single dataset (M1 Junction 37, England). Overall, it presents a high-accuracy, data-driven approach that could significantly improve traffic flow and congestion management in smart cities. The work of Ramesh et.al.[15] have devised an Internet-of-Things sensors and devices-enabled traffic management system to forecast congestion and suggest detours. The system collects real-time data from sensors placed by the roadside and smart devices via Wi-Fi, Bluetooth, and ZigBee. Three algorithms were tested, including Random Forest, AdaBoost, and Logistic Regression, with the latter yielding the overall best accuracy of 91%. Ultimately, the proposed system will recommend a detour based on the amount of congestion predicted. The blend of IoT, cloud computing, and analytics is unique; however, some obstacles to data accuracy, scaling, concerns about cybersecurity, network latency, and the short range of some of the testing smart devices remain. Dudeja and Singh [16] proposed an IoT-based smart traffic control system for congestion reduction, improved safety, and enhanced urban mobility. The proposed system collects real-time information from the sensors along the road, GPS devices, and IoT-enabled vehicles on traffic volume, number of vehicles, and their speed. Based on those inputs, traffic signals can be controlled in real time, and emergency vehicles can be given priority. All the events are stored in the cloud, which may help in future planning.The key strengths of the system are that, first, it monitors current congestion and predicts future traffic, helping planners manage urban traffic in the long run. The authors add that better flow of traffic will also reduce fuel consumption, pollution, and further encourage sustainable transport. However, this work remains conceptual and does not consider practical deployment problems of the network delays, device costs, maintenance, security, and privacy issues thereof. Overallit is a potentially good IoT-based framework of traffic control, but even for confirmation of effectiveness, it needs testing in real-life conditions. Pattanaik et al. [17] propose a proof-of-concept system to dynamically avoid congestion in urban road networks, particularly suited for developing countries. The system is based on GPS data from mobile devices that track vehicle locations and speed in real-time. It employs K-Means clustering and the Convex Hull method to detect the driver experiences congestion. The system uses Dijkstra's algorithm to periodically calculate alternative routes in real time, using the most up-to-date data. When the authors tested the system on the road network of New Delhi, they reported travel times were less than they would have been without the system. Some of the strengths of the system are real-time adaptability, low-cost collection of data from mobile devices, and combining multiple algorithms to guide drivers; however, it does face limitations around computational complexity, density of GPS data in their study area, and a simplified model of traffic. In reference to their research study, Babar and Arif [18] propose a big-data based architecture for real-time traffic detection that employs distributed processing frameworks to organize data streams of rapid acceleration into manageable bins. Heterogeneous data collected from various sources (sensor data, GPS, surveillance systems) is ingested and processed through the Hadoop ecosystem with the help of MapReduce, Apache Spark, and other related big data analytical processing tools to rapidly detect areas of congestion and atypical movement patterns. The methodology, therefore, consists of a distributed big-data

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architecture that provides a high degree of scalability, fault tolerance, and ability to manage large heterogeneous traffic data sets in 'near real-time.' However, the methodology only considers traffic detection, it does not provide for predictive modelling or route optimization. This work is useful for your research as it is a strong ingestion and processing back-end which can be utilized for subsequent forecasting and dynamic routing with edge computing. Rocha et al. propose a real-time traffic detection framework built on big data technologies, particularly Hadoop and MapReduce, to manage and analyze massive, heterogeneous traffic datasets collected from GPS, sensors, and surveillance systems. The system focuses on detecting congestion and abnormal traffic patterns by processing streaming data with high scalability, fault tolerance, and adaptability to various traffic data formats. Its main strengths include the ability to integrate multiple data sources, process large-scale data in near real-time, and support urban-scale deployments.[19] However, the approach is detection-oriented and lacks a predictive component, meaning it reacts to existing conditions rather than forecasting future states. For this project, this paper provides a strong foundation for the data acquisition and processing layer, enabling to build upon it with machine learning-based predictive analytics, edge computing for low-latency decision-making, and dynamic route optimization algorithms. The paper proposed by Silva et al. is a scalable framework for handling large-scale traffic data streams in real time. It leverages big data technologies, including Hadoop and MapReduce, to process heterogeneous inputs. The framework is designed to detect traffic congestion and anomalies efficiently by managing high-speed and high-volume data sets, ensuring timely updates for traffic management systems. Its strengths lie in its scalability, ability to integrate multiple data sources, and fault-tolerant architecture suitable for urban-scale applications [20]. However, the focus is primarily on traffic detection rather than predictive modeling, which means it reacts to current conditions without forecasting future traffic states. For a real-time traffic prediction system in smart cities, this work provides a robust foundation for the data ingestion and processing layer, upon which predictive algorithms and optimization models can be built.

