

ADAPTIVE TRAFFIC PREDICTION USING MACHINE LEARNING AND CONTEXTUAL DATA**Vajjala Sai Ramesh****B. Akhil Singh****Mohammad Squib Jamal****Guide: S. Gayathri Devi**Department of Computer Science and Engineering, J.B. Institute of Engineering and Technology
sairameshvajjala@gmail.com, 2426akhil@gmail.com, saquibjamal484@gmail.com**ABSTRACT**

Adaptive traffic prediction has become a crucial component in modern intelligent transportation systems due to increasing urban congestion and the need for efficient mobility solutions. This paper presents an adaptive traffic prediction system using machine learning and contextual data such as time, location, and historical traffic patterns. The system leverages real-time traffic data obtained from external APIs and applies an XGBoost-based regression model to predict future traffic speeds with improved accuracy.

In addition to prediction, the proposed system performs dynamic route analysis by evaluating multiple routes and identifying congestion levels across segments. A cost-based route scoring mechanism is used to select the most efficient path based on predicted speed, congestion percentage, and worst-case segments. Furthermore, the system integrates an emergency ambulance routing module that identifies the fastest route to nearby verified hospitals and simulates a vehicle alert mechanism to assist in clearing traffic along the selected route.

The implementation is carried out using Python and DRF(Django REST Framework) for backend processing, along with real-time traffic APIs for data acquisition. Experimental results demonstrate that the system effectively predicts traffic conditions, optimizes route selection, and enhances emergency response efficiency. This work highlights the practical applicability of combining machine learning with contextual and real-time data to build intelligent and adaptive traffic management solutions .

Dataset Details:

Parameter	Description
Source	TomTom API
Categories	Urban traffic routes
Data Type	Time-series numerical dataset
Content	Speed, free flow speed, time features, congestion ratio, lag values
Records	~27,000 entries
Purpose	Traffic prediction, route optimization and model evaluation

Novelty Statement:

The novelty of this work lies in combining adaptive traffic prediction with contextual and real-time data for dynamic route optimization. Unlike traditional systems, it predicts future traffic using machine learning. It also integrates ambulance routing with cost-based scoring and vehicle alerts to improve traffic efficiency and emergency response.

INTRODUCTION

Urban traffic congestion has become a significant challenge in modern cities, leading to increased travel time, fuel consumption, environmental pollution, and delays in emergency services. Traditional navigation systems primarily rely on real-time traffic data, which limits their ability to anticipate future congestion and make proactive routing decisions. As a result, these systems often fail to provide optimal solutions during rapidly changing traffic conditions.

With the advancement of machine learning, it is possible to analyze historical and contextual data such as time of day, day of the week, location, and traffic patterns to predict future traffic conditions. These predictive capabilities enable more efficient route planning and improved traffic management compared to conventional approaches that depend solely on current data.

In this work, we propose an adaptive traffic prediction system that leverages machine learning along with contextual and real-time data to estimate traffic conditions dynamically. The system uses a regression-based model to predict traffic speed and classify congestion levels across different road segments. Furthermore, a route optimization module evaluates multiple routes and selects the most efficient path using a cost-based scoring mechanism.

In addition to traffic prediction and routing, the system incorporates an emergency ambulance routing module that identifies the fastest route to nearby hospitals. It also includes a vehicle alert mechanism that helps in clearing traffic along the selected route, thereby improving emergency response time.

The proposed approach aims to provide a practical and scalable solution for intelligent transportation systems by integrating prediction, routing, and emergency handling into a unified framework suitable for real-world smart city applications.

LITERATURE SURVEY

Various approaches have been proposed for traffic prediction and route optimization. Traditional methods like Dijkstra's algorithm compute the shortest path but do not consider real-time or future traffic conditions. Modern systems such as Google Maps and TomTom use real-time traffic data for dynamic routing, but they lack predictive capabilities.

Machine learning-based methods, including regression and time-series models, utilize historical data to predict traffic conditions. Advanced models like LSTM capture temporal patterns effectively but require high computational resources.

Recent research explores hybrid approaches combining real-time data with prediction; however, most systems focus only on prediction or routing and do not integrate emergency response mechanisms. The proposed system addresses this gap by combining prediction, routing, and emergency handling in a unified framework.

