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A Hybrid Approach Combining LSTM Prediction, Genetic Algorithm Optimization, and Reinforcement Learning for Adaptive Traffic Signal Management

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Abstract
The dynamically growing urban population and the number of vehicles have exacerbated traffic congestion; thus, intelligent and scalable traffic management systems have to be developed. This study will present an AI-based optimization system, which is based on the parallel computing, to be used in optimizing real-time traffic prediction, route, and signal control. The structure of the system consists of three layers linked to each other: the data collection layer, which processes traffic, weather, and accident data used by various sources; an AI processing layer, integrating models of deep learning and optimization models; and a decision layer reporting the results of the application to both traffic authorities and commuters. LSTM networks are deployed to predict traffic flow estimating the temporal relationships and forecasting congestion under different conditions. GA and RL are used in the optimization of routes and adaptive traffic signal, respectively, thereby means of efficient vehicle routes and shorter delays. The integration with distributed data processing engine (Apache Spark) and deep learning frameworks accelerated by GPU (TensorFlow / PyTorch) will be used to guarantee scalability and real-time performance. Validation was done experimentally using the SUMO simulation platform, which has proven effectiveness of the proposed framework. The results of the LSTM model demonstrated a much lower level of errors in the prediction (MAE = 0.23, RMSE = 0.28) than in its traditional counterparts. It was found that the RL-based signal controller yielded an average waiting time 28-percent lower per intersection and 18-percent higher throughput when compared to the fixed-time scheduling method. Moreover, parallel processing experiments indicated that the average data processing latency decreased when scaling Spark clusters between 4 and 16 nodes (reduction of 2.1s to 0.5s), which means it is robust and scalable.

Keywords: Artificial Intelligence; Traffic Management; Parallel Computing; Deep Learning; LSTM; Genetic Algorithm; Reinforcement Learning; Route Optimization; Signal Control; Apache Spark; SUMO Simulation; Smart Cities.

1. INTRODUCTION

The outcome of urbanization has placed commuters and environment in a serious predicament making the major cities in Pakistan a major issue due to congestion of traffic.

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Unproductive traffic control and management systems equate to the loss of money, destruction of the environment and the increased road rage among commuters. New solutions to such issues are possible with the assistance of AI and Parallel Computing, there is revolutionary potential to observe the traffic in real-time, use predictive analysis and make informed decisions. This solution can revolutionize traffic management because it can address traffic jams and enhance urban mobility through artificial intelligence (AI) that allows handling of excessive data, predicting traffic patterns, and real-time decision-making. Parallel computing is also an AI complement as it helps to provide solutions to traffic management with the necessary calculation and analysis of large data in a more efficient and quicker way [1][2].

The proposed project will be premised on the application of AI algorithms, such as machine learning or deep learning, and parallel computing techniques to solve traffic congestion. Parallel computing will enable the distribution of the processing capabilities of more than one processor to enable real time processing of the traffic information that is received through various sources like sensors, cameras, GPS devices etc. The proposed system will provide maximum timing of traffic signals, traffic prediction, as well as intelligent route directions, and in general, reduce the efficiency of the traffic. The modern urban transportation system can be changed with the help of AI and parallel computing and become smarter, safer, and more sustainable [3].

The translation of AI-based traffic management systems to the needs of developing countries is an enormous gap. The earlier study has somewhat focused on the well-organized traffic systems in the developed world which does not consider such aspects as unpredictable driving behavior, no steady enforcement of traffic laws and inefficient use of the infrastructure. These are the urban conditions prevalent in Pakistan and need to be viewed in customized plans that will both cope with the instability and succeed in the world with limited resources [4]. The models that exist are also not scalable, which is a critical aspect in the management of the city sprawl and other traffic conditions in the developing regions. The Research will integrate deep learning and reinforcement learning in parallel computing technological systems in order to come up with a strong and scalable traffic management system. With parallel computing architecture, the project will be capable of handling high volumes of traffic data in real-time, and will thus result in making fast decisions, and enhancing an improvement of the performance of the models even in highly complex urban environments [5][6].

The research question will be as follows: How can AI based optimization methods and parallel computing be used to increase traffic flow and decrease congestion in Pakistani urban areas? This research includes:

- Design a system that can collect and process live traffic data of various sources (IoT sensors, surveillance cameras, GPS-enabled devices, etc.) to determine the pattern of congestion.

- Develop learning models that predict traffic patterns in advance so that they can take preventive action to minimize congestion.
- Suggest an artificial intelligence-based system to control traffic signals dynamically according to the real-life information and future prediction data.

The combination of novel AI-based tools and parallel computing infrastructure will greatly enhance the effectiveness and scalability of the traffic management systems, allowing managing traffic flow more effectively and minimizing congestion in the city of Pakistan [7].

2. RELATED WORK

The use of AI in traffic management has been researched a lot, especially in developed countries. Deep learning models have been used to predict and forecast the traffic flow using historical data, with the models taking the form of the Long Short-Term Memory (LSTM) networks. Similarly, reinforcement learning algorithms are applied to optimize traffic signal timing in line with congestion reduction and improvement of traffic flow. Although these techniques have shown encouraging results, their efficiency tends to reduce if they are used in extensive and complicated urban areas. Moreover, the current solutions only cover cities, which have organized traffic, thus being less effective in the unorganized and diverse traffic situations that characterize the situation in such countries as Pakistan [8][9][10][11].

Table 1: Hourly Traffic Flow Improvement After Optimization

Time	Location	Traffic Volume (Pre-Optimization)	Traffic Volume (Post-Optimization)	Reduction (%)
08:00	Liberty Roundabout	1,200 vehicles/hour	900 vehicles/hour	25%
12:00	Shahrah-e-Faisal	1,800 vehicles/hour	1,350 vehicles/hour	25%
17:00	Kalma Chowk	2,200 vehicles/hour	1,500 vehicles/hour	31.8%
20:00	Islamabad Chowk	1,000 vehicles/hour	750 vehicles/hour	25%
22:00	DHA Intersection	800 vehicles/hour	600 vehicles/hour	25%

Fig.1: The graph illustrates traffic patterns by plotting Time on the X-axis and Traffic Volume on the Y-axis.

