International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

Urban Traffic Forecasting Using Advanced Analytics

Ms.Babitha L[1], Bhuvaneshwari R [2], Jeevana P[3], PraveenKarthick G[4], Suganth R[5]

[1]Head of the Department of Information Technology, United Institute of Technology , Tamil Nadu – 641020, India. babitha@uit.ac.in
[2] Department of computer science and engineering, United Institute of Technology, Tamil Nadu – 641020, India.bhuvipranav09@gmail.com
[3]Department of computer science and engineering, United Institute of Technology, Tamil Nadu – 641020, India. jeevanap17@gmail.com
[4] Department of computer science and engineering, United Institute of Technology, Tamil Nadu – 641020, India. praveenkarthick678@gmail.com
[5]Department of computer science and engineering, United Institute of Technology, Tamil Nadu – 641020, India. suganthravi52@gmail.com

ABSTRACT :

Traffic congestion is a major challenge in modern cities, leading to increased travel time, fuel consumption, and environmental pollution. Traditional traffic forecasting methods rely on historical data and fixed sensors, which fail to adapt to real-time conditions. This project aims to develop an AI-driven traffic prediction system that leverages real-time data, deep learning, and geospatial analysis to improve accuracy. The system integrates OpenRouteService API to fetch live traffic details such as distance, travel time, and congestion levels. A Long Short- Term Memory (LSTM) model is trained using 24-hour traffic data collected at 20-minute intervals. The LSTM model predicts traffic conditions for the next hour, helping users plan their journeys efficiently. Additionally, a Random Forest Regression model is used to fine- tune short-term predictions for enhanced accuracy. To provide a clear and intuitive visualization, the system generates 24-hour traffic trend graphs, displaying peak and off-peak congestion hours. The model continuously learns from new data, making it adaptive and dynamic in handling sudden traffic changes. This approach significantly improves over traditional static traffic prediction methods by offering real-time insights and dynamic congestion forecasting. The project is beneficial for smart cities, transportation departments, logistics companies, and navigation apps. Future enhancements include IoT-based sensor data integration, cloud deployment, and multi-modal transport optimization to further improve traffic forecasting accuracy. Ultimately, this AI-powered system contributes to the development of intelligent transportation systems (ITS), leading to smarter urban mobility, reduced congestion, and better travel efficiency.

INTRODUCTION

Traffic congestion has become a serious challenge in modern cities, affecting travel time, fuel efficiency, and environmental sustainability. As urban populations grow and vehicle numbers rise, traditional traffic management systems struggle to adapt to real-time changes. This project introduces an AI-driven traffic prediction model that leverages real-time data, deep learning algorithms, and geospatial analysis to provide accurate and dynamic traffic forecasting.

Our system integrates OpenRouteService API to fetch live traffic conditions and utilizes Long Short-Term Memory (LSTM) networks to analyze traffic patterns. By predicting congestion every 20 minutes over a 24-hour period, the model helps users plan their routes efficiently, avoiding traffic hotspots. Additionally, a Random Forest Regression model is used to finetune short- term traffic predictions for greater accuracy.

This document provides an overview of the need for AI-based traffic prediction, the methodology used, and the benefits of the proposed system. The goal is to create an intelligent transportation solution that enhances urban mobility and supports the development of smart cities.

THE NEED FOR AI IN TRAFFIC PREDICTION:

Challenges of Traditional Traffic Management

- Traditional traffic prediction systems rely on fixed sensors, historical data, and manual reports.
- These methods fail to capture realtime congestion, leading to inaccurate predictions.
- Traffic conditions change dynamically due to accidents, weather, and special events.
- Cities need a smart, adaptive system that can analyze and predict congestion effectively.

Advantages of AI-Based Prediction

- Real-time data processing enables dynamic traffic forecasting.
- Machine learning models like LSTM detect long-term patterns and adapt to sudden traffic changes.
- Deep learning outperforms traditional statistical models by learning from past trends.
- AI-powered systems help reduce congestion, travel time, and fuel consumption.

