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CitySense – AI-based Smart City Dashboard for AQI & Traffic Monitoring

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Abstract- ***Rapid urban expansion in Indian cities has significantly improved infrastructure and accessibility, but it has also intensified environmental challenges such as air pollution and traffic congestion. Existing systems often provide fragmented real-time data without predictive capabilities, limiting their usefulness for proactive decision-making.In this work, we design and develop CitySense, an AI-based smart city dashboard that integrates air quality monitoring and traffic analysis into a unified framework. The system utilizes real-time data from APIs such as OpenAQ, WeatherAPI, and Google Maps, and applies machine learning models including ARIMA, Prophet, and LSTM to forecast AQI levels and traffic patterns. Experimental observations across cities such as Delhi, Mumbai, and Amritsar indicate that LSTM achieves higher prediction accuracy compared to traditional models. The system also highlights a strong relationship between traffic density and air pollution levels. The results are presented through an interactive visualization dashboard, enabling users to understand trends, predict future conditions, and receive alerts.The proposed system aims to move beyond passive monitoring by enabling proactive decision-making for citizens, urban planners, and researchers, thereby contributing to the development of smarter and more sustainable cities.***

Keywords— Smart City, AQI Prediction, Traffic Forecasting, Machine Learning, LSTM, ARIMA, Data Visualization

I. INTRODUCTION

Urbanization has played a crucial role in transforming modern cities by improving economic growth, infrastructure, and connectivity. However, this rapid expansion has also introduced several environmental and infrastructural challenges, among which air pollution and traffic congestion are the most critical. These issues directly impact public health, productivity, and overall quality of life.

Air quality in major urban regions frequently reaches hazardous levels due to emissions from vehicles, industries, and construction activities. At the same time, traffic congestion leads to increased travel time, fuel consumption, and stress for commuters. What makes this problem more complex is the strong interconnection between traffic and air pollution. High traffic density contributes significantly to increased emissions, which in turn deteriorates air quality.

Despite the availability of various platforms that provide environmental and traffic-related data, most systems operate independently and focus only on real-time or historical information. They lack predictive capabilities that could help users anticipate future conditions and make informed decisions.

To address these limitations, this paper proposes CitySense, an integrated AI-based system that combines real-time monitoring with predictive analytics. By leveraging machine learning models and multiple data sources, the system provides a unified dashboard that enables users to analyze trends, understand correlations, and predict future AQI and traffic conditions.

Main Contribution:
The main contribution of this work is the development of a unified framework that integrates AQI prediction and traffic analysis using real-time data and machine learning models, supported by interactive visualization.

II. LITERATURE REVIEW

Previous research has explored various approaches for predicting air quality and traffic patterns using statistical and machine learning techniques. Time-series models such as ARIMA have been widely used for air quality prediction due to their simplicity and effectiveness in handling sequential data. However, these models are limited in capturing non-linear relationships present in real-world datasets.

Deep learning models such as Long Short-Term Memory (LSTM) networks have demonstrated improved performance in handling sequential data

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and capturing long-term dependencies. These models are particularly useful in environmental prediction tasks where multiple factors influence the outcome.

Similarly, traffic prediction systems have been developed using machine learning techniques to estimate congestion levels and travel time. However, many of these systems are limited to specific scenarios such as highway traffic and do not fully capture the complexity of urban environments.

The lack of integration between air quality and traffic data is a big problem with current systems. Most solutions look at either predicting the AQI or analyzing traffic on its own, without taking into account how they affect each other. Also, a lot of platforms only show data without making predictions, which makes them less useful in real life.

This work overcomes these limitations by combining AQI and traffic prediction into one system, which gives us a better picture of how cities work.

III. METHODOLOGY

A. System Architecture

CitySense is created on the basis of a modular architecture consisting of four major levels: data collection, data processing, prediction, and visualization.

Data collection level includes collecting data in real time from various sources such as OpenAQ API for air quality-related metrics, WeatherAPI for weather forecasts, and the Google Maps API for traffic data. This helps in acquiring the required diversity of data for further analysis.

Data processing level refers to pre-processing of data obtained on the previous level. This level comprises such tasks as filling out missing data, resolving inconsistencies, and structuring the data.

Prediction level comprises the use of various machine learning algorithms for predicting AQI and traffic patterns. The use of ARIMA algorithm is required for short-term predictions, Prophet for forecasting long-term tendencies and seasonal effects, and LSTM for modeling more complex processes.

Visualization level includes presenting findings on the interactive Power BI dashboard.