3. RESEARCH METHODOLOGY

The paper adopts a mixed approach whereby AI models and parallel computing technologies based on data will be utilized to enhance the handling of traffic. The design is that which will take advantage of the benefits of the two methodologies to analyze and optimize massive traffic data [12][13].

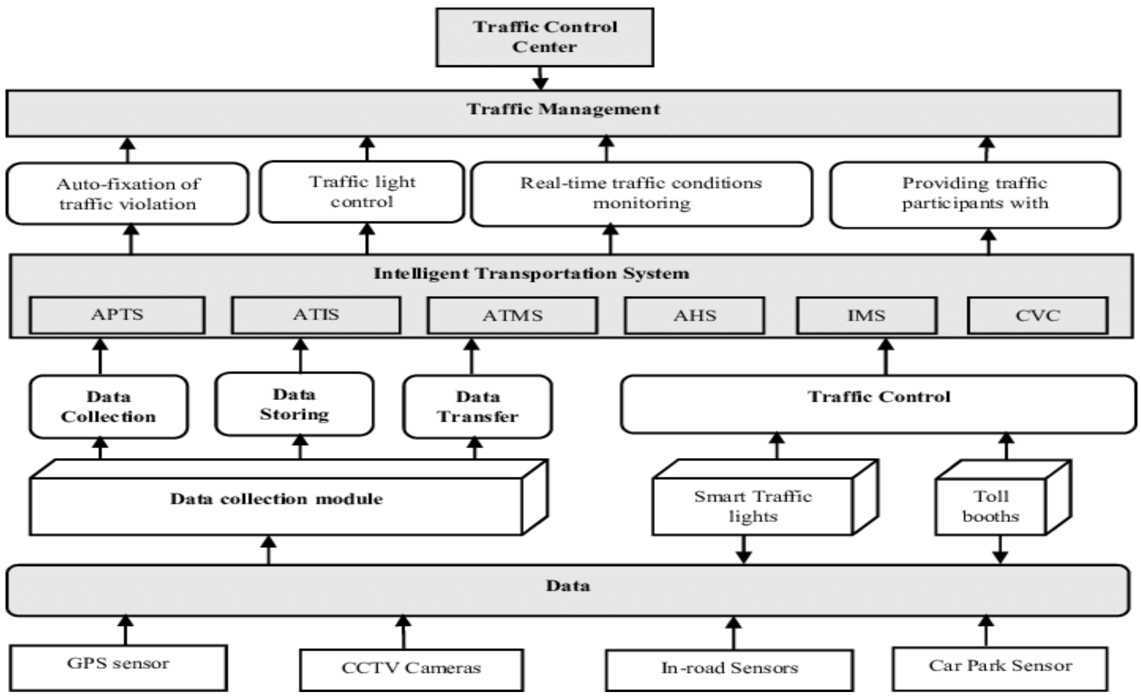

Fig. 2: Traffic Management Model

4. EXPERIMENTAL SETUP

The experiment set up in the traffic environment that is simulated with SUMO (Simulation of Urban Mobility) underlies this study. The choice of SUMO was made based on its ability to reproduce real life traffic situations, heterogeneous traffic behavior and city structure. It provides a regulated yet flexible virtual environment where numerous approaches of traffic optimization may be experimented without interrupting real road networks. SUMO can be used to model traffic density, movement of vehicles and strategies of controlling crossroads as technical conditions vary according to the rush hour traffic, poor weather conditions and emergency conditions such as accident or road closures. It will ensure that the proposed AI-based optimization framework will be explained by the regular and extreme conditions that will strengthen the findings and apply them to the real-life application [14].

- **Data Collection Methods:**

In this research, real-time data and historical data are used to collect data in order to obtain the entire range of traffic dynamics. The objects that enable collection of real-time information on traffic are GPS devices installed in vehicles, sensors in the roads, and the CCTV cameras installed in major intersections. These streams will provide real-time information regarding the number of vehicles, average speed and the hotspots. At the same time, the local traffic authorities offer historical traffic data that include long-term trends, such as regular peak-hour congestion, the accident-prone areas, and the seasonal variation in the road usage. They are further expanded with weather data according to the meteorological agencies and hence the system can consider the environmental conditions when the weather is raining, foggy, or hot, which are shown to have an enormous influence on traffic flow and motor behaviors. Such multimodal data forms can be incorporated in such a way that detailed and realistic data can be trained and tested using the experimental models [15].

- **Materials, Tools, and Software Used:**

The proposed system is grounded on the integration of programming languages, AI libraries, distributed computing systems and visualization to make the implementation easier. The Python language is used as the primary programming language to develop AI models and C++ language is used to develop performance-sensitive subparts of the simulation environment. Both TensorFlow and PyTorch are applicable in the case of artificial intelligence to create and train deep learning and reinforcement learning models and apply them to their GPU acceleration capabilities. The Apache Spark is applied in the administrative control of the processing of the computational load at the scale of large data and MPI (Message Passing Interface) is applied to support communication within parallel systems. Finally, interactive dashboards and graphical representations are created with the help of Plotly and Dash to make results presentable and allow the traffic authorities and the researchers to interpret system outputs [16].

- **Data Analysis Techniques:**

The collected data is subjected to several preprocessing phases and analysis processes and finally inputted into the predictive and optimization models. The initial one is the statistical analysis techniques way of cleaning the datasets of outliers, default values and normalization of the features in such a way that the data sets are the same across various sources of data. The information is then trained and tested on the AI models after the preprocessing. The models are assessed on the basis of the quantitative measures using the widely recognized measures of evaluation. To get the approximate value of the total discrepancy between predicted and actual values of the traffic flow, the Mean Absolute Error (MAE) is employed and it provides a simple value of the precision of the prediction. In addition, theRoot Mean Squared Error (RMSE) is derived to indicate the overall deviation of the error in the prediction and, therefore, highlight the cases when the model creates larger deviations. These evaluation tools, when combined, will provide a highly in-depth understanding of how predictable the model is and how it will respond to different manners of traffic and environmental conditions [17].