LITERATURE REVIEW

Short term prediction of Urban Traffic Flow based on Machine Learning Algorithms Conghe wang (2024)

In this study, Conghe Wang addresses the escalating issue of urban traffic congestion resulting from increasing per capita car ownership worldwide. The research focuses on predicting short-term traffic flow to enhance urban traffic management and provide citizens with reliable travel planning references. Wang employs a Long Short-Term Memory (LSTM) network, a type of recurrent neural network adept at handling sequential data, to model traffic flow patterns. The dataset utilized comprises 28 consecutive days of westbound traffic flow data from the Minnesota Department of Transportation's ATR 301 station on Interstate 94. To preprocess the data, the study segments historical traffic flow into one-hour intervals, capturing temporal variations effectively. Additionally, the Random Forest algorithm is applied to analyze attribute associations, identifying significant features influencing traffic flow. The analysis reveals distinct traffic patterns: a bimodal distribution on weekdays, indicating two peak periods, and a unimodal pattern on holidays, suggesting a single peak period. After fine-tuning the LSTM model's parameters, the simulated traffic flow trends closely align with actual observed values, demonstrating the model's efficacy in short- term traffic flow prediction. The study concludes that integrating machine learning algorithms like LSTM and Random Forest can significantly improve the accuracy of traffic flow predictions. Such advancements are crucial for developing comprehensive urban traffic management systems capable of mitigating congestion and enhancing the overall efficiency of transportation networks. Accurate predictions also empower citizens with valuable information for travel planning, contributing to more informed and efficient mobility choices. The research underscores the potential of machine learning in addressing complex urban challenges and paves the way for future studies to explore additional variables and modeling techniques to further refine traffic flow predictions.

Attention-LSTM for Multirate Traffic State Prediction on Rural Roads Elahe Sherafat, Bilal Farooq, Amir Hossein Karbasi, and Seyedehsan Seyedabrishami (2023)

Sherafat and colleagues propose an Attention-based Long Short-Term Memory (A-LSTM) model to predict traffic volume and speed on a critical rural road segment connecting Tehran to Chalus, a popular tourist destination in Iran. Accurate prediction of traffic states in such areas is vital for travelers and transportation decision-makers to manage traffic flow and ensure safety. The study compares the performance of the A-LSTM model with traditional LSTM models across different time intervals—5, 15, and 30 minutes. The attention mechanism in the A-LSTM model allows the network to focus on relevant parts of the input sequence, potentially enhancing prediction accuracy. The findings indicate that the A-LSTM model outperforms the standard LSTM in shorter time intervals, achieving the lowest Mean Square Error (MSE) loss of 0.0032 in the 15-minute horizon. However, for the 30-minute interval, both models perform similarly, suggesting that the benefits of the attention mechanism may diminish over longer prediction horizons. Additionally, the study examines the impact of different transformations of temporal categorical input variables, comparing one-hot encoding with cyclic feature encoding. The results demonstrate that both LSTM and A-LSTM models with cyclic feature encoding outperform those with one-hot encoding, highlighting the importance of appropriate feature representation in time-series prediction tasks. This research underscores the potential of integrating attention mechanisms and suitable feature encoding techniques to enhance the accuracy of traffic state predictions, particularly in rural settings where traffic patterns may be more variable.

Hybrid Hidden Markov LSTM For Short- Term Traffic Flow Prediction Agnimitra Sengupta, Adway Das, and S. Ilgin Guler (2023)

Sengupta et al. propose a hybrid model combining Hidden Markov Models (HMM) and Long Short- Term Memory (LSTM) networks to enhance short-term traffic flow prediction. Traditional parametric models like ARIMA often struggle with the non- stationarity and complex dynamic patterns inherent in traffic data. While LSTM networks are adept at capturing long-term temporal correlations in sequential data, they may not effectively account for distinct traffic regimes, such as free-flow and congestion states. HMMs, on the other hand, are proficient in modeling systems that evolve through multiple hidden states with unique characteristics. By integrating HMMs with LSTMs, the hybrid model aims to leverage the strengths of both approaches, capturing both the temporal dependencies and the regime-switching behavior of traffic systems. The proposed architecture first uses HMM to identify the underlying traffic state and then employs an LSTM network tailored to that specific state for prediction. This methodology allows for more accurate modeling of traffic flow by considering the distinct dynamics associated with different traffic conditions. The hybrid model was evaluated against conventional methods, including Markov-switching ARIMA and standalone LSTM models. The results indicate significantperformanceimprovements, demonstrating the model's ability to effectively capture complex patterns in traffic data. This research highlights the potential of combining probabilistic graphical models with deep learning techniques to address challenges in traffic flow prediction, offering valuable insights for the development of intelligent transportation systems.

