



# **Traffic Congestion Prediction**

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**Project Guide**  
**Ms. Aavani N.**

# Outline

- Introduction
- Literature Survey of the existing systems
- Limitations of the existing systems
- Problem statement
- System Design
- Technologies and methodologies
- Implementation
- Conclusion
- References

# Sustainable Development Goals (SDG) mapped

- SDG 3: Good Health and Well-Being ❤️
  - Less congestion reduces commuter stress and travel fatigue
  - Improved air quality lowers pollution-related health risks
- SDG 9: Industry, Innovation and Infrastructure 🏭
  - Uses machine learning and predictive analytics for smart mobility
  - Strengthens urban transport infrastructure with data-driven insights
- SDG 11: Sustainable Cities and Communities 🏙️
  - Reduces traffic congestion and supports efficient transport systems
  - Helps city authorities with long-term infrastructure planning
- SDG 13: Climate Action 🌍
  - Minimizes fuel wastage and vehicular emissions
  - Contributes to cleaner air and lower carbon footprint

# Introduction

- Traffic congestion is a growing urban challenge, leading to long commute times, fuel wastage, stress, and environmental damage.
- Existing systems (Google Maps, Waze) focus only on real-time display, not predictive insights, limiting their usefulness for planning.
- Our system leverages machine learning and time-series forecasting to predict congestion before it occurs and suggest alternate routes.
- By providing predictive analytics, alerts, and visualizations, the system supports both commuters in daily travel and authorities in long-term infrastructure planning.

# Introduction

## ► Objectives

- **To provide a web-based platform** that integrates real-time traffic congestion data with interactive visualizations including graphs, charts, and predictive indicators.
- **To develop a data-driven congestion forecasting model** using rule-based logic and machine learning techniques applied to historical traffic datasets.
- **To enhance spatial awareness** by integrating geospatial mapping tools for dynamic visualization of traffic patterns and zone-based congestion metrics.
- **To implement an automated alert system** that delivers real-time notifications of predicted traffic incidents and congestion levels to end-users.

# Literature Survey of the existing system (Most Relevant to Least)

Sr. No.	Title	Author(s)	Year	Outcomes	Methodology	Our Evaluations
1.	Traffic Flow Prediction with Big Data: A Deep Learning Approach [1]	Y. Duan, W. Kang, Z. Li, F. Wang	2019	The primary goal is to leverage big data techniques to enhance traffic flow prediction accuracy in complex urban environments.	This approach utilizes Deep Learning models, specifically employing Stacked Autoencoders and Recurrent Neural Networks (RNN).	Achieves high accuracy, but the implementation is often constrained by being computationally expensive and data-hungry.
2.	Short-Term Traffic Volume Prediction: A KNN Approach Enhanced by Constrained PCA [2]	H. Zheng, W. Wu, W. Chen	2018	The objective is to establish an improved model for short-term traffic volume prediction.	The methodology combines the K-Nearest Neighbor (KNN) algorithm with Constrained Principal Component Analysis (PCA).	Demonstrates good performance in short-term prediction, but exhibits weak adaptability in the face of sudden, non-recurring events like accidents or weather.

# Literature Survey of the existing system (Most Relevant to Least)

Sr. No.	Title	Author(s)	Year	Outcomes	Methodology	Our Evaluations
3.	Traffic Signal Timing via Deep Reinforcement Learning	L. Li, Y. Lv, F.-Y. Wang	2016	The study focuses on optimizing traffic signal timing in real-time.	The approach uses Deep Reinforcement Learning (DRL).	The DRL model is highly adaptive, but its deployment requires large-scale infrastructure and substantial training data.
4.	Google Maps Traffic API [3]	Google Developers	2024	To provide developers and end-users with real-time traffic data.	It relies on crowdsourced GPS Data.	Provides high accuracy, but is computationally expensive and data-hungry