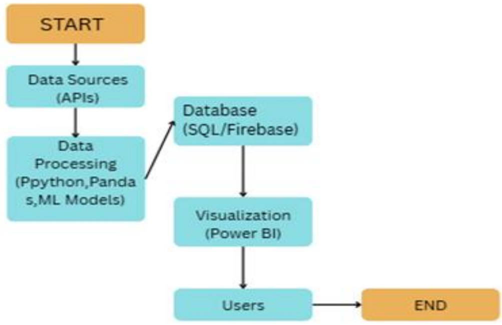

Fig. 1. System architecture of the CitySense framework illustrating data collection, processing, prediction, and visualization layers.

The overall system architecture is illustrated in Fig. 1.

B. Traffic Data Integration

Traffic data is an integral part of the entire system, and it is collected via Google Maps API. It includes traffic density, speed, and congestion in various parts of the region.

The system defines several levels of traffic density and studies their effect on vehicle speed and emission rate. This analysis helps establish the connection between the two.

Fig. 2. City and Forecast

C. Data Preprocessing

Preprocessing is an essential step that comes before using any machine learning algorithm, where operations like removal of missing values, normalization, and time series format are conducted. Extraction of features is done in order to obtain

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significant features, for example, humidity, CO concentration, and speed of vehicles.

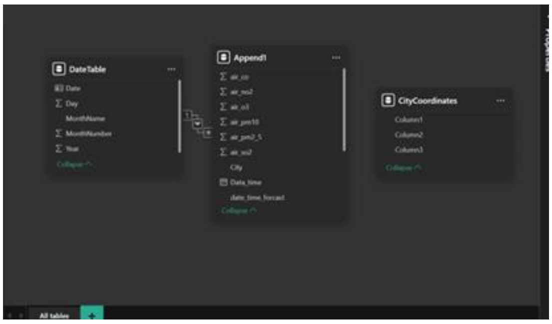
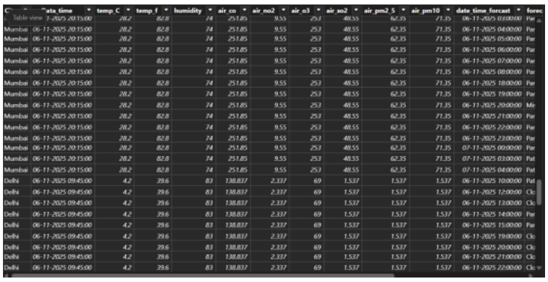


Fig. 3. Data model representing relationships between temporal, spatial, and air quality attributes used in analysis.