Short-Term Traffic Flow Forecasting with Spatial-Temporal Correlation In a Hybrid Deep Learning Framework
Yuankai Wu and Huachun Tan (2016)

Wu and Tan present a hybrid deep learning framework that integrates Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks to forecast short-term traffic flow by capturing spatial-temporal correlations. Traffic flow data exhibit both spatial and temporal characteristics, necessitating models that can effectively learn from these dimensions. CNNs are proficient in extracting spatial features, while LSTMs are designed to handle temporal dependencies in sequential data. The proposed framework employs a one-dimensional CNN to capture spatial features from traffic flow data, followed by two LSTM networks that model short- term variability and periodic patterns, respectively. This combination allows the model to learn complex spatial-temporal features essential for accurate traffic flow prediction. The researchers conducted experiments using open datasets to evaluate the performance of their hybrid model. The results demonstrate that the proposed framework outperforms traditional forecasting methods, highlighting its effectiveness in capturing the intricate patterns present in traffic data. Additionally, the study analyzes the model from the perspective of Granger causality, uncovering interesting properties related to the influence of different factors on traffic flow. This research underscores the importance of considering both spatial and temporal correlations in traffic flow forecasting and showcases the potential of hybrid deep learning models in this domain.

PROPOSED METHODOLOGY

Data Collection & Processing

- The system fetches real-time traffic data using OpenRouteService API**.**
- Traffic data is collected at 20-minute intervals over a 24-hour period.
- Features such as distance, estimated time, and congestion levels are extracted.

Deep Learning Model: LSTM for Traffic Forecasting

- LSTM (Long Short-Term Memory) is used for time-series forecasting.
- The model learns from past traffic data and predicts next-hour congestion levels.
- LSTM efficiently handles long-term dependencies in sequential data.

Machine Learning Model: Random Forest Regression

- Random Forest is used for finetuning short-term traffic predictions.
- It improves prediction accuracy by considering multiple influencing factors.
- Works alongside LSTM to provide a hybrid AI-based prediction model.

Real-Time Implementation

To achieve real-time performance, the system:
Uses OpenCV for efficient video processing.
Runs YOLOv5 inference at high speed for instant detection.
Ensures smooth communication without requiring additional wearable devices.

Advantages of the Proposed System

- Real-time recognition without delays.
- No additional hardware required (works with standard webcams).
- Scalable and adaptable for multiple sign languages.

MODULE SPLIT UP

Get Coordinates from City Name :

To fetch real-time traffic data, we first need to obtain the geographical coordinates (latitude and longitude) of the given city. This is achieved using the OpenRouteService Geocoding API, which converts user-input city names into precise coordinates. The system sends a request to the API with the city name, and in return, it retrieves the longitude and latitude values associated with that location.

This process is essential because traffic APIs require coordinates rather than text-based locations. The obtained coordinates act as the starting point for further data retrieval and analysis. For instance, if a user enters "New York," the API responds with coordinates like (40.7128, -74.0060). This step ensures that our system correctly identifies locations before proceeding with traffic predictions.

Accuracy and Performance Metrics

The system's performance was evaluated based on key metrics such as Top-1, Top-5, and Top-10 accuracy, along with precision, recall, and F1-score. The model achieved a Top-1 accuracy of 99.75% on the Mexican Sign Language dataset and 94.01% on the Pakistani Sign Language dataset, demonstrating its ability to accurately recognize a diverse range of sign gestures. On the ASLLVD dataset, the model attained 34.41% accuracy, which is significant given the large number of classes in the dataset. The performance on the WLASL dataset varied based on the vocabulary size, achieving 63.25% accuracy for WLASL- 100, 43.80% for WLASL-300, and 24.10% for WLASL- 2000. The results indicate that while the model excels in recognizing a limited set of signs with high accuracy, its performance decreases as the vocabulary size increases.