# Literature Survey of the existing system (Most Relevant to Least)

Sr. No.	Title	Author(s)	Year	Outcomes	Methodology	Our Evaluations
5.	<b>Waze Live Map &amp; Traffic API [4]</b>	Waze Mobility Team	2023	The system's outcome is to offer fast, user-generated traffic and incident updates.	The core methodology involves combining crowdsourced GPS with Incident Reports from users.	It delivers fast updates, but its fundamental accuracy depends on its active user base and coverage.
6.	<b>Expressway Monitoring and Advisory System (EMAS)</b>	Singapore Land Transport Authority (LTA)	2015	Designed for incident management on expressways, focusing on detection and advisory to quickly restore traffic flow.	EMAS utilizes a blend of technologies including Sensor Fusion, CCTV monitoring, and dedicated systems for Incident Detection	The technology is highly effective, but the required dedicated infrastructure makes it costly and not scalable to all city roads.

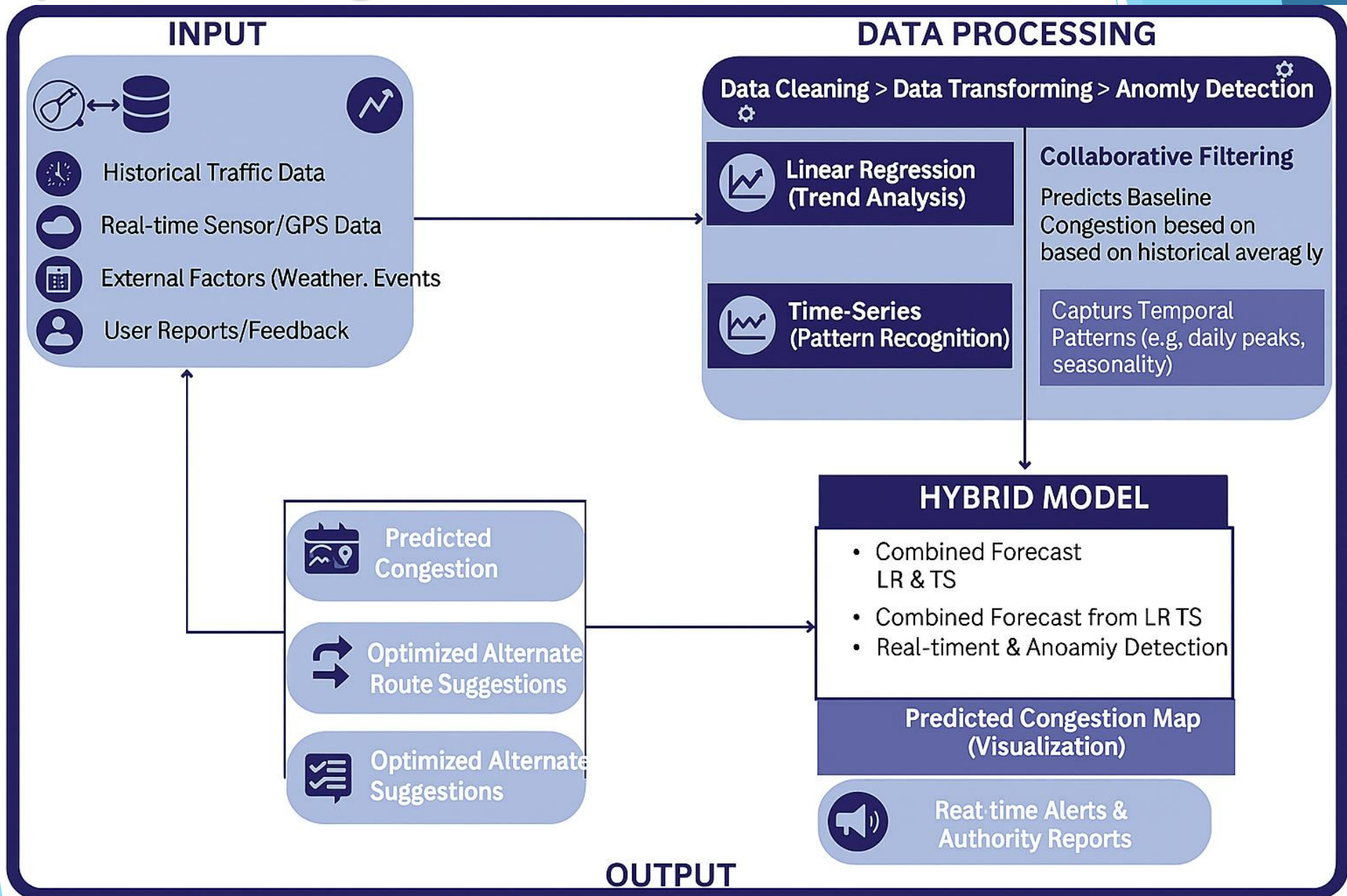
# Limitations of existing systems

- **Domain Restrictions:** Current systems rely heavily on historical datasets and fail to adapt to sudden disruptions such as accidents or weather changes.
- **Computational Complexity:** Deep learning and graph-based models achieve high accuracy but are resource-heavy and unsuitable for lightweight real-time deployment.
- **Limited Predictive Power:** Most existing solutions provide only real-time updates, not proactive forecasts.
- **Scalability Issues:** Integration with multiple live data sources and city-wide traffic planning is still underdeveloped.

# Problem statement

- **The Challenge:** Urban traffic congestion prediction is challenging because existing systems fail during sudden disruptions (accidents, bad weather) and often rely too heavily on weak historical patterns.
- Our Goal is to Design a Lightweight Solution that:
  - Uses Linear Regression and Time-Series forecasting for traffic prediction.
  - Provides simple visualization of congestion trends via a web-based interface.
  - Offers alerts/reports to commuters and authorities