Comparison of Existing Methods:

Model	Technique	Advantages	Limitations
Traditional Routing	Dijkstra Algorithm	Simple, Fast	No traffic awareness
Google Maps / TomTom	Real-time data	Dynamic Routing	No future prediction
Regression Models	Statistical ML	Simple and Interpretable	Limited Temporal Learning
LSTM Models	Deep Learning	Captures time pattern	High complexity

From the comparison, it is evident that while existing systems provide either real-time routing or predictive modeling, there is a lack of integrated solutions that combine prediction, routing, and emergency handling. The proposed system addresses this gap by incorporating machine learning-based traffic prediction, cost-based route optimization, and ambulance routing within a unified framework.

Proposed work:

The proposed system focuses on developing an adaptive traffic prediction model using machine learning and contextual data such as time, location, and historical traffic patterns. An XGBoost-based regression model is used to predict future traffic speeds and classify congestion levels based on real-time and contextual inputs.

In addition to prediction, the system performs dynamic route optimization by evaluating multiple routes and

selecting the most efficient path using a cost-based scoring mechanism. This ensures better decision-making under varying traffic conditions.

Furthermore, the system incorporates an emergency ambulance routing module that identifies the fastest route to nearby hospitals. A vehicle alert mechanism is also integrated to assist in clearing traffic along the selected route, improving emergency response efficiency.

Overall, the proposed work provides a unified framework that combines traffic prediction, route optimization, and emergency handling for intelligent transportation systems.

Model	Technique	Advantages	Limitations
Proposed Model	XGBoost + Contextual Data	Predictive + Efficient + Practical	Limited dataset size

1. METHODOLOGY

The proposed system follows a structured pipeline for adaptive traffic prediction and route optimization using machine learning and real-time data. Initially, the user provides location inputs (latitude, longitude, or source–destination). The system retrieves live traffic data from external APIs, including parameters such as current speed, free flow speed, and confidence.

Contextual features such as time, day, and historical traffic patterns are combined with live data to form a feature vector. This is processed using a machine learning model to predict future traffic speed and determine congestion levels. The system then evaluates multiple routes and selects the optimal path using a cost-based scoring mechanism.

For emergency scenarios, the system identifies the nearest hospital, computes the best route, and triggers a vehicle alert mechanism to improve response time.

Mathematical Formulation:

$$\text{Predicted speed} = f(x)$$

where,

X represents traffic and contextual features.

Training Details:

- Model: XGBoost
- Data: ~27,000 records
- Framework Scikit-learn

Model Configuration

- Inputs: Time, speed, congestion, lag features
- Output: Predicted speed
- API: TOM TOM Traffic api
- Routing: Cost-based scoring

2. SYSTEM ARCHITECTURE:

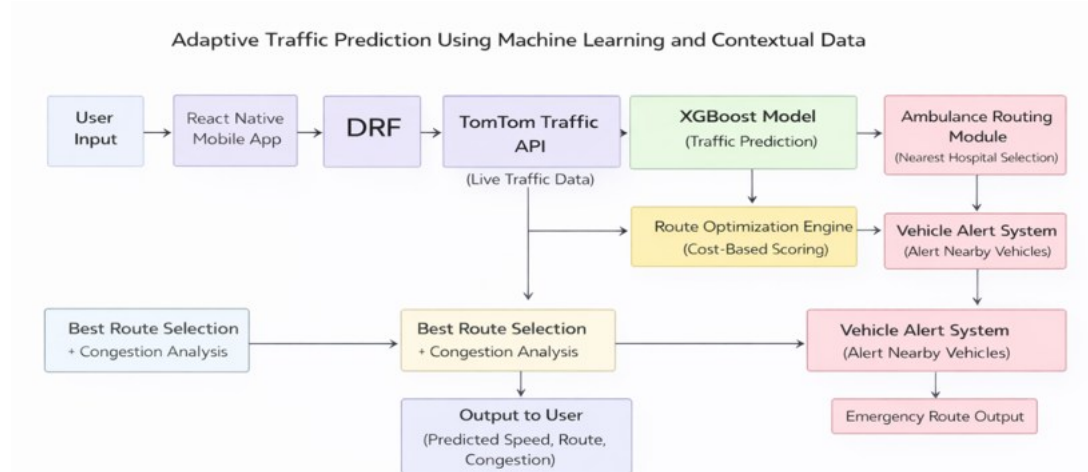
The proposed system follows a modular architecture that integrates machine learning, real-time traffic data, and routing logic to provide adaptive traffic prediction and optimization. The system consists of four main components: data acquisition, feature processing, prediction engine, and routing module.

