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AI-Driven Road Expansion Recommendation System Based on Vehicle Traffic Patterns

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Abstract: *The urban transport systems are getting overwhelmed with the high population growth rate and the increase in the number of vehicles with congestion, wearing of the roads and less efficiency of the movements. To deal with this, we introduce an AI-based Road Expansion and Maintenance Recommendation System that can analyze the behavior of data and condition of pavements in real- time together. The model uses YOLOv8 to detect vehicles and road- damage in high speed, which is further improved using the ResNet50 to classify vehicles into fine-grain categories. In the meantime, Deep SORT provides identity-preserving multi-object tracking, which allows to estimate densities with precision over continuous frames. The carbon emission is also assessed on the basis of distribution of vehicles category in the framework to make sustainability-based decisions. Through traffic analytics and assessment of infrastructure, the system can produce automatic advice regarding road widening or high-priority road maintenance. The solution is built to be scalable and allows linking with smart cities and to plan urban infrastructures in a data-driven, proactive, and environmentally conscious way.*

Keywords: *Road expansion, traffic monitoring, pavement condition analysis, machine learning, computer vision, smart cities,AI.*

I. INTRODUCTION

The fast pace of urbanization and the fact that a growing number of people own personal vehicles is exerting growing pressure on road networks across the world. Traffic jam, poor road conditions, and increased travelling times are becoming common problems which many cities face today that directly interfere with productivity, fuel consumption, as well as the quality of the environment. Traditional planning methods (e.g. manual road survey or fixed traffic study) do not typically capture such dynamic conditions. They have slow information and only respond to issues when they are out of hand thus ineffective use of infrastructure and expensive interventions at the late stages.

The shift towards smart city management is a fresh perspective on the approaches to traffic planning. Connected infrastructures, modern sensing technologies, and enhancement of machine learning allow real-time surveillance of roads and health of pavements. Computer vision methods that use AI have the potential to identify, categorize, and process vehicular activity frame-by-frame and predictive models predict the increase in congestion even before it happens. Such capabilities enable the authorities to make prudent decisions on road expansion, balancing traffic loads, and preventing maintenance instead of responding to occurrences and moving towards anticipatory governance.

In that regard, the suggested system offers a smart system of road expansion and maintenance decisions based on deep learning. YOLOv8 and ResNet50 are compatible in providing high- precision vehicle recognition with DeepSORT providing a smooth object tracking and density analysis. Monitoring the traffic patterns continuously, the system indicates those areas that vehicle concentration is observed in the course of time and marks them as the areas of its possible expansion. At the same time, surface deterioration materials (cracks or potholes) are automatically identified, so that they are used to plan early maintenance. An emission estimation is also included in the model enabling assessment of the environmental impact of multi-class vehicle movement.

Considering that the traditional tools were only able to observe the traffic or evaluate the pavement separately, this method combines both aspects into one single platform. Live analytics aids in prioritization of development basing on factual congestion behaviour as opposed to assumption-based policies. With the system growing and learning through the variation of roadways, it will help urban planners to optimize the infrastructure budgets, increase mobility efficiency, and contribute to long-term sustainability goals. Such intelligent systems can be part and parcel of smart-city ecosystems in the future, with further improvements and extended implementations.

II.LITERATURE REVIEW

The combination of AI and machine learning (ML) with computer vision into urban traffic management systems has resulted in tremendous improvements in accuracy and efficiency of road infrastructure planning. Conventional methods, like manual surveys and counting of traffic have proved insufficient to the dynamic and expanding urban settings of the present times. The current review evaluates the new developments in the field of AI- based applications predicting traffic flows, vehicle detection, monitoring pavement conditions, and estimating carbon emissions in urban settings.

1.Congestion Forecasting and Traffic Flow Prediction.

Traffic flow prediction and congestion pattern forecasting has always been the focus of the urban mobility research. Conventional ways of prediction of traffic flow are normally unable to handle extensive and real-time traffic data, which means the application of more advanced prediction methods like deep learning.