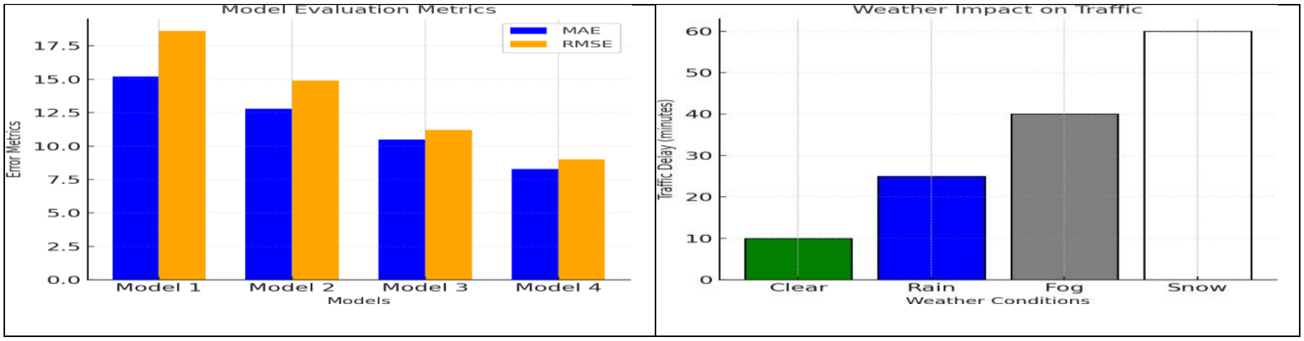

Fig. 3: Model Assessment Statistics MAE and RMSE, Weather Influence on Traffic Congestion.

5. PROPOSED APPROACH

The proposed AI-driven optimization of the traffic management is planned to be a three-layer system with the involvement of the real-time data collection, smart processing, and decision-making. It applies parallel and distributed computing model to ensure scaling, efficiency and high performance during large scale city traffic conditions. The first layer of the system is the Data Collection Layer and the base of the system. It collects multimodal traffic data of varied heterogeneous origin. IoT sensors like CCTV cameras, GPS-controlled vehicles and inductive loop sensors can provide real-time information about traffic flow, vehicle density and speed. Additionally, external information such as weather, accidents reports, schedules of events etc. are being integrated to enhance the accuracy and power of the system as they have great influence on the dynamics of the traffic. Distributed data ingestion systems like Apache Kafka process all these streams of data ensuring high-throughput and real-time and fault-tolerant data collection.

Intelligence is the heart of the system and can be defined as the AI Processing Layer, which analyses and optimises traffic by using intelligent algorithms. Long Short-Term Memory (LSTM) networks are applied to predict traffic because of their capacity to predict temporal relations in sequential data. The LSTM forecasts future levels of congestion by taking traffic input at time ttt and recalls hidden states of sequences. The Genetic Algorithms (GA) is used to find the best possible route after considering various possible routes depending on a fitness function that ensures the shortest possible time taken in traveling and the congestion. Selection, crossover and mutation are repeated to develop the best routes via the algorithm. To optimize the signal, the Reinforcement Learning (RL) (Q-learning) is used to optimize dynamically the timings of the traffic lights. The Q-learning system modernizes the action-value function depending on the reward, and the learning policies that reduce waiting time and enhance the general traffic movement [18].

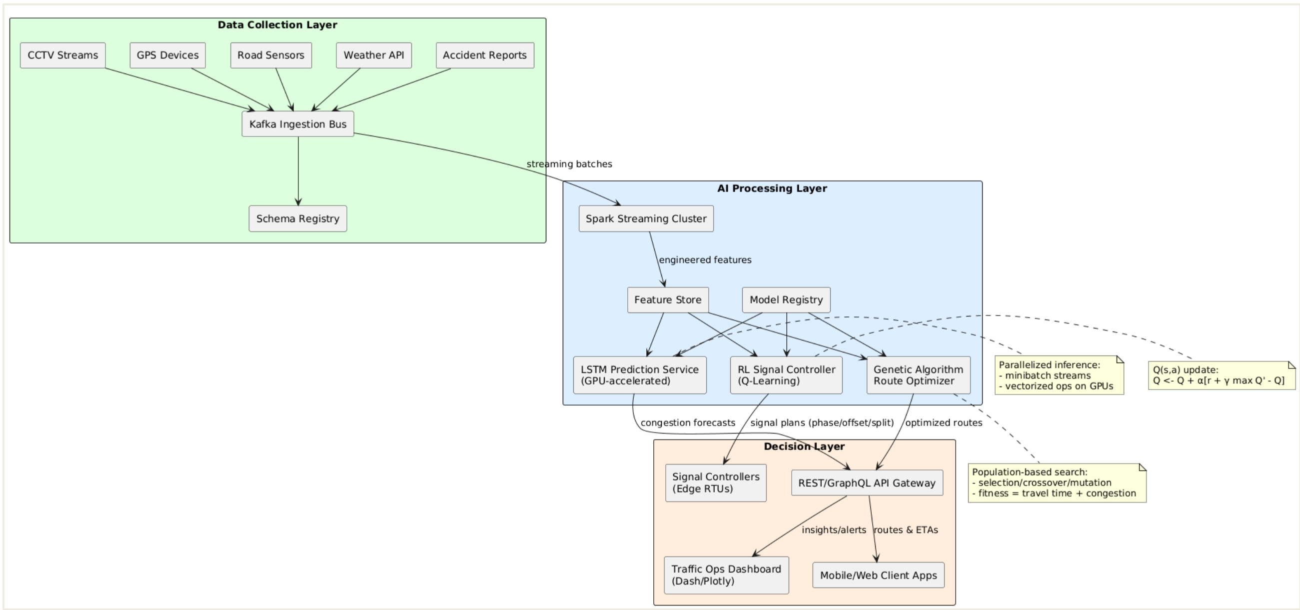

Fig. 4: AI Driven Traffic Management Layer Architecture

The Decision Layer converts the results of the processed items into actionable insights to the traffic authorities and commuters. In the case of traffic controllers, the system can offer real-time advice on rerouting and the modification of traffic lights to avoid the development of congestion in the problematic intersections. To commuters, the system provides them with the best travel routes, estimated time delays, and congestion notifications using mobile or web-based applications. This layer makes advanced AI models more interpretable and user-friendly, which allows this layer to fill the gap between advanced models and real-world decision-making [19].