The process begins with user input, where location details such as coordinates or source–destination points are provided. The system then fetches real-time traffic data using external APIs. This data is combined with contextual features such as time and historical patterns to generate a structured feature vector.

The feature vector is passed to a machine learning model, which predicts future traffic speed and determines congestion levels. Based on these predictions, the routing module evaluates multiple routes and selects the optimal path using a cost-based scoring mechanism.

For emergency scenarios, the system includes an ambulance routing module that identifies the nearest hospital and computes the fastest route. A vehicle alert mechanism is also integrated to notify nearby vehicles and facilitate

smoother movement along the selected route.



3. Traffic Prediction and Routing Algorithm

Step 1: Accept user input (current location or source–destination coordinates).

Step 2: Fetch real-time traffic data using the TomTom Traffic API.

Step 3: Extract contextual features such as time, day, speed, congestion ratio and historical lag values.

Step 4: preprocess the features and encode route-related information

Step 5: Predict future traffic speed using the trained XGBoost model.

Step 6: Perform route analysis using cost-based scoring (average speed, congestion %, worst segment penalty).

Step 7: For emergency mode, identify the nearest hospital and compute the optimal route.

Step 8: Trigger vehicle alert system for nearby vehicles along the selected route.

Step 9: Return optimized route, congestion level, and predicted traffic conditions.

Uses:

- Enables accurate short-term traffic prediction using contextual and real-time data.
- Supports intelligent route selection for both normal users and emergency vehicles.
- Enhances emergency response time through optimized ambulance routing.

Optimization:

- Sampling of route points reduces API calls and improves response time
- Cost – based scoring balances speed, congestion and bottleneck segments.
- Use of contextual features improves prediction accuracy over basic models.

Innovation:

- Integration of real-time traffic data with machine learning predictions.
- Unified system combining traffic prediction, route optimization, and emergency handling.
- Vehicle alert mechanism for proactive congestion reduction during emergencies.

Implementation

The system is implemented using Python with a machine learning-based approach for traffic prediction and routing. The backend is developed using DRF(Django REST Framework) to handle API requests and integrate real-time traffic data. The implementation includes modules for data collection, feature engineering, prediction, route optimization, and emergency handling. Supporting libraries such as NumPy, Pandas, and Requests are used for data processing and API communication.

Dataset:

- Source: TomTom Traffic API (Real-time data) + Simulated historical traffic data.
- Categories: Traffic speed, congestion levels, route data, contextual features
- Data Type: Numerical time-series and geospatial data.

Training Details:

- Model: XGBoost Regression Model

- Training Type: Supervised learning on historical + contextual traffic data
- Features Used: Time, day, speed, congestion ratio, lag features, route encoding
- Output: Predicted future traffic speed

System Configuration:

