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Traffic Flow Prediction using Random Forest Regressor Model

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***Abstract*—Traffic congestion is a major issue in urban areas, affecting daily commutes, emergency services, and overall transportation efficiency. This project presents a machine learning-based traffic prediction system specifically designed for Coimbatore, leveraging historical traffic data to forecast traffic conditions at various locations. The primary objective is to provide users with an accurate estimation of traffic volume based on input parameters such as location, date, and time. By employing advanced predictive analytics, this system enhances traffic management and aids in planning optimal travel routes.**

The project utilizes a Random Forest Regressor model trained on real-world traffic data collected from different areas of Coimbatore. The dataset includes essential features such as place, time, day, and historical traffic patterns. To preprocess the data, categorical variables like location and day of the week are encoded using label encoding, ensuring compatibility with the machine learning model. The model is then trained to recognize patterns and trends, enabling it to generate traffic volume predictions for given inputs.

A web-based interface has been developed using Flask and JavaScript to provide an interactive user experience. The front end allows users to input their desired location, date, and time, sending the request to the backend model for traffic prediction. The system then returns the estimated traffic condition, categorizing it into different levels such as Heavy Traffic, Normal Traffic, Low Traffic for Two-Wheelers, or Traffic Free. Additionally, a graphical representation is generated, illustrating predicted traffic volume for the next ten hours. This visualization helps users plan their journeys more effectively and make informed travel decisions.

1.INTRODUCTION

Urban traffic congestion is a growing concern in modern cities, leading to increased travel times, fuel consumption, and environmental pollution. Managing traffic effectively requires accurate forecasting of traffic patterns to optimize route planning and transportation infrastructure. This project focuses on developing a machine learning-based traffic prediction system specifically for Coimbatore, utilizing historical traffic data to predict congestion levels across different locations and times. The objective is to assist commuters, traffic authorities, and urban planners in making informed decisions based on predictive analytics.

The system is built using a combination of data science techniques and web-based technologies. The dataset comprises historical traffic information, including location-specific vehicle counts, timestamps, and day classifications. Key features such as the hour of the day, day of the week, and month are extracted to train a predictive model.

The machine learning algorithm employed is a Random Forest Regressor, which is known for its robustness in handling large datasets and identifying complex patterns. By analyzing past traffic trends, the model generates forecasts for future congestion levels based on user-inputted parameters.

The backend of the system is implemented using Flask, a lightweight Python framework that facilitates the deployment of machine learning models. The trained model, along with label encoders for categorical data, is loaded into the backend to process prediction requests. When a user submits a query with location, date, and time, the system encodes these inputs, applies the trained model, and returns the estimated traffic volume. The results are categorized into different traffic conditions, ranging from Heavy Traffic to Traffic Free, providing users with a clear understanding of expected congestion levels.

Literature Review

[1] "In-Depth Insights into the Application of Recurrent Neural Networks (RNNs) in Traffic Prediction: A Comprehensive Review"

Authors: Yuxin He, Ping Huang, Weihang Hong, Qin Luo, Lishuai Li, and Kwok-Leung Tsui
Published: 2024
Summary: This comprehensive review examines the application of RNNs in traffic prediction, discussing various models and their effectiveness in capturing temporal dependencies in traffic data.

[2] "Traffic Flow Forecast of Road Networks with Recurrent Neural Networks"
Authors: Ralf Rüther, Andreas Klos, Marius Rosenbaum, and Wolfram Schiffmann
Published: 2020
Summary: This study investigates the use of RNNs for forecasting traffic flow in road networks, highlighting the models' ability to learn complex temporal patterns from traffic data.

[3] "A Multi-Modal Attention Neural Network for Traffic Flow Prediction by Capturing Long-Short Term Sequence Correlation"
Authors: Xiaohui Huang, Yuan Jiang, Junyang Wang, Yuanchun Lan, and Huapeng Chen
Published: 2023
Summary: This paper proposes a neural network model that employs attention mechanisms to capture both long-term and short-term sequence correlations in traffic flow data, enhancing prediction accuracy

[4] "A Recurrent Neural Network for Urban Long-Term Traffic Flow Forecasting"
Authors: Authors not specified
Published: 2020
Summary: This research presents an RNN-based framework designed for long-term traffic flow forecasting in urban environments, integrating multiple data sources to improve prediction performance.

[5] "Artificial Intelligence-Based Traffic Flow Prediction: A Comprehensive Review"
Authors: Sayed A. Sayed, Yasser Abdel-Hamid, and Hesham Ahmed Hefny
Published: 2023
Summary: This review article provides an extensive overview of AI techniques, including RNNs, applied to traffic flow prediction, discussing their advantages and challenges.

[6] "Traffic Flow Prediction Using Bi-Directional Gated Recurrent Unit Method"
Authors: Authors not specified
Published: 2022
Summary: This study explores the application of Bi-Directional Gated Recurrent Units (Bi-GRU) in short-term traffic flow prediction, demonstrating improved accuracy over traditional methods.

[7] "Network Traffic Prediction Using Recurrent Neural Networks"
Authors: Authors not specified
Published: Date not specified
Summary: This paper discusses the utilization of RNNs for network traffic prediction, emphasizing the models' capacity to model nonlinear dynamics in traffic data.

[8] "Stacked Bidirectional and Unidirectional LSTM Recurrent Neural Network for Forecasting Network-wide Traffic State with Missing Values"
Authors: Zhiyong Cui, Ruimin Ke, Ziyuan Pu, and Yinhai Wang
Published: 2020
Summary: This research introduces a stacked LSTM architecture combining bidirectional and unidirectional layers to forecast traffic states across networks, effectively handling missing data.