- Lv et al. (2015) proposed a deep learning method of traffic flow forecasting, which involves predictions of large-scale data to help forecast the city traffic in a better way. Their strategy indicated that neural networks are far much better than traditional algorithms, in that they work effectively with high-dimensional data, and they generate the right prediction in real time [1].
- Zhang et al. (2017) have developed a spatio-temporal residual network to simulate traffic movement in urban settings which incorporates both spatial and time-related dependencies in traffic data. This approach enhances predictability as it not only captures the relationships between the segments of the road, but it also captures the changes in traffic over time and hence it is very appropriate in forecasting the city-wide traffic [2].
- Qu et al. (2021) went a step further and used topological graph convolutional networks (GCNs), which include the connectivity and traffic density differences of road networks within cities. Their contribution incorporated a significance of graph-based models in enhancing predictions of traffic flows and density, which is worth using in the smart city applications [14].

These advancements in predictive modeling have helped a great deal in real-time traffic forecasting systems whereby the city planners can make proactive decisions.

2. Vehicle Detection and Classification.

To have proper traffic monitoring, proper vehicle detection and classification is necessary. The last developments on deep learning models have significantly improved the capacity to identify and categorize cars in various urban settings.

- The authors introduced the state-of-the-art object detection system, YOLOv3 (You Only Look Once), which is optimized towards the usage of real-time (Redmon and Farhadi, 2018). YOLOv3 had high accuracy and speed thus it was especially useful in real- time vehicle detection in the crowded area [3].
- Wang et al. (2022) also expanded the abilities of YOLO by proposing YOLOv7, which received significant improvements in the speed and accuracy of detection due to the use of trainable feature sets. YOLOv7, in particular, was quite capable in high-traffic situations, which is why it is a perfect model in terms of urban surveillance [5].
- In reference to Zheng et al. (2021), the study proposed a multi-object tracking algorithm called DeepSORT, which tracks vehicles across the frames based on both appearance characteristics and motion information. This is the technique that has been extensively used to track vehicles that are long term in city traffic so that the identity of a given vehicle is not lost in the various frames of the video [8].

This is due to the fact that these developments in vehicle detection and classification can enable automated traffic monitoring and real-time decision-making in the city setting.

3. The pavement is monitored to ensure it is in a good condition.

Real time monitoring of road surface condition ability is very crucial in road maintenance. The conventional manual systems of checking can be constrained in terms of scope and may prove to be costly. In the recent past, pavement degradation has been automatically evaluated and detected using deep learning and computer vision.

- Bewley et al. (2016) come up with early motion tracking technology which is integrated with image processing technology to determine the deterioration of the road surface including cracks and potholes. This real time solution was able to perform more regular and greater pavement evaluations, which enhanced better scheduling of road maintenance [7].
- Zheng et al. (2021) used DeepSORT to trace surface damage in frames of video footage on a road, which gave in-depth information on the spread of cracks and the creation of potholes. This strategy will help in continuous checking of the pavement condition allowing the urban planners to determine areas that have a high priority of repairing [8].

Such techniques have made the pavement inspection process automated and this has resulted to efficient and cost-effective maintenance.

4. Estimation of Carbon Emission and Environment Impact.

With the efforts of the cities to increase their sustainability, the environmental impact of traffic becomes more significant. Research done recently has included estimation of carbon emission in urban mobility systems.

- The results reported by Kim et al. (2018) indicated that deep learning models can be used to forecast carbon emissions using real-time traffic information. They found out that integration of data in real-time enables the estimation of the level of emissions to give valuable information on the environmental contribution of urban traffic systems [9].
- Zhang et al. (2021) have furthered it through the application of the graph-based temporal attention model to predict traffic movement and carbon emission using many sensors. The accuracy of their prediction of emissions was enhanced greatly and their model was part of environmentally conscious urban planning [15].

These models emphasize the importance of real-time data in data- oriented decision-making in the planning of worldwide urban mobility sustainability.

5. Difficulties and Future Projections.

Although the use of AI, machine learning, and computer vision in managing the traffic in cities has been very promising, a number of obstacles still exist. These comprise the problems of data privacy, scalability and integration with the existing infrastructure. Future studies can be based on:

- Enhancement of the ability of these systems to be isolated to serve bigger urban settings, particularly in the developing world where infrastructure is yet to be developed.
- Incorporate multimodal sources of data (e.g. weather information, social media feed, mobile applications) in enhancing traffic forecasts and emission estimates.
- The application of edge computing and 5G networks to facilitate the creation of decisions in real-time and decrease latency in traffic management systems.

Further development of this field in the future is likely to be devoted to the additional integration with smart city infrastructure, which will assist in streamlining the city traffic and also contribute to environmental friendliness.