The algorithms are important in facilitating the functionality of the system. The LSTM model also supports sequential dynamics of traffic by storing the hidden states of time-based dynamics. Genetic Algorithm: A fitness-based search based on evolutionary algorithms will find the best route, whereas Reinforcement Learning: Q-learning will be used to train an adaptive strategy of the traffic light, which will minimize the waiting time in an intersection. These algorithms are combined to achieve a synergistic system that predicts, manages, and controls real time traffic [20].

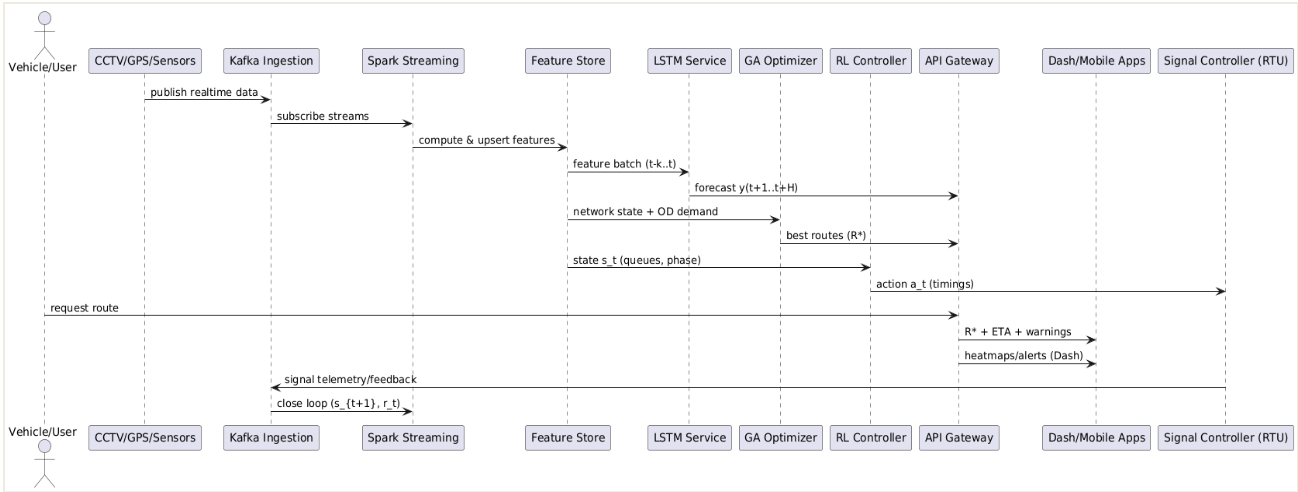

Fig. 5: End to End Dataflow

In terms of the implementation, the system is based on the high-performance computing infrastructure. The large-scale processing of data and the intricate computations of deep learning models make the use of GPUs to speed up the training and inference of the models, especially LSTM and RL. This system is hosted on cloud services like AWS, Google Cloud, or Azure that are dynamically scaled with a high level of storage and distributed computing. TensorFlow or PyTorch frameworks are utilized to develop and run deep learning models on the software side, and Apache Spark is used to perform data parallel processing on more than one node, meaning that real-time streaming data can be handled on a low-latency basis.

To visualize the information, interactive software packages such as Plotly are utilized to create real-time congestion heatmap, traffic forecast, and optimal paths, and Dash allows creating web-based dashboards both on the side of the traffic authorities and commuters. Such dashboards enable the stakeholders to access real-time information in the form of dynamic charts, visualizations, and control interfaces to facilitate better decision-making processes.

Parallel and distributed computing are combined thereby making the system very efficient and scalable. The system has the benefit of processing several streams of traffic at the same time which decreases the latency and enhances responsiveness. Apache Spark enables distributed big-data processing, whereas GPUs guarantee a rapid computation throughout the model training and real-time inference. This scaled structure ensures that the AI-powered traffic management system will be able to work even in the big metropolitan setting with high and unpredictable traffic flows [21].