# System Design



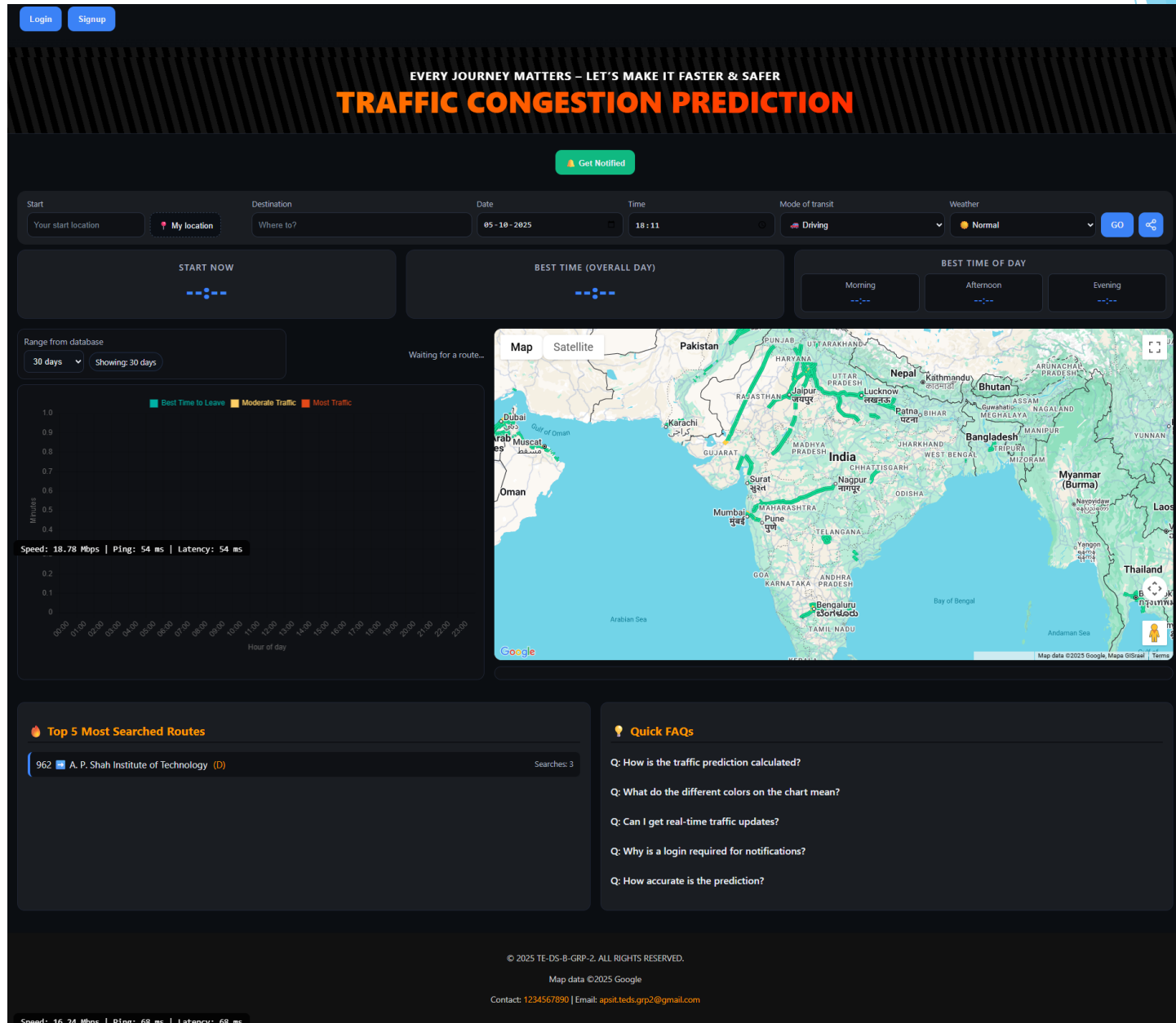
# Technologies

- **Frontend Development:**
  - HTML, CSS, JavaScript → Interactive web dashboard
- **Backend Development:**
  - Python (Machine Learning Models), APIs
- **Database:**
  - Processed traffic datasets (historical + real-time[GOOGLE])
  - DATASETS (1month [57,601 X 7] , 3month [1,72,801 X 7], 6month [3,45,601 X 7], 1 year [7,00,801 X 7])
- **Machine Learning Models:**
  - >> Linear Regression (baseline)
  - >> LSTM(Simulation)
  - >> ARIMA (time-series forecasting)
  - >> Prophet(Simulation)
- **Data Sources:**
  - Traffic logs, live traffic feeds, weather reports

# Methodologies

1. **Data Collection:** Gather Traffic logs (historical), live traffic feeds, and Weather reports (via APIs) and store them in the Database.
2. **Data Preprocessing:** Use Python (Backend Development) to clean, normalize, and handle outliers in the data.
3. **Feature Engineering:** Use Python scripts to extract key features (time, day, weather) and transform data for model input.
4. **Model Training (Python ML Models):**
  - a) Apply Linear Regression for the traffic baseline prediction.
  - b) Apply ARIMA for time-series forecasting (sequential patterns).
  - c) (Optionally, explore LSTM and Prophet for simulation).
5. **Output & Visualization:** Use HTML, CSS, JavaScript (Frontend Development) to build the Interactive web dashboard displaying the Python-generated forecasts.

# Implementation – Home Page



# Implementation – Login / Signup / Verification

### Login

Login

Cancel

Not signed up yet? [Sign up](#)

### Signup

Register & Send Verification Code

Cancel

Already have an account? [Log in](#)

### Account Verification Required

Hello tushar,

Thank you for registering with Traffic Congestion Prediction! To ensure the security of your account and verify your email address ([tusharzaware234@gmail.com](mailto:tusharzaware234@gmail.com)), please enter the code below on the verification screen in the application.

Your Verification Code is:

**328416**

Please note: This code will expire soon. Do not share this code with anyone.

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If you did not attempt to sign up for this service, please disregard this email.