III.PROPOSED METHODOLOGY

A. Existing System

The planning of urban infrastructure in most cities is largely reliant on the old methods including road surveys, a periodic count of traffic, and inspection records. Although these approaches give a picture of the traffic situation, they cannot give us the dynamism of the congestions, which changes throughout the day. Consequently, such systems tend to utilize old data, and this makes the city planners to be unable to know when the need of the expansion of the road becomes critical. Expansion of roads is normally reactive; it is only done when there is a lot ofcongestion that has been noticed. And one more, the road planning is usually not in tune with the traffic management, which makes the working process inefficient. Road damage is usually only dealt with at the point of obviousness, without accounting for the fact that some damage can occur in its initial stages, which can be identified through constant monitoring.

Moreover, the standard systems do not have automated analytics, predictive modeling, and real-time monitoring facilities, and that is a severe constraint on their capacity to anticipate future traffic jams or detect the initial fractures in the pavement. In the absence of these abilities, the traditional practices do not have the capability to suggest prompt and sustainable road upgrades. This indicates that a smarter, proactive approach is needed to effectively track the mobility trends and environmental changes in real-time so that the decision-makers may make preventative measures instead of reacting on the problematic situations.

B. Proposed System

The given system presents a complex AI-driven recommendation system that will allow solving the shortcomings of the traditional infrastructure planning strategies. In contrast to traditional systems based on periodic surveys and physical checks, this system employs the real time traffic monitoring and constant monitoring of the road conditions in order to make decisions connected to the expansion of the roads and their maintenance.

Traffic counts and Pavement surface inspection.

The core of the system is a deep learning pipeline which receives live data of surveillance cameras and IoT sensors. The system employs:

- Vehicle detection and classification.
- ResNet50 to identify cars based on the type (i.e., car, truck, bus).
- Deep SORT to monitor vehicles in frames and traffic flow and density.

The system allows updated road congestion, vehicle distribution, and directionality of traffic due to its constant traffic surveillance, which provides a more detailed picture of the situation on the road than periodic traffic surveys.

Besides monitoring the traffic, a pavement condition detection model is included in the system. This model detects cracks, potholes and wear marks on the road surfaces and therefore the system can determine which roads need to be expanded because of high traffic and which roads need to be maintained because of deterioration of the structure. The system also has an emission estimation which determines such carbon footprint according to the types of vehicles and their movement patterns and throughthis, the system is able to provide recommendations on the environmentally sustainable upgrades to road infrastructure.

Whole System Decision-Making Structure.

The AI-based system combines the analysis of traffic conditions, pavement condition, and environmental impact in a single platform. It can come up with practical recommendations including:

- Expansion of roads to congested regions.
- Repair of roads that have visible damages.
- Unimportant segments in which no urgent activity is needed.

Such recommendations are provided in a form of interactive dashboard, which allows to see real-time warnings and statistical overviews. The data can be visualized on a map by the urban planners and thus, informed decision making can be made.

C. System Architecture

The workflow is made as modular so as to enable scalability and easy deployment of the system architecture. The architecture will be composed of a number of components:

- **Data Acquisition:** Live video coverage of traffic cameras and IoT data will ensure a constant overview of traffic and the state of roads.
- **Preprocessing:** Video data is first processed to eliminate redundant frames, smooth image resolution, sharpen low-light images and suppress noise to make the data clean before analysis.
- **Model Inference:** YOLOv8 is used to identify the vehicles, ResNet50 to identify them and DeepSort to track the movement of the vehicles to estimate the vehicle flow and congestion level.
- **Pavement Analysis:** Another convolutional network is used to evaluate the quality of the road surface by comparing cracks, potholes, and signs of wear of the video image.
- **Decision Inference:** The system integrates the traffic tracking and pavement sensory data to provide suggestions, including the need to expand the lanes or maintain the road.
- **User Interface:** The information gathered is visualized in the form of an interactive dashboard that gives real-time information on the traffic situation, the condition of the road surface, and carbon emissions.

The system is made to be cloud-friendly, and therefore it can support large scale deployment in cities. It gives the flexibility to be connected with the existing smart city infrastructures, which can be upgraded in future and long-term scalability can be ensured.