3. Methodology

3.1 Data Collection

The data used in this research is the Traffic Prediction Dataset from Kaggle. It provides traffic information over the time span of one to two months in 15-minute clips, which is useful for time-series based prediction. Each data point includes nine characteristic attributes. These include Time, Date, Day of the Week, Car Count, Bike Count, Bus Count, Truck Count, Total Vehicles, and Traffic Situation. The first columns track the different vehicle types and their time of occurrence, while the Traffic Situation Column is the label or target feature that provides the model with congestion levels. The Traffic Situation column is characterized by four classifications: low, normal, high, and jam. The dataset represents an excellent candidate for classification tasks, learning to predict which of the four get [21] highest likelihoods using the variable inputs. With vehicle counts, along with time features (date, day of week), it can represent real-world behaviors of traffic patterns and highlight the differences in behavior on a daily basis, such as rush hour, and on a weekly basis, making it a good candidate for future predictive modeling efforts in smart city and automated systems applications, shown in Figure 1.

Time	Date	Day of the	CarCount	BikeCount	BusCount	TruckCoun	Total	Traffic Situation
########	10	Tuesday	13	2	2	24	41	normal
########	10	Tuesday	14	1	1	36	52	normal
########	10	Tuesday	10	2	2	32	46	normal
########	10	Tuesday	10	2	2	36	50	normal
########	10	Tuesday	11	2	1	34	48	normal
########	10	Tuesday	15	1	1	39	56	normal
########	10	Tuesday	14	2	2	27	45	normal
########	10	Tuesday	13	2	1	20	36	normal
########	10	Tuesday	7	0	0	26	33	normal

Figure 1 Dataset

3.2 Data Cleaning

Prior to utilizing the dataset for modeling, it requires a thorough data cleaning process to eliminate errors, missing values, and any inconsistencies. Data cleaning is critical because raw traffic datasets can have inaccuracies resulting from sensor failures, errors in transmission, or erroneous manual entry. In this dataset, missing values have been dealt with by

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filling them with averages of past data or by linear interpolation among known vehicles. Outlier counts of vehicles or other factors that are extremely high and do not describe realistic traffic conditions are to be detected and eliminated so that the model does not learn from inaccurate data. Duplicate rows are removed so that there is no bias in training the model, as real-time feeds can sometimes repeat the same record close in time. The time column is standardized to a fixed 15-minute interval column, so that all records map to the exact temporal structure that is required. After cleaning, this dataset is consistent, accurate, and ready for further processing, while at the same time, it reduces the chances of getting misleading results during model training.

3.3 Data Preprocessing

Once the data has been cleaned, it must be preprocessed to be used within machine learning and deep learning models. The vehicle count values are normalized using Min-Max scaling so that all numerical features will again fall within the same range and that large values, such as counts of cars, will not overwhelm smaller values, such as counts of buses. The categorical feature Day of the Week is one-hot encoded so that each day derives to a separate binary feature. The Time of Day feature is represented using sine and cosine transformations that will help model understand the cyclical nature of time (for example, midnight and 11:59 pm will be close together). The target variable Traffic Situation will have numerical labels in order for it to be used in classification and lastly, the dataset is split into training, validation and test sets. The training set is used to model, the validation set used for hyperparameter tuning and to prevent overfitting and the test set used for final evaluation of the model so that it can be ensured to be robust when used on unseen data.