City	Data_time	temp_C	temp_f	humidity	air_co	air_no2	air_o3	air_so2	air_pm2_5	air_pm10	date_time_forcast	forec
	1-2025 20:15:00	28.2	82.8	74	251.85	9.55	253	48.55	62.35	71.35	06-11-2025 03:00:00	Par
Mumbai	06-11-2025 20:15:00	28.2	82.8	74	251.85	9.55	253	48.55	62.35	71.35	06-11-2025 04:00:00	Par
Mumbai	06-11-2025 20:15:00	28.2	82.8	74	251.85	9.55	253	48.55	62.35	71.35	06-11-2025 05:00:00	Par
Mumbai	06-11-2025 20:15:00	28.2	82.8	74	251.85	9.55	253	48.55	62.35	71.35	06-11-2025 06:00:00	Par
Mumbai	06-11-2025 20:15:00	28.2	82.8	74	251.85	9.55	253	48.55	62.35	71.35	06-11-2025 07:00:00	Par
Mumbai	06-11-2025 20:15:00	28.2	82.8	74	251.85	9.55	253	48.55	62.35	71.35	06-11-2025 08:00:00	Par
Mumbai	06-11-2025 20:15:00	28.2	82.8	74	251.85	9.55	253	48.55	62.35	71.35	06-11-2025 18:00:00	Par
Mumbai	06-11-2025 20:15:00	28.2	82.8	74	251.85	9.55	253	48.55	62.35	71.35	06-11-2025 19:00:00	Par
Mumbai	06-11-2025 20:15:00	28.2	82.8	74	251.85	9.55	253	48.55	62.35	71.35	06-11-2025 20:00:00	Mi
Mumbai	06-11-2025 20:15:00	28.2	82.8	74	251.85	9.55	253	48.55	62.35	71.35	06-11-2025 21:00:00	Par
Mumbai	06-11-2025 20:15:00	28.2	82.8	74	251.85	9.55	253	48.55	62.35	71.35	06-11-2025 22:00:00	Par
Mumbai	06-11-2025 20:15:00	28.2	82.8	74	251.85	9.55	253	48.55	62.35	71.35	06-11-2025 23:00:00	Par
Mumbai	06-11-2025 20:15:00	28.2	82.8	74	251.85	9.55	253	48.55	62.35	71.35	07-11-2025 00:00:00	Par
Mumbai	06-11-2025 20:15:00	28.2	82.8	74	251.85	9.55	253	48.55	62.35	71.35	07-11-2025 03:00:00	Pat
Mumbai	06-11-2025 20:15:00	28.2	82.8	74	251.85	9.55	253	48.55	62.35	71.35	07-11-2025 04:00:00	Pat
Delhi	06-11-2025 09:45:00	4.2	39.6	83	138.837	2.337	69	1.537	1.537	1.537	06-11-2025 10:00:00	Pat
Delhi	06-11-2025 09:45:00	4.2	39.6	83	138.837	2.337	69	1.537	1.537	1.537	06-11-2025 12:00:00	Clo
Delhi	06-11-2025 09:45:00	4.2	39.6	83	138.837	2.337	69	1.537	1.537	1.537	06-11-2025 13:00:00	Clo
Delhi	06-11-2025 09:45:00	4.2	39.6	83	138.837	2.337	69	1.537	1.537	1.537	06-11-2025 14:00:00	Par
Delhi	06-11-2025 09:45:00	4.2	39.6	83	138.837	2.337	69	1.537	1.537	1.537	06-11-2025 15:00:00	Par
Delhi	06-11-2025 09:45:00	4.2	39.6	83	138.837	2.337	69	1.537	1.537	1.537	06-11-2025 19:00:00	Clo
Delhi	06-11-2025 09:45:00	4.2	39.6	83	138.837	2.337	69	1.537	1.537	1.537	06-11-2025 20:00:00	Clo
Delhi	06-11-2025 09:45:00	4.2	39.6	83	138.837	2.337	69	1.537	1.537	1.537	06-11-2025 21:00:00	Clo
Delhi	06-11-2025 09:45:00	4.2	39.6	83	138.837	2.337	69	1.537	1.537	1.537	06-11-2025 22:00:00	Clo

Fig. 4. Sample dataset containing air quality parameters and meteorological features used for model training.

The data structure and sample dataset are presented in Fig. 3 and Fig. 4.

IV. RESULTS AND ANALYSIS

The system was tested on data obtained from cities like Delhi, Mumbai, and Amritsar.

As seen in Fig. 5, It has been found that pollution in Delhi is always high in comparison with other cities, while pollution in cities like Mumbai and Amritsar varies moderately. This variation could be due to various reasons like traffic, industries, etc.

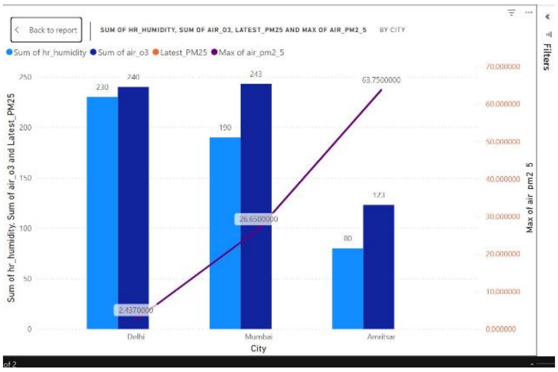


Fig. 5. Multi-parameter comparison of environmental indicators including humidity, ozone (O_3), PM2.5, and maximum PM2.5 across cities.

The multi-parameter comparison is shown in Fig.5. According to the traffic analysis, there is an inverse relationship between the density of traffic and the speed of vehicles, whereby increased traffic density causes reduced speeds of vehicles. This results in increased fuel use and pollutant emissions. Analysis of traffic data also indicates a high AQI during traffic peaks.

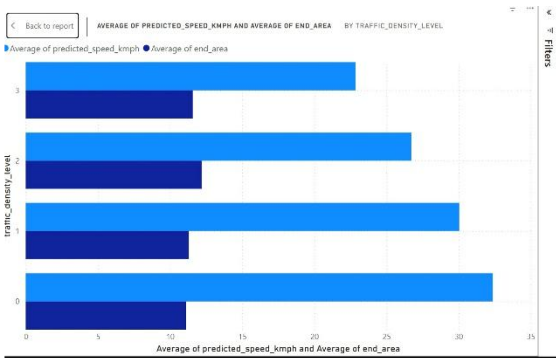


Fig. 6. Relationship between traffic density levels and predicted vehicle speed.