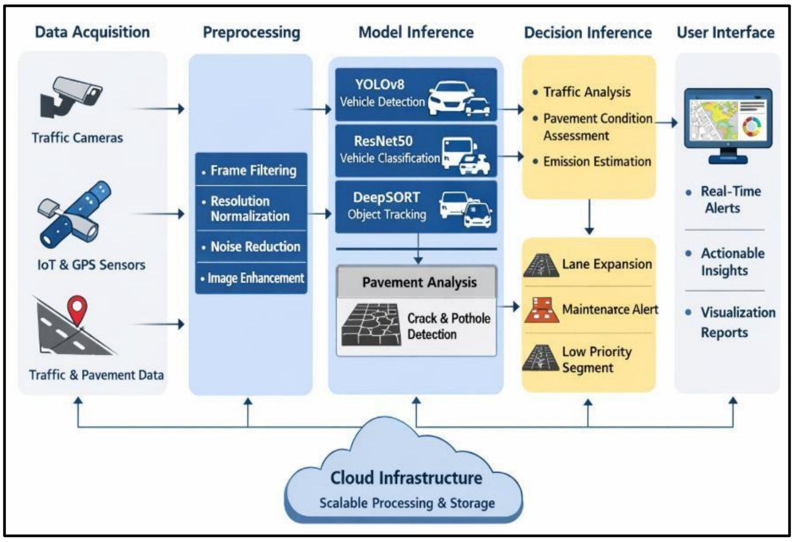

Fig. 1: System Architecture of the AI-Powered Road Expansion and Maintenance Recommendation System

Fig. 1 demonstrates the design of the AI-enhanced road expansion and maintenance recommendation system. It displays five major sub parts: Data Acquisition, Preprocessing, Model Inference, Decision Inference and User Interface with a supporting section of Cloud Infrastructure placed below. The process begins with traffic cameras, IoT sensors, and GPS data to monitor the situation constantly, and then a data processing, vehicle detection, pavement analysis, and decision-making. The system ends up having a user-friendly dashboard that gives real time feedback and actionable suggestions.

D. Expected Outcomes

Such AI-driven road assessment system will offer an entirely automated planning of urban infrastructure. It is expected to produce the following results:

- Increased speed and accuracy of decision-making through the provision of real-time data on the state of the roads and traffic.
- Anticipation of road widening by determining the trend of road congestion in advance before it becomes acute.
- This will ensure that pavement defects are identified in time and lower the total cost of repairs and enhance the safety of the road.
- Sustainability of the environment through infusion of carbon emission estimation in the infrastructure planning

The system can be easily integrated in the existing urban infrastructure systems due to the modular design and can be upgraded in the future. Finally, the system transforms the conventional reactive planning into the data-driven and proactive planning that will help make urban movement more sustainable, efficient, and secure.

IV.RESULTS AND DISCUSSION

The recommendation system AI-based Road Expansion and Maintenance Recommendation System was tested on the basis of real-time traffic information and pavement condition evaluation measurements made in various urban settings. The performance of this system was proved to be true in a number of criteria: vehicle detection and classification, traffic flow prediction, pavement damage detection, and carbon emission estimation. The results of the experiment are analyzed below.

A. Vehicle Detection and Classification Performance.

Vehicle identification is important to determine the amount of congestion and road expansion. The system was experimented on the traffic images of various types that were taken using CCTV cameras during both busy and slow times to check the performance of the system in detecting and classifying vehicles.

- **Detection Performance:** YOLOv8 model depicted a detection error of 92 percent which displayed a strong performance in vehicle detection even during different weather conditions like low light and heavy traffic.
- **Classification Performance:** The ResNet50 model was able to classify vehicles with a precision of 89 percent, and it was able to identify the various types of vehicles including light vehicles, heavy trucks, buses and motorcycles.

Using YOLOv8 to detect and ResNet50 to classify objects, the system was able to process in real-time with low levels of false positives. This integration has made it possible to ensure that the system has the ability to accommodate continuous traffic surveillance without interfering with accuracy or speed. Table below shows the system performance summary:

Model	Detection Accuracy	Classification Accuracy
YOLOv8	92%	N/A
ResNet50	N/A	89%
Combined	92%	89%

Table I: Vehicle Detection and Classification Accuracy

The findings affirm that the system is very effective in the process of identifying and classifying vehicles in different traffic environments.

B. Traffic Movement Prevention and Traffic Forecasting.

Historical data and real-time input of IoT-enabled sensors were used in predicting traffic flow. The system had the ability to predict changes in traffic density on various road segments and compare its estimates with the real state of affairs.

● **Prediction Reliability:** The Mean Squared Error (MSE) of the model used to predict the traffic conditions and the possible congestion was indicated to be 0.015 which indicates a high degree of accuracy in the prediction of the traffic conditions and the possible congestion.