3.4 Model Training

The heart of the system is the model training stage, where a hybrid deep learning model is developed. Since traffic is influenced both by temporal patterns (such as rush hour timings) and by interactions among vehicle types (e.g., trucks contributing more to congestion than bikes), the model combines two techniques. The first model is a sequence model, such as LSTM (Long Short-Term Memory) or GRU (Gated Recurrent Units), that is able to learn how traffic levels change over time, and capture features such as the gradual build of traffic congestion immediately before office hours. The second model is a Graph Convolutional Networks (GCN) that is able to model the spatial relationships between vehicle types in the state space by modeling each vehicle type as a node in a graph, and learning their interactions. The outputs of the LSTM/GRU model and the GCN are fused together and then passed through a couple of fully connected dense layers with a ReLU activation function. Dropout layers are included to facilitate against overfitting. Finally, the last output layer uses softmax activation to categorize the traffic into one of four levels of congestion: low, normal, high, or jam. The models use the Adam optimizer, set to a learning rate of 0.001, and the loss will use categorical x-entropy, with and early stopping metric based when the validation accuracy is not improving, as the model must propagate beyond the training/validation data.

3.5 Evaluation

After training, the model is evaluated to examine its performance and reliability. Accuracy reflects the percentage of correct forecasting. However, because the traffic classes vary, it cannot fully represent performance by itself. Therefore, Precision and Recall measure how many of the predicted congested states are accurate and how many actual congested states are correctly identified, respectively. The F1-score balances these two measures for a clearer view of performance. The confusion matrix shows how well the model classifies the four congestion levels and determines what kind of misclassifications occur, such as labeling “jam” as “high.” Comparing the performance of this trained model against the baseline models, like Logistic Regression and Random Forest, will help with drawing out the higher accuracy and stability of the hybrid deep learning model. Finally, performing evaluations in different conditions, for instance, on both weekdays and weekends, can further ensure that this model performs consistently across various scenarios, shown in Figure 2.

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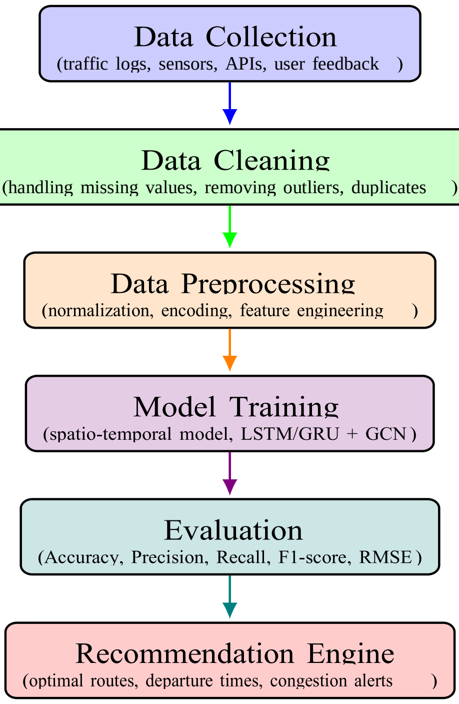