Traffic-speed relationship is illustrated in Fig. 6.

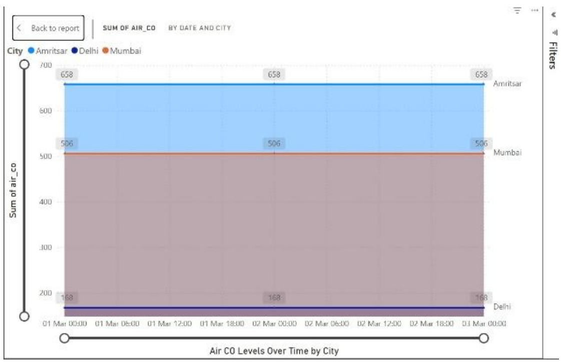


Fig. 7. Time-series analysis of CO levels across cities highlighting temporal variation in pollution.

Analysis using geospatial tools helps identify those parts where the concentration of traffic is greatest because they will show the maximum pollution levels in these places as well.

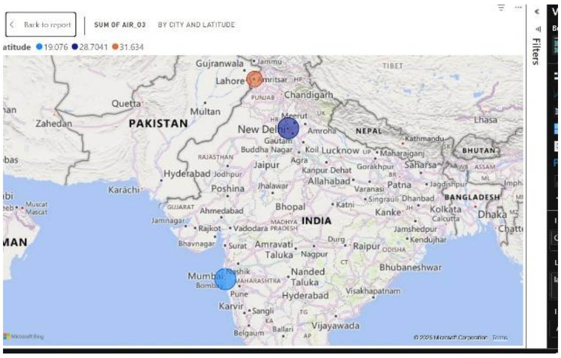


Fig. 8. Geospatial distribution of air quality across major cities represented using bubble intensity.

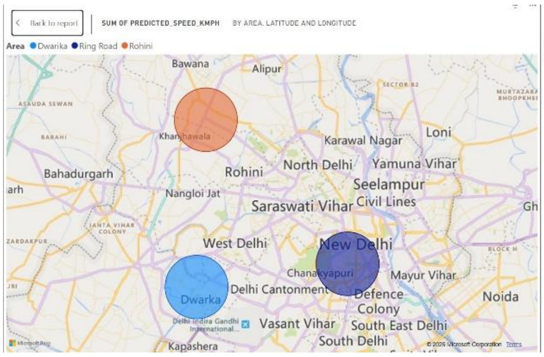


Fig. 9. Area-wise traffic analysis showing variation in predicted speed across different regions of Delhi.

The traffic fluctuations in the region also reinforce the relationship between congestion and the degree of air pollution.

Model Accuracy

The effectiveness of various predictive models was measured by parameters like accuracy, RMSE, and MAE, which are displayed in Table 1 below.

Table 1 Performance comparison of prediction models

Model	Accuracy	RMSE	MAE
ARIMA	82%	12.3	8.5
Prophet	85%	10.2	7.1
LSTM	91%	8.1	5.2

From the findings, the reason why LSTM performs better than other models is because it is able to detect complicated patterns and relationships.

This combination of visual representations proves that the proposed model can effectively detect patterns and relationships within urban air pollution and traffic data.

V. DISCUSSION

Combining AQI and traffic gives a more holistic perspective regarding city conditions. As opposed to previous systems that only involved monitoring, CitySense uses the combination of monitoring and prediction to enable the user to know what is to happen.

It is clear from the findings that traffic influences air pollution greatly. This means that proper measures can be taken concerning the management of traffic to enhance air quality. However, there are several weaknesses associated with the system, for example, the use of API.

Despite the shortcomings, it shows how integrating machine learning with real-time integration helps to develop efficient data-driven systems.

It shows how integration can be used to address problems in urban areas through prediction analytics.

VI. CONCLUSION

The present study introduces CitySense as an integrated approach to monitor and forecast air pollution and traffic information. Through the integration of machine learning algorithms and real-time datasets, the developed system offers significant benefits beyond conventional monitoring systems.

The findings highlight the necessity of taking traffic and environment into account when solving urban issues. The proposed framework supports the concept of smart cities and promotes evidence-based decision-making processes.

VII. FUTURE WORK

Further enhancements can be made in the future that can include IoT sensor-based data gathering, consideration of new environmental variables like water pollution and noise, development of an app version, and prediction accuracy through hybrid algorithms.

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