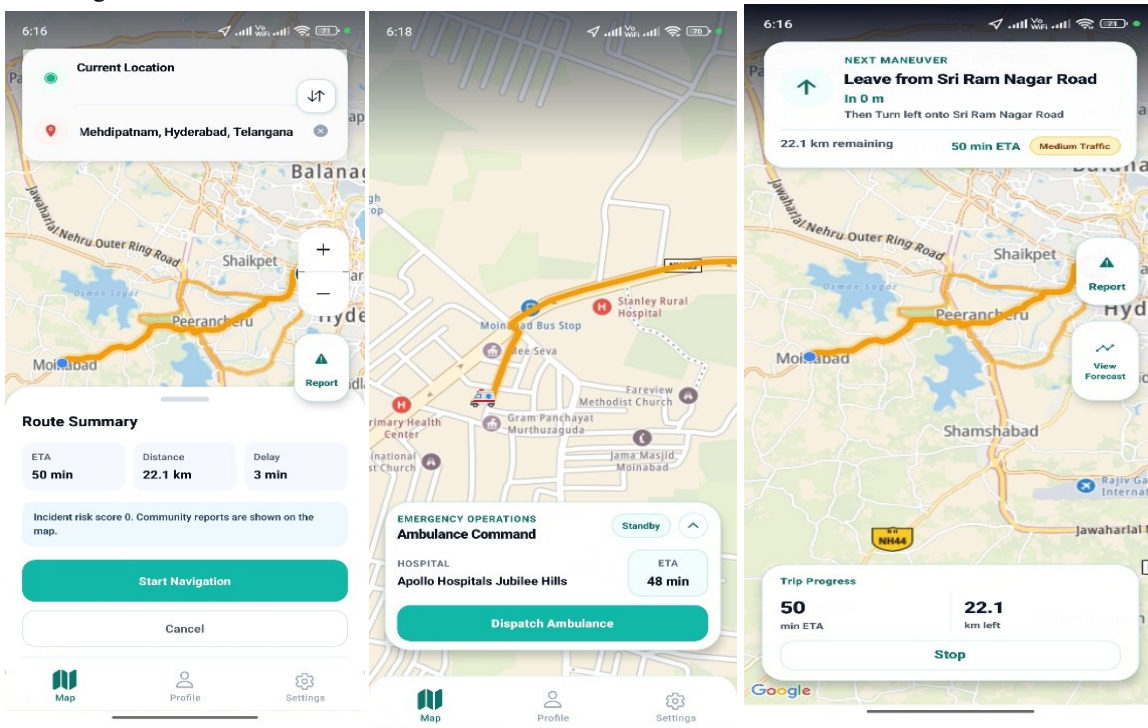
- Processor: Intel i5 / equivalent
- RAM: 8 GB
- GPU: Not required (CPU-based execution)
- Framework: DRF(Backend), XGBoost(ML Model)

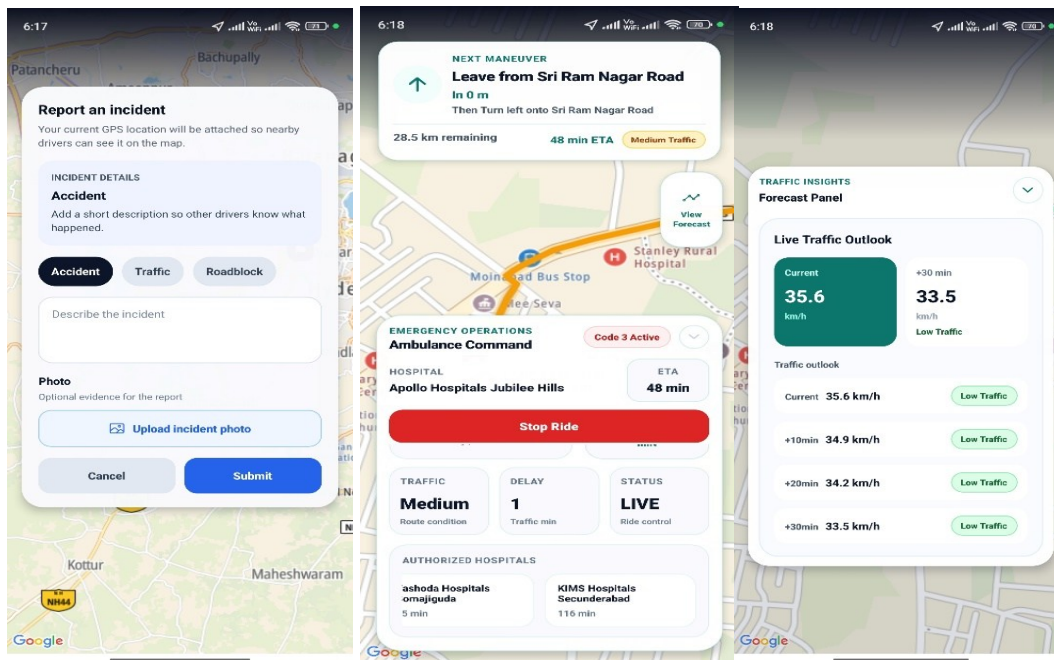
Runtime:

- Normal traffic prediction: ~1-5 seconds
- Route-based prediction: ~30-90 seconds (depending on the route length and sampling)
- Ambulance routing: ~30-60 seconds after optimization

3. EXPERIMENTAL RESULTS

The system was evaluated using real-time traffic scenarios, demonstrating accurate short-term traffic prediction using live and contextual data. It effectively optimized routes by analyzing congestion and predicted speeds through a cost-based approach. The ambulance module successfully identified the fastest routes to nearby hospitals under dynamic conditions. Additionally, vehicle alerts improved emergency response efficiency. Overall, the system provides reliable prediction, efficient routing, and practical support for real-world traffic management.