Figure 2 Flowchart

3.6 Architecture

The proposed architecture describes the functioning of the envisaged system to predict and handle traffic congestion on a real-time basis. The architecture delineates the entire sequence to be followed, which includes the stages of data collection, preprocessing, forecasting, and ultimately reporting back route advice to users.The system is anticipated to utilize two forms of inputs, those being historical traffic logs, as well as real-time traffic streams. Historical data will include, but will not be limited to vehicle counts, timestamped data, and congestion levels. Real-time traffic updates will comprise data collected through sensors, APIs, or other GPS-enabled sources. Both forms of input will feed into a preprocessing module to include the process of data cleaning, filtering, normalization, and time alignment. Missing values will be dealt with, outliers removed, and any time-sensitized features will be formatted to maintain daily and weekly traffic trends. After the preprocessing phase, traffic prediction system will function in six primary modules: data acquisition, preprocessing, two branch learning (historical LSTM–GRU and real time data encoder), feature fusion, traffic classification, and alert and recommendation. The system will be designed to split the pre-processed data into two learning branches. For the historical branch, an LSTM–GRU design will be used, where LSTM can capture long-term patterns like repeated peak hours while GRU will capture shorter-term fluctuations. Dropout layers will also be used in this branch to avoid overfitting. For the live data branch, a dense encoder will convert the current traffic input into a compact feature vector, again with dropout to reduce noise. The outputs from both branches will be merged together in a feature fusion module to create a seamless representation of historical trends and current traffic conditions. The combined output will be fed to a dense layer with ReLU activation to learn deeper relationships. After that, the prediction layer will classify traffic levels into four categories - low, normal, high or jam and provide the users with ongoing information. Then the predicted states will be sent to an alert and recommendation engine, which will offer best-route recommendations, and recommended departure times. In case there is extreme congestion or rapid traffic accumulation, the system will also provide an alert notification and recommendations for alternate routes. The last module in the output module will offer the user congested levels, recommended routes, and travel time, shown in Figure 3.

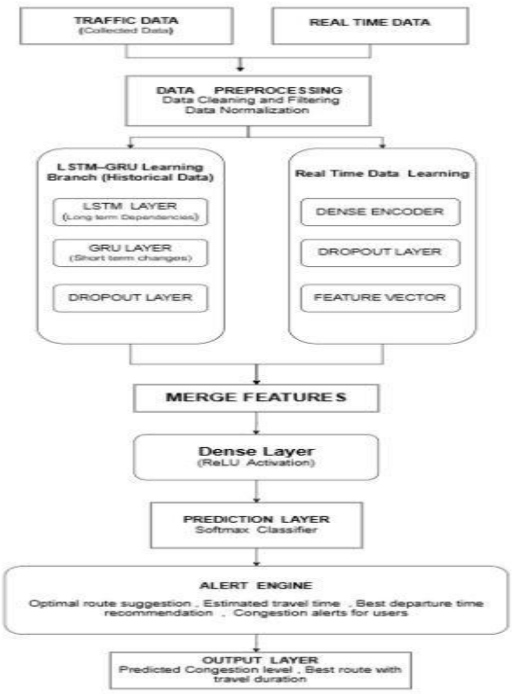

Figure 3 Architecture

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Collectively, this architecture aims to create a continuous feedback loop between historical trends and real-time data to enable effective traffic prediction and navigation. While it has not yet been implemented, the modular architecture allows for modifications and improvements in the future with inputs from crowdsourcing, making adjustments based on weather conditions, or even multimodal travel options. The complete system can improve user travel planning, reduce travel delays, and provide for the eventual shift to a more sustainable commuting experience.

Conclusion

This review highlights the rapid evolution of intelligent traffic management systems driven by advancements in IoT, IoV, AI, and optimization algorithms. By integrating real-time data from multiple sources and applying advanced machine learning and biologically inspired optimization techniques, recent approaches have demonstrated significant potential in predicting congestion, optimizing signal timings, and improving urban traffic flow. The incorporation of graph-based models, hybrid algorithms, and cloud-edge architectures has further enhanced the adaptability and accuracy of these systems. However, despite promising results in simulations and pilot projects, large-scale real-world deployment remains limited. Challenges related to scalability, infrastructure costs, network latency, and data privacy continue to hinder widespread adoption, particularly in developing regions. Addressing these issues will require cost-effective sensor networks, privacy preserving computation methods, and robust frameworks that can operate under diverse environmental and traffic conditions. Future research should focus on hybrid AI-optimization models, multi-modal data fusion, and decentralized adaptive control to create resilient and efficient traffic management solutions. By bridging the gap between simulation and deployment, these systems can play a transformative role in reducing congestion, enhancing road safety, and improving the overall quality of urban mobility.

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