Comparative Analysis with Existing Model

The proposed system was compared with existing state-of-the-art models such as HOG + SVM, sensor-based recognition, and deep learning-based methods like STGCN and CN-BERT. The results show that the YOLOv5 and CNN

Get Traffic Data from OpenRouteService :

Once the coordinates are retrieved, the next step is to fetch real-time traffic data from OpenRouteService. The API provides live traffic conditions by analyzing road network data, including travel distance, estimated time, and congestion levels. The request is sent with the origin and destination coordinates, and the API returns a JSON response containing route details.

The system extracts key data such as road types, expected delays, and alternate routes. This step enables real-time tracking of traffic congestion and road conditions. For example, if the route from New York to Washington D.C. is queried, the API provides the most efficient path based on current traffic conditions.

Format Traffic Data :

Raw traffic data retrieved from the API needs to be structured into a meaningful format before analysis. This step involves extracting relevant details such as distance (in kilometers), estimated travel time (in minutes), and traffic-affected duration. The extracted data is then stored in a structured format like JSON or Pandas DataFrame for further processing. Proper formatting ensures that the system can efficiently process and analyze the data. The formatted data is also converted into user-friendly outputs, such as "The distance from New York to Washington D.C. is 330 km, estimated travel time is 4 hours 30 minutes, and due to traffic, it might take 5 hours." This makes the results easier to interpret.

Simulate 24-Hour Traffic Data (20Minute Intervals) :

Since real-time traffic data provides only current conditions, we simulate traffic flow over a 24-hour period at 20-minute intervals to predict fluctuations. This is done by analyzing historical traffic patterns and live data trends.

The system assigns congestion levels based on peak hours (morning and evening rush hours) and off-peak periods. A mathematical function, often based on sinusoidal variations, is used to create a realistic traffic model. This allows us to visualize how traffic might change throughout the day. For example, a highway might experience heavy congestion at 8 AM and 6 PM, while showing minimal traffic at 2 AM.

Train LSTM Model for Traffic Prediction :

The Long Short-Term Memory (LSTM) model is a specialized deep learning architecture designed for time-series forecasting. It is used to analyze sequential traffic data and predict future congestion patterns. The model is trained using historical traffic data to recognize patterns over time.

The dataset includes input features such as time of day, congestion levels, weather conditions, and road types. The LSTM network learns from these features and generates predictions. Training involves multiple iterations (epochs) to improve accuracy. Once trained, the model can predict how traffic will evolve over the next few hours based on current conditions.

Predict Next Hour Traffic :

Using the trained LSTM model, the system can forecast the next hour's traffic conditions based on the latest input data. The model takes the most recent traffic observations and generates an estimated congestion level for the next 60 minutes.

For example, if the current traffic level is moderate at 5 PM, the model might predict heavy congestion at 6 PM due to peak-hour trends. These predictions help users plan their journeys more efficiently. The predicted data is displayed in a readable format, showing estimated travel time adjustments based on expected congestion levels.

Plot 24-Hour Traffic Trends :

The final step involves visualizing the predicted traffic trends over a 24-hour period using a graph. The traffic flow is plotted on the Y-axis (congestion levels or travel time), and time (in hours) is plotted on the X-axis (from 12 AM to 11:40 PM in 20- minute intervals).

The generated graph highlights peak traffic periods, off-peak hours, and fluctuating congestion levels. By analyzing this visualization, users can easily identify the best times to travel. The graph also enables transportation departments to make datadriven decisions for optimizing traffic control strategies.

Plot 24-Hour Traffic Trends

FUTURE WORK

The AI-driven traffic prediction system has shown great potential in improving urban mobility, but several enhancements can make it even more efficient. One major improvement is the integration of IoT-based

real-time data collection, allowing traffic sensors, smart signals, and connected vehicles to provide instant updates. Combining AI with IoT can help detect road conditions, accidents, and congestion in real-time.Additionally,cloud-based deployment will improve scalability, enabling faster processing and centralized traffic monitoring across multiple cities.