Evaluation Metrics:

- Prediction accuracy is evaluated using the difference between predicted and current traffic speeds.
- Route efficiency is measured using ETA, delay, and congestion levels.
- System responsiveness is assessed based on real-time API performance and update latency.

Performance Analysis:

- The system provides consistent short-term traffic predictions aligned with live conditions.
- Route optimization effectively reduces delay by selecting less congested paths.
- The ambulance routing module improves emergency response time through dynamic traffic conditions.

Comparison with Existing Models:

- Traditional navigation systems rely mainly on real-time data without prediction capability.
- The proposed system integrates machine learning for proactive traffic forecasting.
- It demonstrates improved decision-making and adaptability under dynamic traffic conditions.

Overall, the results validate the effectiveness of the proposed system in providing accurate traffic prediction and efficient route optimization in real-world scenarios.

The system achieves reliable performance by combining machine learning with real-time data and contextual analysis.

CONCLUSION

This paper presented an adaptive traffic prediction and routing system that integrates machine learning with real-time and contextual data. The system demonstrates how predictive analytics can improve traffic flow estimation and support proactive route optimization. Experimental results show that the model provides reliable short-term traffic predictions and enhances navigation efficiency under dynamic conditions. The integration of an ambulance routing module further highlights the system's practical applicability in emergency scenarios.

Final Statement:

This work demonstrates a practical implementation of a machine learning-based traffic prediction system that combines real-time data, contextual features, and intelligent routing. The system effectively supports both general navigation and emergency response, highlighting its relevance in real-world urban environments. The proposed framework provides a scalable and efficient solution for intelligent transportation systems by bridging prediction, routing, and user interaction in a unified platform.

Future Enhancement:

Future work can focus on incorporating additional data sources such as weather conditions, road incidents, and vehicle-to-vehicle (V2X) communication. Model performance can be further improved using advanced deep learning architectures and larger datasets. The system can also be extended to smart city infrastructure for real-time traffic management and automated emergency handling.

REFERENCES

1. Li Y., Yu R., Shahabi C., & Liu Y., “[Diffusion Convolutional Recurrent Neural Network: Data-Driven Traffic Forecasting.](#)” *International Conference on Learning Representations (ICLR)*, 2018.
2. Yu. B., Yin. H., & Zhu. Z., “[Spatio-Temporal Graph Convolutional Networks: A Deep Learning Framework for Traffic Forecasting.](#)” *IJCAI*, 2018.
3. Lv Y., Duan Y., Kang W., Li Z., & Wang F. Y., “[Traffic Flow Prediction With Big Data: A Deep Learning Approach.](#)” *IEEE Transactions on Intelligent Transportation Systems*, 2015.
4. Zhao, Z., Chen, W., Wu, X., Chen, P. C. Y., & Liu, J. (2017). [LSTM network: A deep learning approach for short-term traffic forecast.](#) *IET Intelligent Transport Systems*, 11(2), 68–75..
5. Polson N. G., & Sokolov V. O., “[Deep Learning for Short-Term Traffic Flow Prediction.](#)” *Transportation Research Part C: Emerging Technologies*, 2017.
6. Afrin T., & Yodo N., “[A Survey of Road Traffic Congestion Measures Towards a Sustainable and Resilient Transportation System.](#)” *Sustainability*, 2020.
7. Kumar, S. V., & Vanajakshi, L. (2015). [Short-term traffic flow prediction using seasonal ARIMA model with limited input data.](#) *European Transport Research Review*, 7, 21.
8. Rachana K P, Aravind R, Ranjitha M, Spoorthi Jwanita, Soumya K., “[IOT Based Smart Traffic Management System.](#)” *International Journal of Engineering Research & Technology*, 2021.
9. Government of India. (2020). *Open Government Data (OGD) Platform India*. Retrieved from <https://data.gov.in>
10. Hyderabad Traffic Police, “Live Traffic Updates and Incident Reporting System,” 2023