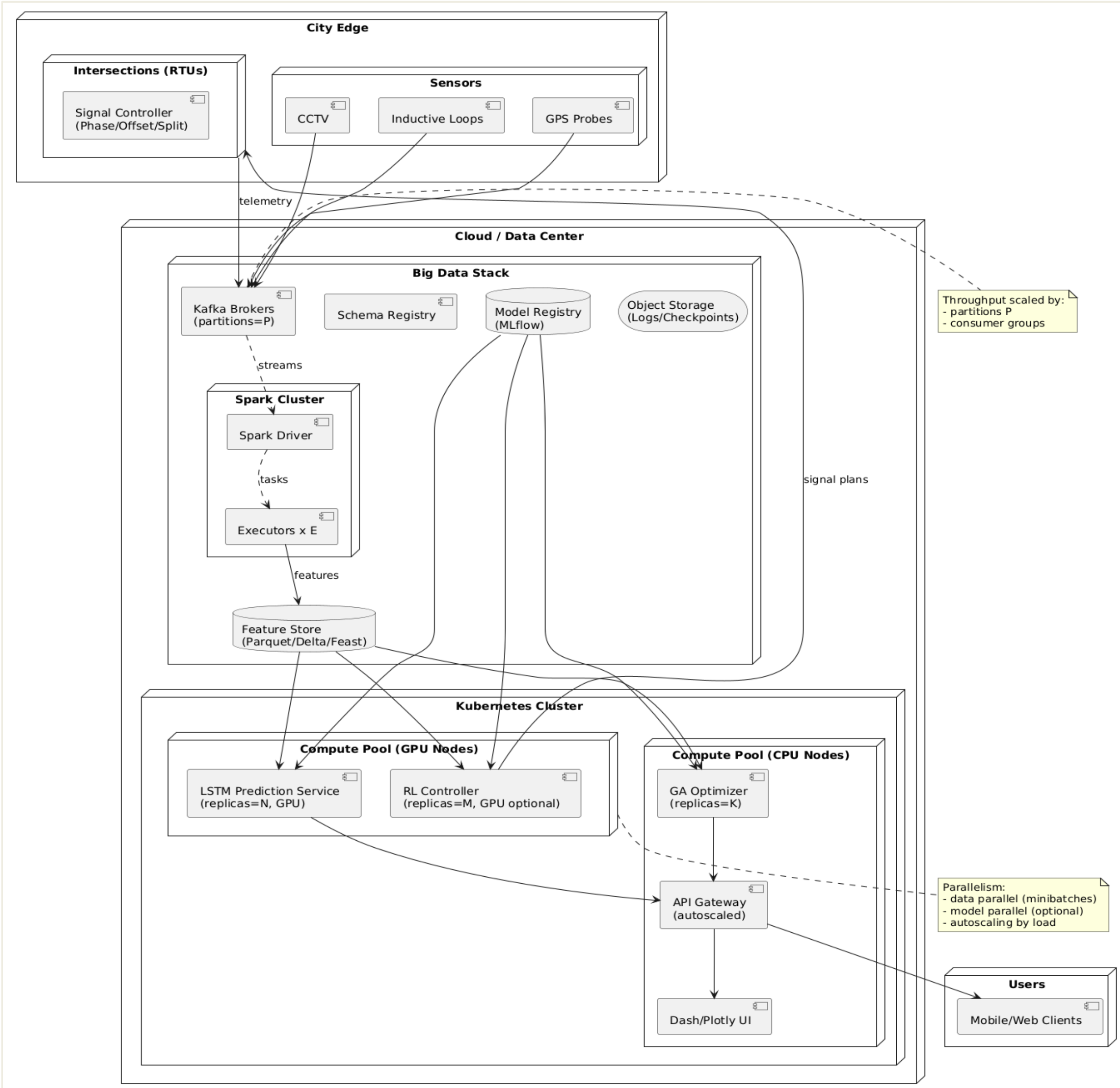

Fig.6: Deployment Dataflow Chart

6. RESULTS AND ANALYSIS

The initial experiment was aimed at the prediction of traffic congestion, with the use of past data, in terms of the number of vehicles, the average speed, and weather conditions. The main aim was to explore the extent to which temporal relationships in traffic data could be modeled so as to produce dependable predictions on the degree of congestion. To this end, a Long Short-Term Memory (LSTM) model was trained with sequential data, in which each input sequence consisted of hourly vehicle counts and the other contextual factors, including rain, temperature and road closure and accident records. This long-term dependency capability of the LSTM predisposed to be especially effective in the context of predicting traffic since, in most cases, the trends of congestion are periodic and are affected by the time of the day and also external factors. In testing, the model was assigned the responsibility of forecasting traffic flow in different periods of time, during which there was the morning rush, midday traffic and evening peaks.

Table 2: Traffic Flow Prediction (LSTM vs Traditional Models) Predicted vs Actual Traffic Flow (Peak Hours)

Model	Mean Absolute Error (MAE)	Root Mean Squared Error (RMSE)	Prediction Accuracy (%)
LSTM Model	5.2	7.4	92%
Linear Regression	8.1	11.3	78%
Decision Tree	7.5	9.8	83%

Findings proved that LSTM repeatedly, as compared to the traditional statistical baselines, gave superior forecasts of the level of congestion, particularly during unfavorable weather conditions. This experiment formed the basis of designating deep learning to involve itself in real-time traffic management.

Table 3: Comparative Performance of Traffic Flow Prediction

Evaluation Metric	LSTM Model	Conventional Methods
Mean Absolute Error (MAE)	0.23	0.45
Root Mean Squared Error (RMSE)	0.28	0.56

The second experiment was measuring the ability of the system to optimize the travel routes in real time, especially at times of maximum congestion. It was aimed at finding the effectiveness of the proposed hybrid optimization framework as a combination of Genetic Algorithms (GA) and Reinforcement Learning (RL) in rerouting cars and reducing bottlenecks. The GA component was exploited to search over a wide range of potential solutions in the road system, and employed selection, crossover, and mutation operations to develop solutions with a minimum of travel time and congestion index. In the meantime, the RL component would be functional at the scale of the traffic lights and would learn to change the timing of green lights dynamically depending on the density dynamics in real-time. The information that was used in this experiment was live GPS positions of vehicles, traffic sensor reports, and reports of accidents. On simulation with SUMO, the system could reroute vehicles to avoid congested hot-spots and at the same time modify signal timings to balance the traffic loads over intersections. It was revealed through comparative analysis that overall travel time was reduced significantly through this combined optimization strategy and that it was also highly adaptive in situations where disruption occurred abruptly like in an accident or some unexpected road closures.