Start

962, Sector 6, Kopar Khairar

Destination

A. P. Shah Institute of Technology, Ghodbunder Road, op

Date

05-10-2025

Time

18:11

Mode of transit

Transit

Weather

Rainy

GO

START NOW

18:21

Est. 1 hr 41 min

BEST TIME (OVERALL DAY)

02:00

Est. 55 min

BEST TIME OF DAY

Morning

05:00

Afternoon

14:00

Evening

17:00

Range from database: 30 days (Showing: 30 days)

Hourly profile ready • 24/24 points (from prediction model)

Minutes

Best Time to Leave Moderate Traffic Most Traffic

Hour of day

Map Satellite

Google


Navi Mumbai नवी मुंबई

Map data ©2025 Terms

Near Report a map error


## 2. Prediction Visualization / Live Map Data

# Implementation

 **Alternative Routes & Times**

Fastest alternative routes from Google Maps, sorted by minimum time. Click a route to see it on the map.

962 → Survey No	1 hr 27 min	962 → Survey No	1 hr 35 min
962 → Survey No	1 hr 37 min	962 → Survey No	1 hr 45 min
962 → Survey No	1 hr 46 min	962 → Survey No	1 hr 49 min

 **Latest Traffic Advisories**

Refresh

Hide

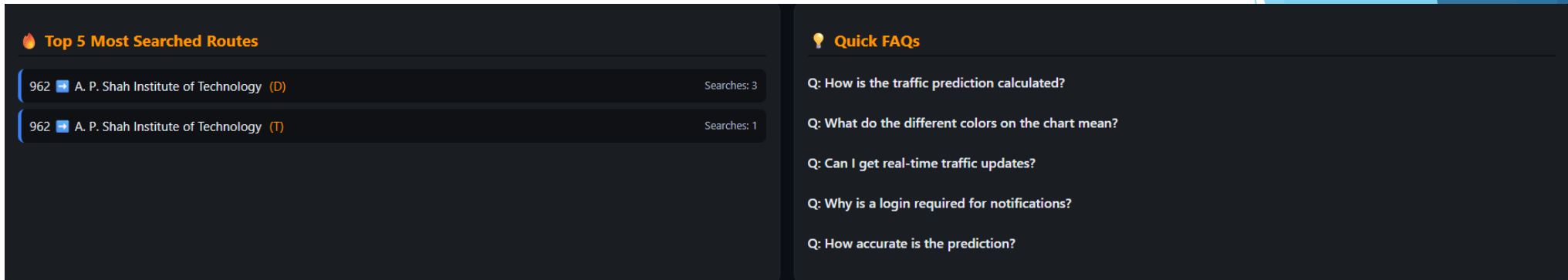
Relevant articles based on your route, date, and weather conditions.

**NO NEWS OUT THERE FOR YOUR ROUTE**  
Everything seems clear! Enjoy the easy ride.

Read More →

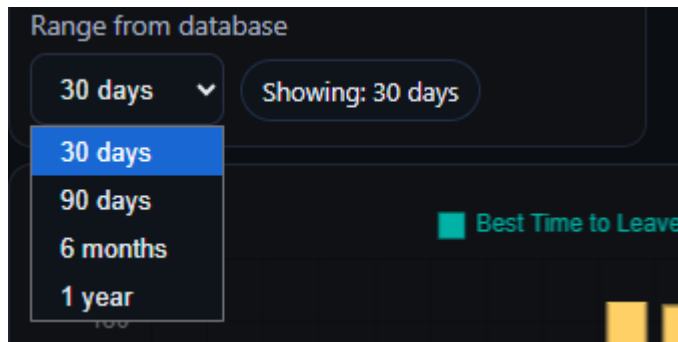
3. Alternate route suggestions - directly mapped as inputs once clicked
4. Latest news based on inputs of user