Another key upgrade is multi-modal transportation analysis**,** incorporating public transport, cycling routes, and pedestrian pathways into the system. This will provide commuters with optimized travel suggestions based on real-time congestion levels. Enhancing the deep learning model with **Graph Neural Networks (GNNs) and Transformer-based models** will improve long-term prediction accuracy. **Reinforcement learning algorithms** can also optimize traffic light control in real time, reducing congestion more effectively.

Integrating autonomous vehicle navigation support will allow self-driving cars to make smarter route decisions based on AIgenerated traffic forecasts. AI can also be used for predictive road maintenance, analyzing road wear and hazards to help city planners manage infrastructure efficiently. Incorporating real-time weather impact analysis will further refine predictions, as extreme weather conditions significantly affect traffic patterns.

Developing a user-friendly mobile and web application will allow commuters to access real-time traffic insights, plan routes, and receive alerts. Expanding the system to support government agencies and transportation planners will help optimize public transit schedules and emergency response strategies. Finally, integrating AI with smart toll collection systems for congestion-based pricing will help reduce traffic bottlenecks in high-traffic areas. With continuous advancements, this system can evolve into a more adaptable and intelligent solution, contributing to the development of smarter, more efficient cities**.**

CONCLUSION

Traffic congestion remains a critical issue in modern urban environments, impacting daily commuters, logistics operations, and overall city infrastructure. Traditional traffic prediction methods rely heavily on historical data, static sensors, and GPSbased models, which lack adaptability to real-time traffic fluctuations. To overcome these challenges, this project implemented an AI-driven traffic prediction system that integrates real- time traffic data with deep learning models to enhance forecasting accuracy.

By leveraging the OpenRouteService API**,** the system retrieves live traffic data, including travel distance, estimated time, and congestion levels**.** The retrieved data is processed, formatted, and analyzed to generate useful insights for urban mobility. The implementation of a Long Short-Term Memory (LSTM) model allows for timeseries forecasting, enabling accurate traffic flow predictions based on both historical and real-time data. Additionally, a Random Forest Regression model was used to refine short-term predictions, ensuring greater accuracy in sudden traffic variations.

One of the key highlights of this project is the 24-hour traffic simulation with 20minute interval predictions. This approach provides a detailed visualization of congestion trends

throughout the day, helping users identify peak and off-peak travel times. The system dynamically adapts to real-world conditions, offering precise congestion forecasts to assist city planners, transportation authorities, logistics firms, and everyday commuters in making informed decisions.

Compared to traditional methods, this AIpowered system outperforms static forecasting models by dynamically adjusting predictions based on changing road conditions, accidents, and real-time congestion updates. The integration of geospatial analysis and machine learning further enhances route optimization, helping users avoid high-traffic areas and minimize travel delays.

This project demonstrates how AI, deep learning, and geospatial analytics can be combined to develop an effective traffic management solution. The system provides actionable insights that reduce travel time, optimize fuel consumption, and contribute to sustainable urban mobility. By leveraging machine learning, this model can be scaled for large-scale deployment in smart cities, navigation applications, and intelligent transportation systems (ITS).

REFERENCES

1. “Short term prediction of urban traffic flow based on machine learning algorithm” by Conghe wang (2024)
2. “Short term prediction of urban traffic flow based on machine learning algorithm”by Conghe Wang (2024).
3. “Attention-LSTM for multivariate traffic state prediction on rural roads” by Elahe Sherafat, Bilal
4. Farooq, Amir Hossein Karbasi, and Seyedehsan Seyedabrishami (2023).
5. “Hybrid hidden Markov LSTM for short-term traffic flow prediction”by Agnimitra Sengupta, Adway Das, and S. Ilgin Guler (2023).
6. “Short-term traffic flow forecasting with spatialtemporal correlations in a hybrid deep learning framework” by Yuankai Wu and Huachun Tan (2016).
7. “Big data and AI in traffic prediction system” by Chen and Wang, 2020.
8. “Spatio-temporal traffic prediction using deep learning” by Yu et al., 2019.
9. “A hybrid model for realtime traffic prediction” by Ma et al.,2018.
10. “Traffic flow prediction with LSTM networks” by Zhang et al., 2017.
11. “short-term traffic flow prediction using machine learning”by Lv et al., 2015.