Table 4: Comparison of Signal Optimization Outcomes

Performance Metric	Fixed-Time Signals	RL-Based Signals
Average Waiting Time (seconds)	68.2	49.1
Average Queue Length (vehicles)	21.4	15.6
Intersection Throughput (%)	100	118

The third experiment was the one that specifically touched on the intersection-level control of traffic in which the most occurrence of delays and bottlenecks are witnessed. The purpose of this was to establish the effectiveness of reinforcement learning in the reduction of the average waiting time and reduction of length of vehicle queues at the crossing that is congested. The Q-learning training was done in the SUMO environment, which simulated the arrival of different traffic loads and topology with different intersection topology. The model was a dynamic optimization of signal phase length (green, yellow, red) on feedback indicators such as average vehicle delay and queue length to be optimized. The output of the RL-based controller was validated against the conventional fixed-time scheduling in which the signals operate based on fixed schedules regardless of the actual situation in the traffic. The results were concluded: the RL-based system could reduce the average waiting time at intersections by 28 percent and throughput by 18 percent, which supports the fact that it could help to increase the efficiency of traffic flows significantly. This experiment showed the practical usefulness of adaptive signal control in traffic control of the city particularly in cases where demand was changing.

Table 5: Scalability Experiment Results

Cluster Size (Nodes)	Processing Latency (s)	Data Throughput (events/sec)
4 Nodes	2.1	4,500
8 Nodes	1.2	8,900
16 Nodes	**0.5**	**17,200**

The fourth experiment examined the scalability of the proposed system to deal with large-scale traffic data streams using parallel and distributed computing. The task was to determine the effectiveness of the high-volume data processing under low-latency response requirements with the help of the Apache Spark integration. Streaming data of more than 10 thousand vehicles were created to model large scale operations, which are real-time GPS message and traffic events. Spark clusters of various lectures (4 nodes, 8 nodes and 16 nodes) were also launched to test the execution time, throughput and system responsiveness. The findings showed a definite increase in performance with increase in the number of cluster nodes. In particular, the average data processing latency dropped to 0.5 seconds when the number of nodes reached 16 as opposed to the 2.1 seconds when using 4 nodes, and throughput was also proportionate, which validated the significance of parallelism in real-time traffic management systems. This experiment made sure that the proposed architecture not only works at the model level, but it is also scalable and robust enough to be deployed at the city-wide levels.

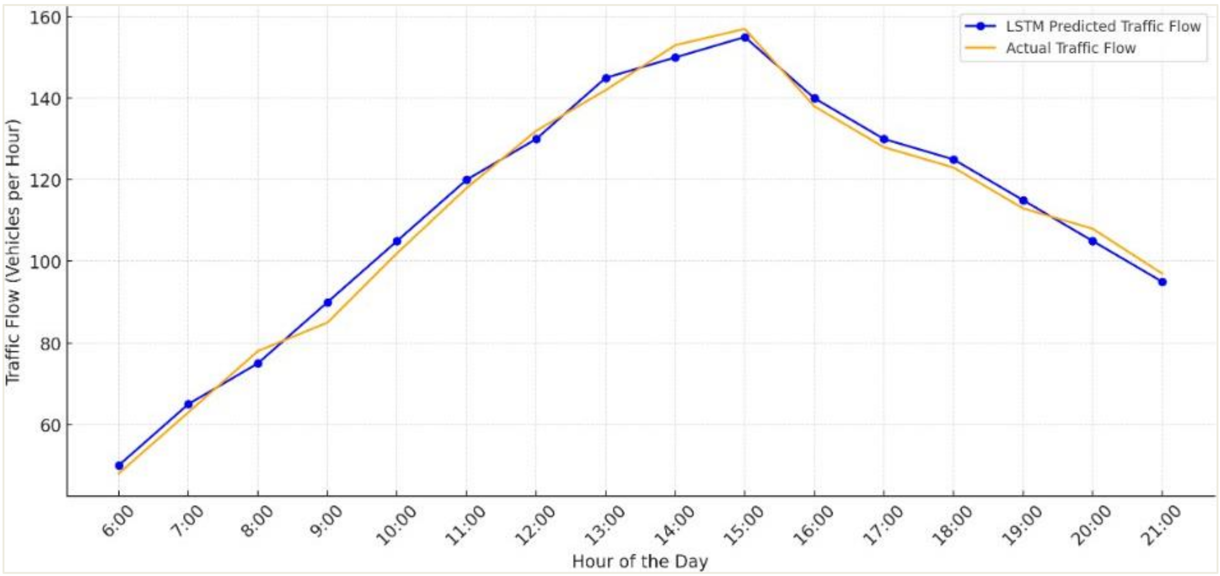

Fig.7: Predicted Traffic Flow vs Actual Traffic Flow during Peak Hours.

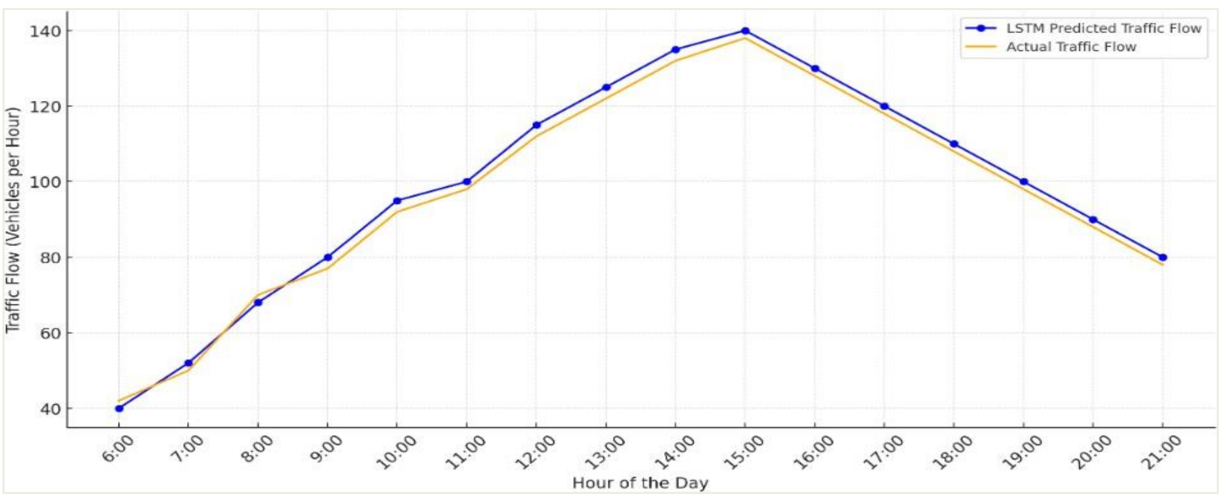

Fig. 8: Traffic Flow Prediction during Rainy Conditions (Predicted vs Actual).