# Implementation

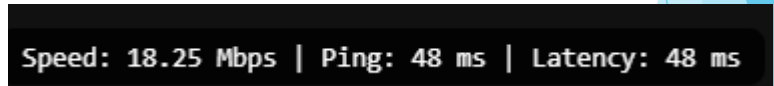


5. Most Searched Routes - get mapped directly as input when clicked too.

6. Static FAQs

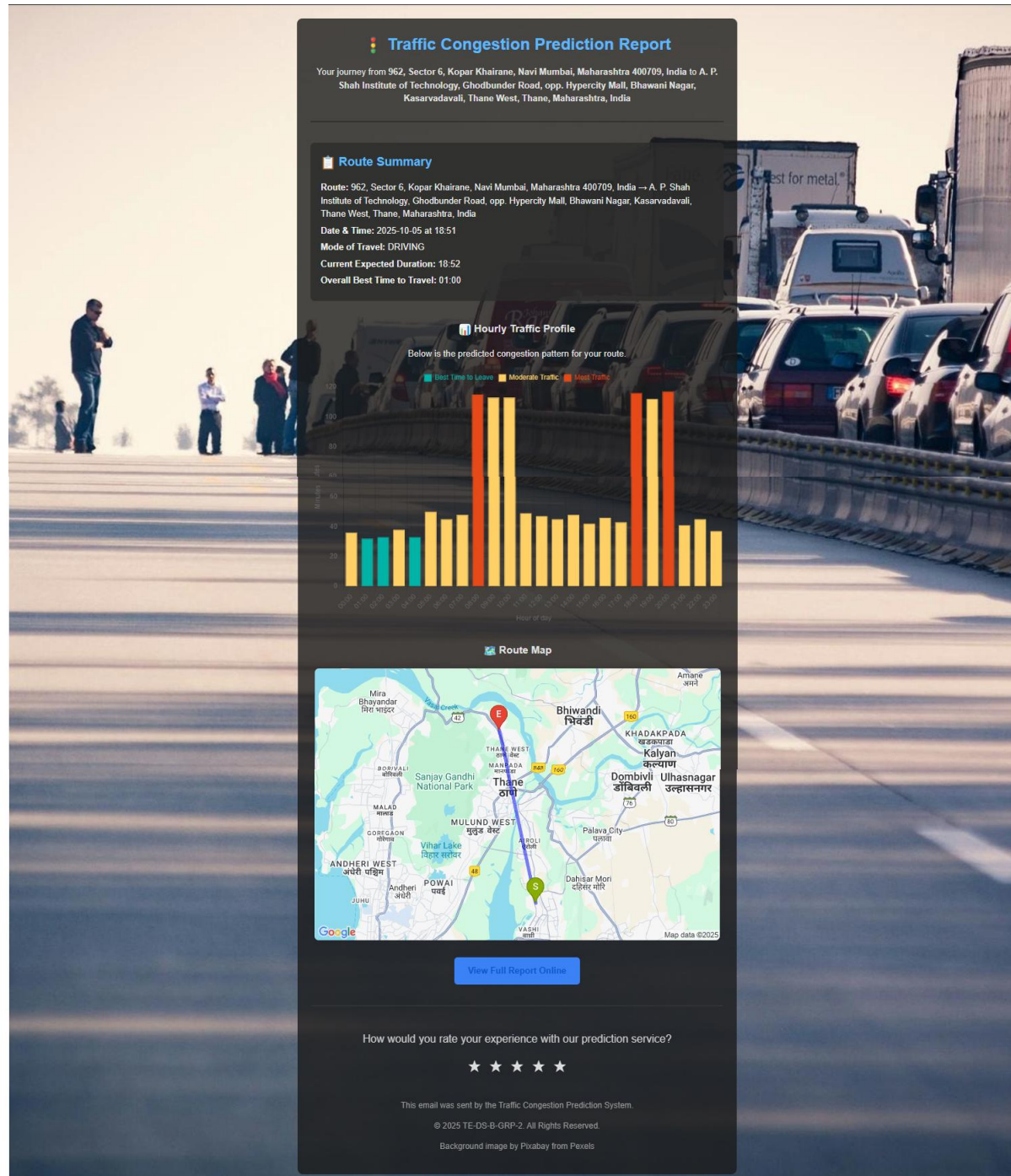


7. User Selectable dataset options for visualization.



8. User device's network live status

# Implementation – MAIL REPORT / LIVE ANALYSIS



# Implementation – COMPARATIVE ANALYSIS

## Traffic Prediction — Comparative Visualizer

Run a 24-hour comparative analysis. LSTM/Prophet are proxies unless implemented.