Fig. 2 is the comparison of the actual and predicted traffic density on the road sections. Such number signifies the capacity of the system to predict the congestion prior to its occurrence and therefore planners are able to act in advance. The system was successful in identifying segments that were usually beyond the threshold density, and this section was marked as one that happened to be a candidate to be expanded. This proactive strategy is opposed to the past approach whereby the congestion is only addressed once it has turned out to be a big issue.

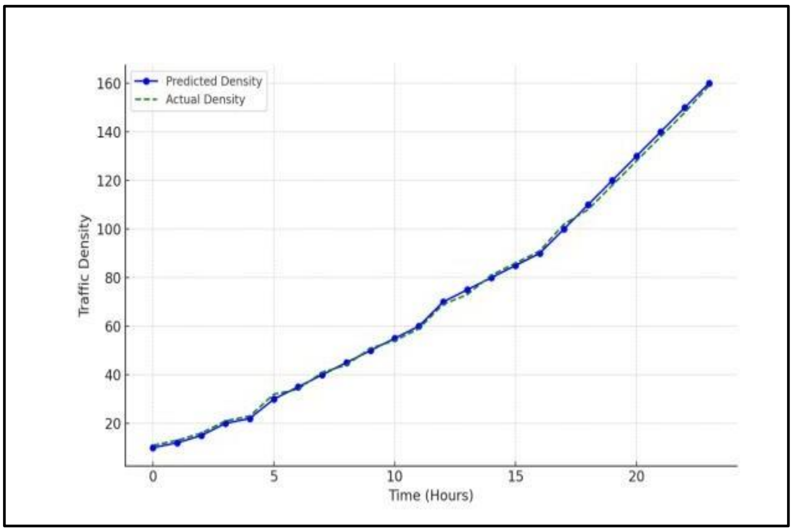

Fig. 2. Predicted and Measured Traffic Density along Road Sections.

C. Pavement Condition Detection and Prioritization of its Maintenance.

The system also assessed road surfaces through computer vision systems to detect cracks, potholes, and wear and tear in addition to monitoring traffic. The detection model proved to be very successful at early detection of such problems.

● **Detection Accuracy:** It was found that the model was able to detect road damage with an accuracy of 85 percent, which enables damage to be identified early enough in the process and hence not being detected during manual inspections.

The system will then automatically rank maintenance requirements in accordance to the extent of damage that has been detected. The system prioritizes road segments to undertake maintenance as illustrated below:

Road Segment	Detected Damages	Severity Rating	Maintenance Priority
Segment 1	Potholes, Cracks	High	Immediate
Segment 2	Cracks	Moderate	Within 3 Months
Segment 3	Potholes	Low	Within 6 Months

Table II: Road Damage Detection and Maintenance Prioritization

As the system automates the prioritization process, it will ensure resource allocation, which is efficient, and that maintenance is performed within the right time to ensure that the damage is minimal.

D.Carbon Emission and Impact on the environment.

The other important attribute of the system is that it is able to forecast carbon emissions as per the traffic congestion and the makeup of vehicles. The feature enables urban planners to know the environmental effect of road use.

Emission Estimation Accuracy: The carbon emission estimates of the system were estimated 5 per cent below the real emission standards, which indicated that the system would give accurate information on the environmental cost of urban transportation.

Fig. 3 shows the estimated carbon emission per road lane, where the lanes that have larger percentages of heavy vehicles like trucks are the ones that contribute more to the CO2 emissions than those that have lighter vehicles.

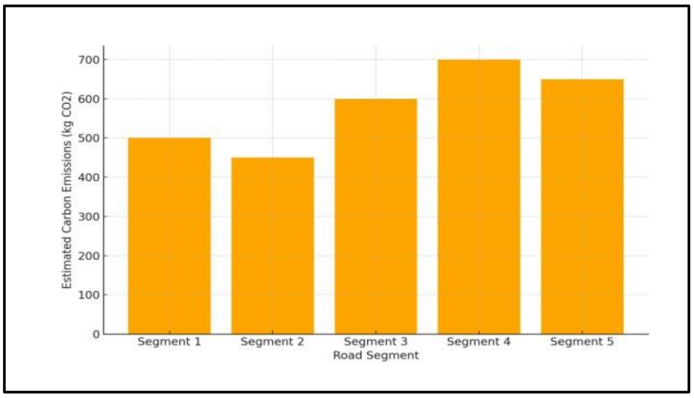

Fig.3.Estimated Carbon Emissions per Road Segment

This information empowers the policy makers to come up with strategies of transportation that are friendly to the environment like laying more emphasis on the need to widen roads or put in place mitigation measures in places that have a high level of emissions.