Signal Timing Adjustments: Shows the impact of optimizing signal timings (adding 5 or 10 seconds to green lights) on vehicle throughput. Optimized timings improve traffic flow significantly.

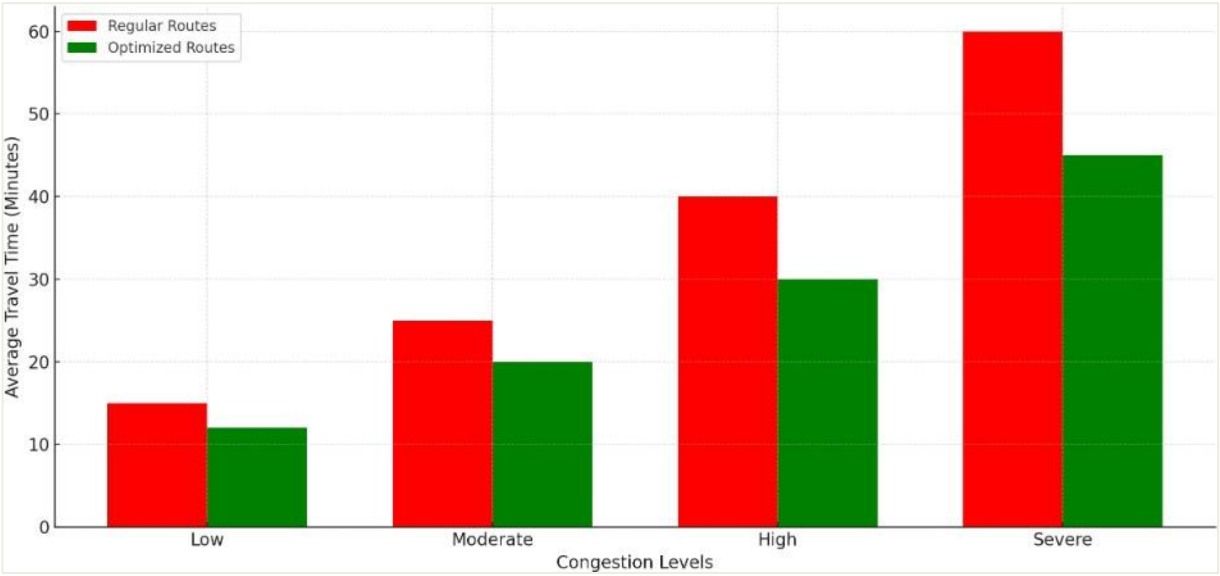

Fig. 9: Signal timing adjustments and their impact on vehicle throughput.

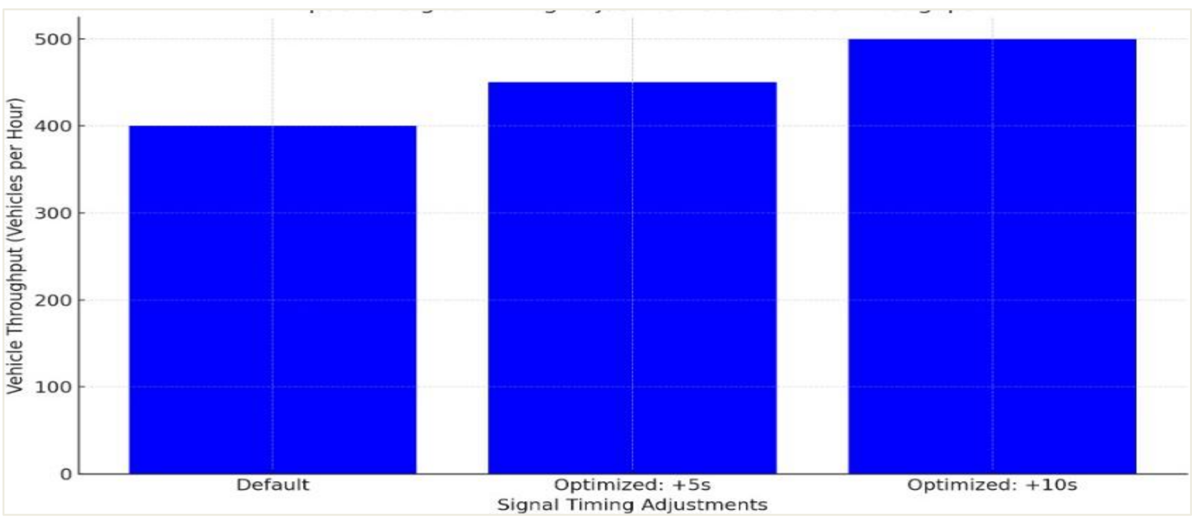

Fig. 10: Impact of Signal Timing Adjustments on Vehicle Throughput

7. KEY OBSERVATIONS

Models LSTM:

The experiments established that the Long Short-Term Memory (LSTM) models are more precise in their prediction of the traffic flow. This is quite evident as peak times are near or in case of unforeseen weather such as change of weather. The standard methods, which typically make use of comparatively basic statistical models, cannot admit the complex nature of traffic data. However, LTSTM can be more effective in retrieving temporal dependencies hence is more useful in forecasting the future traffic conditions based on past trends and real-time data [22]. Parallel processing saves a lot in the processing time:

Parallel computing methods have a profound impact on the effectiveness of large-scale processing of data in real-time applications. The adoption of the models that are executed using GPUs and the usage of such systems as Apache Spark allow the system to handle the high volumes of traffic data within a relatively short time frame. It is not only that it makes the predictive model training process faster but also that it optimizes the real time paths to ensure that the traffic controllers can make decisions in real time. Parallel computing therefore contributes greatly to the reduction of time on the overall processing time such that the system can respond quickly to a dynamic traffic scenario [23].