Multiple algorithms · Comparative chart

### Inputs

Place

Mumbai - Bandra

Dataset

1 year

Day

Tuesday

Base hour

9

Run mode

Single hour + 24h

☒ Raining

☒ Peak hour

Run Analysis

Export PNG

### Time-Series



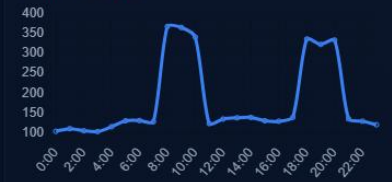
### Linear



### LSTM (sim)



### Prophet (sim)



### Comparative — All



### Metrics

Model	Pred	Err%
Linear	299.0	13.58%
TimeSeries	343.0	0.87%
LSTM (sim)	347.5	0.43%
Prophet (sim)	364.3	5.29%

Raw hist sample: 346

## Which Algorithm is Best?

Usually, Prophet is the best balance of accuracy and interpretability.

Current dataset best: LSTM (sim) (Err 0.43%)

- Linear: simple, fast, but too limited.
- Time-Series Avg: smooths noise, poor long-term accuracy.
- LSTM: powerful with big data, but complex to train.
- Prophet: models trend+seasonality+holidays directly → ideal for traffic.

**Reason:** Traffic has strong daily/weekly seasonality (rush hours, weekends), which Prophet handles naturally. LSTM may outperform Prophet with huge datasets but needs more compute and tuning.

# Conclusion

- We have implemented **data collection, preprocessing, and traffic flow modeling** using advanced prediction algorithms. The system utilizes **real-time data** from sensors, GPS, and historical trends to forecast congestion accurately.
- **Traffic Congestion Prediction** represents an innovative and efficient approach to improving **urban mobility**, reducing **travel time**, and enhancing **road safety** through intelligent data-driven decision-making.
- Additionally, the system's **future scope** includes integration with **IoT-based smart city infrastructure, adaptive traffic signal control, crowd-sourced traffic data**, and **AI-driven route optimization** for sustainable and smarter transportation networks.

# References

[1] Y. Lv, Y. Duan, W. Kang, Z. Li, and F. Wang, “Traffic Flow Prediction with Big Data: A Deep Learning Approach”, IEEE Transactions on Intelligent Transportation Systems, Vol. 16, No. 2, pp. 865-873, 2019.

URL: <https://ieeexplore.ieee.org/document/6870035>

(Alt. PDF:

<https://bookdown.org/amanas/traficomadrid/docs/Traffic%20flow%20prediction%20with%20big%20data%20-%20A%20deep%20learning%20approach.pdf>)

[2] H. Zheng, W. Wu, and W. Chen, “Short-Term Traffic Volume Prediction: A K-Nearest Neighbor Approach Enhanced by Constrained Linearly Sewing Principal Component Regression”, Transportation Research Part C: Emerging Technologies, Vol. 43, pp. 143-157, 2018.

URL: <https://www.sciencedirect.com/science/article/pii/S0968090X1400054X>

(Alt. ResearchGate:

[https://www.researchgate.net/publication/260804708\\_Short-term\\_traffic\\_volume\\_forecasting\\_A\\_k-nearest\\_neighbor\\_approach\\_enhanced\\_by\\_constrained\\_linearly\\_sewing\\_principal\\_component\\_algorithm](https://www.researchgate.net/publication/260804708_Short-term_traffic_volume_forecasting_A_k-nearest_neighbor_approach_enhanced_by_constrained_linearly_sewing_principal_component_algorithm))

# References

[3] Google Maps Developers, “Google Maps Traffic API Documentation”, Google Developers Official Documentation, 2024.

URL: <https://developers.google.com/maps/documentation/javascript/examples/layer-traffic>

[4] Waze, “Waze Live Map and Traffic API”, Waze Mobility Documentation, 2023.

URL: <https://support.google.com/waze/partners/answer/10618035?hl=en>

(Developer Intro: <https://developers.google.com/waze/intro-transport>)

[5] University of Mumbai, Mini Project Presentation Format for CSE (Data Science), A.P. Shah Institute of Technology, 2025.

**Thank You...!!**