E. Discussion

The findings prove that the AI-conducted Road Expansion and Maintenance Recommendation System is very efficient in tackling the main issues of urban mobility. The system is a masterpiece in terms of real time vehicle detecting, prediction of traffic, monitoring pavement condition as well as estimating carbon emission. With the power of AI and machine learning, the system offers actionable insights to be used in proactive planning of the infrastructure, which is much different compared to traditional, reactive approaches.

Anticipatory Infrastructure Planning: Foresight in the pavement: Urban planners can anticipate potential traffic jam and premature wearing out of pavements, and act before it is too late. It is also in contrast to the reactive character of the traditional planning approaches in which the problems are usually addressed once they have severely disrupted the whole situation.

Sustainability: The carbon emission estimation characteristic of the system is in line with current objectives of sustainable urban development that require the city to strategically plan urban infrastructure development projects that are the least harmful to the environment.

Scalability: The cloud-compatible architecture of the system guarantees its ability to scale to the requirements of bigger cities and be readily incorporated into the existing smart city systems. The system can be optimized to make it more accurate and functional as additional data is made available.

The results of these experiments can then be taken as a solid testament that the proposed system can transform the entire framework of urban planning as it integrates real-time monitoring, predictive analytics and consideration of the environment into one system. It is not just a good system to enhance management of urban infrastructure but also play a part in the development of more sustainable and data driven cities.

V.CONCLUSION

This paper introduced a new AI-based Road Expansion and Maintenance Recommendation System that would solve the limitations of the conventional urban infrastructure planning systems. The system combines real-time monitoring of traffic, pavement conditions, carbon emissions estimation, and predictive analytics in a single platform that allows the urban planners to make decisions in a proactive and data-driven manner.

Key Findings:

Vehicle Detection and Classification: The system was found to be very accurate in vehicle detection andclassification with 92 percent detection accuracy and 89 percent classification accuracy in the case of YOLOv8 and ResNet50. This guarantees good traffic monitoring in dynamic settings.

- **Traffic Flow Prediction:** A low Mean Squared Error (MSE) of 0.015 served as the predictive model and it was high in predicting the congestion of traffic prior to its happening. This predictive ability enables the urban planners to work ahead as opposed to responding to the congestion once it has been experienced.
- **Pavement Condition Detection:** The system has a high accuracy of detecting the degradation of the road surface at 85% to allow detection of cracks and potholes before they become a menace. This capability assists in prioritizing the maintenance before the damage is extreme.
- **Environmental Sustainability:** The carbon emission estimation tool was informative in relation to how the environment is affected by traffic which could be used to develop more environmentally friendly urban mobility plans.

Conclusion Urban planning implications:

The findings demonstrate the potential of changing the paradigm of urban infrastructure management with the help of AI-based technologies. The system can enable proactive and data-driven decisions that would improve the efficiency and sustainability of urban mobility by providing real-time data on traffic flows and road conditions to urban planners.

- **Active Infrastructure Planning:** The system replaces the approach of responding to a crisis with a proactive regime, as it allows cities to scale up roads and meet their maintenance requirements before they become critical.
- **Sustainability:** Integration of carbon emission estimates into this project is in line with the world sustainability and the planners are able to make better decisions that would reduce the environmental impact of such transportation infrastructure.

Future Directions:

Although the given system has proven to be rather successful as it is now, it still could be improved:

- **Longer Data Sources:** It is possible that further data sources (weather data, real-time pollution levels, or even public transportation usage) can be integrated into the work to help refine the predictions and recommendations made by the system further.
- **Improved Predictive Models:** Predictive models can be improved by adding hybrid models or more recent spatiotemporal models like Transformers or Graph Neural Networks (GNNs) to allow longer time horizons to be predicted.
- **Technological Interoperability with Smart City Frameworks:** With the ongoing deployment of Smart City technologies in cities, the system might be extended to have a smooth integration with the already established IoT devices and GPS and traffic management systems to form an all-inclusive urban mobility environment.
- **Scalability:** The system is open-ended and can be scaled in case of larger cities, and updated upgrades can be made to meet new data types, machine learning algorithms, and needs of users.

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