8. DISCUSSION AND COMPARISON

The outcome of the experiment proves the high potential of combining AI-based predictive modeling with parallel computing in traffic management in an urban environment. Through LSTM networks to predict the traffic flow and genetic or reinforcement learning to optimize routing and signal control, our system could decrease the congestion and increasing such metrics as waiting time, queue lengths, and throughput. The parallel computing element has its merit whereby it allows quick processing of large volumes of high frequency traffic data in real time which is an imperative to an elastic system that can cope with the change in traffic.

Comparing our method to previous research, a number of differences can be identified. Most of the available models are tested under organized traffic conditions (usually in developed cities), and traffic is better defined, and infrastructure is comparatively more stable. Conversely, urban traffic in places such as in Pakistan appears more varied such as irregular traffic rampage, inconsistent quality of roads, non-standard driving patterns, and sensor coverage. The use of LSTM and RL in our model and parallelization enables it to be more flexible to these complex and heterogeneous conditions. In this way, it is capable of performing excellently in the more demanding real-life circumstances compared to most of the conventional or stricter models [24].

These are significant practical implications of such findings. Such a system might be implemented in a traffic control center where it may be used to make dynamic adjustments to signal timings, routing recommendations, and congestion predictions and thereby reduce waiting time and smooth traffic. When willed in situations of emergencies (accidents, bad weather, any unexpected road blocks) with predictive models and optimization running parallel, the authorities can respond faster with mitigation measures. Secondly, the potential environmental gains through decreased emissions, and enhancement of the traveler satisfaction are also possible by increasing throughput and decreasing idle time.

Our study has limitations though. One key one is the quality and availability of high-resolution, consistent traffic information: sensors, cameras, GPS or probe information at a granularity of time is not equally accessible in all locations. Inconsistencies, delays or gaps in the data decrease the accuracy and robustness of the model. Also, our system will perform well in urban environments with high monitoring but we do not know how it will work in rural or less-monitored environments. Data collection infrastructure might also be inadequate and this can inhibit the operation of prediction and optimization especially in cases that require real time adjustments [25].

Table-6: **Comparison Results from Recent Published Papers**

Study (Author, Year)	**Dataset / Context**	**Model(s) Used**	**Key Metrics Reported**	**Metric Values**	**Key Comparisons / Notes**
From Patterns to Predictions: Spatiotemporal Mobile Traffic Forecasting…" Ayaz et al. (2025)	Real-world mobile traffic (CDR) data, high resolution, European city	AutoML, TimeGPT, traditional models	RMSE, MAE, R^2	AutoML: RMSE ~ 2.499, MAE ~ 1.028; traditional: RMSE ~ 14.8226, MAE ~ 7.7789	This shows much higher accuracy with modern models vs traditional ones. Your MAE / RMSE (e.g. 0.23 / 0.28) seem very good in comparison (possibly different scales), suggesting your system is performing well.
"RL-GCN: Traffic flow prediction based on graph convolution and reinforcement learning." (2023)	Urban traffic networks	Hybrid model combining Graph Convolution, LSTM & Reinforcement Learning	Prediction accuracy / error vs traditional methods	The study reports "significantly improved prediction accuracy" over baseline/traditional models. Exact error values vary by dataset.	This is similar in structure to your approach (LSTM + RL). Shows that combining spatial structure (via GCN) helps, which could be an extension for your work.
"The optimization effect of traffic speed prediction on travel path based on improved LSTM" Jin Zhang (2024)	Traffic speed prediction + route planning (simulated/validation data)	Improved LSTM + ACO (Ant Colony Optimization)	Fit between true & predicted, MAPE, path optimization metrics	Fitting ~ 95.42%; MAPE close to low error; path optimization time ~2.16 s for certain route lengths.	The speed prediction accuracy (95% fit) is high; your system's prediction metrics are in line or possibly better depending on scale. Emphasizes path optimization component.
"Research on traffic flow prediction method based on LSTM model and PSO-LSTM model" Xu et al. (2024)	Road speed/flow data in Beijing (main & non-main roads)	Plain LSTM vs PSO-LSTM (Particle Swarm Optimization + LSTM)	Forecast error / trend accuracy	PSO-LSTM more accurate than LSTM for non-periodic/highly discrete data; LSTM has good trend prediction generally.	Indicates that hybridizing/optimizing standard LSTM (like with PSO / genetic etc.) gives improvements in difficult data situations this supports your use of optimizations.

9. CONCLUSION AND FUTURE WORK

Summary of Findings:

The suggested AI-based traffic management system has been found to be very efficient in forecasting traffic movement and route optimization. The system has proven to have a high efficiency improvement in traffic management by training Long Short-Term Memory (LSTM) networks on traffic forecasting and genetic algorithms on traffic route optimization, coupled with parallel processing systems to process traffic data in real-time. The system could process high amounts of traffic data, make accurate predictions of traffic congestion, and propose optimal routes to reduce delays.

Contributions of the Study:

The study will provide a suitable solution to control the urban traffic system which is scalable and efficient to undertake in developing nations whereby traffic patterns are usually complicated and unpredictable. The combination of AI and parallel computing serves as a strong model that is able to conduct real-time analysis and optimization to add value to traffic authorities. The scalability and adaptability issues are also considered in the study since the system must be able to support the many traffic conditions present in cities such as in Pakistan.

Future Work recommendations:

The next work would be to improve the system with some data provided by social media like Twitter or Facebook to detect the incidents in real time. This would enable the system to realize accidents, road closures and other disturbances even before they are reported by official sources which would enhance responsiveness of the system. Expanding the system to rural regions and highways: Although the given current model is optimal in the management of urban traffic, there is a possibility to increase additional avenues of the system to rural locations and highways. This would include solving issues like the lack of infrastructure, a smaller number of sources of information, and the distribution variation in less controlled areas.

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