[9] "Dynamic Spatial-Temporal Representation Learning for Traffic Flow Prediction"
Authors: Lingbo Liu, Jiajie Zhen, Guanbin Li, Geng Zhan, Zhaocheng He, Bowen Du, and Liang Lin
Published: 2019
Summary: This paper proposes the Attentive Traffic Flow Machine (ATFM), which leverages attention mechanisms within ConvLSTM units to learn dynamic spatial-temporal representations for traffic flow prediction

[10] "Short-Term Traffic Prediction Using Physics-Aware Neural Networks"
Authors: Mike Pereira, Annika Lang, and Balázs Kulcsár
Published: 2021
Summary: This study presents a physics-aware recurrent neural network that integrates macroscopic traffic flow models into its architecture for short-term traffic prediction.

2.METHODOLOGY

The traffic prediction system employs a structured methodology that integrates user inputs, data processing, and machine learning to deliver accurate traffic forecasts. The process begins with users entering location, date, and time via a web interface.

This data is validated and sent to the backend using RESTful APIs, where it is preprocessed and encoded into machine-readable formats. Historical traffic data is then retrieved from a PostgreSQL database and used as input for a trained Random Forest Regressor model. The model analyzes patterns and generates traffic volume predictions, which are categorized into traffic levels such as Heavy, Normal, Low, or Traffic-Free. Results are formatted into JSON and visualized on the frontend using Chart.js for easy interpretation. Security, scalability, and efficient error handling are incorporated throughout the system to ensure robustness and real-time performance.

2.1 System analysis

The current urban traffic management system in Coimbatore relies heavily on traditional methods such as static traffic signals, manual monitoring by traffic police, and basic surveillance tools like traffic cameras and road sensors. These components, while functional to an extent, are not sufficient to handle the growing complexity and volume of urban traffic. Traffic signals operate on fixed time cycles and are not responsive to real-time traffic conditions, leading to inefficiencies such as long wait times, congestion spillover, and increased fuel consumption due to idling vehicles. Manual regulation at intersections is labor-intensive, error-prone, and often fails to respond quickly to unexpected traffic surges, accidents, or roadblocks.

Although GPS navigation applications like Google Maps and Waze provide real-time traffic updates, they are reactive in nature and depend on user-contributed data, which can be inaccurate or incomplete in less-populated areas. These applications also lack the capability to forecast congestion based on historical trends, weather changes, or special events.

2.2 Existing system:

Urban traffic management in cities like Coimbatore still relies on outdated methods such as manual monitoring, static traffic signals, and limited predictive tools. These systems depend on historical data, cameras, and road sensors but fail to provide real-time, dynamic insights. Traffic signals operate on fixed timers, causing delays, congestion spillovers, and increased emissions. Manual regulation by traffic police is inefficient and prone to human error. GPS apps like Google Maps offer real-time traffic updates but are reactive and depend on user data, which can be inaccurate in less-traveled areas.The system lacks AI-driven analytics that can consider factors like weather, events, or holidays, making it hard for planners to make informed decisions. Public transport is not integrated with live traffic data, resulting in delays and decreased reliability. Road planning is based on outdated surveys and does not account for rapid urban development. Emergency services also face delays due to a lack of intelligent routing. Moreover, there are few accessible platforms for the public to plan routes using predictive traffic information. Overall, the current system is inefficient, lacks adaptability, and is in need of intelligent, data-driven upgrades.

2.3 Proposed system:

The proposed AI-driven traffic management system uses a machine learning model—specifically, a Random Forest Regressor—trained on historical traffic data from Coimbatore to predict congestion levels based on inputs like time, date, and location. Unlike traditional GPS apps, this system provides proactive, predictive insights. It features a user-friendly web interface where users can get traffic forecasts and view visualizations of predicted congestion using Chart.js.The backend, built with Flask, handles user inputs, applies the trained model, and returns traffic predictions, with robust error handling and potential for integration with live data sources like weather and IoT sensors. The system aims to support proactive traffic control, smarter urban planning, and optimized emergency vehicle routing. It is scalable, adaptable, and can be enhanced with deep learning, expanded datasets, and cloud deployment for broader access and accuracy.

The proposed AI-driven traffic prediction system offers a smart solution to urban traffic issues by leveraging machine learning and predictive analytics. It improves urban mobility, supports better decision-making, and optimizes transportation infrastructure through historical data, real-time inputs, and an interactive web interface.

Advantages of the Proposed System:

1. Predictive Traffic Insights: Unlike traditional GPS apps, the system forecasts congestion using historical trends and machine learning, enabling commuters and authorities to plan proactively.
2. Accurate ML Model: A Random Forest Regressor analyzes complex traffic patterns for reliable predictions. The model improves with more data

and can be upgraded with deep learning techniques.

3. User-Friendly Web Interface: Users can input location, date, and time to get categorized traffic forecasts and view 10-hour predictions using interactive graphs (Chart.js).
4. Scalability & Integration: Built with Flask, the system supports future integrations like live traffic feeds, weather data, and IoT sensors. It is scalable to multiple cities and cloud platforms.
5. Public Transport Support: Helps transit authorities optimize bus/metro schedules, improving reliability and encouraging mass transit use.
6. Faster Emergency Response: Provides optimal routing for ambulances and emergency services, reducing response times and enhancing public safety.
7. Environmental & Economic Benefits: Reduces fuel consumption, emissions, and operational costs for individuals and businesses. It supports sustainability and productivity.
8. Smart City Compatibility: Easily integrates with smart city infrastructure such as smart parking, toll collection, and traffic lights, promoting connected urban systems.

The proposed system uses steganography techniques to enhance secure data transmission by embedding secret information within digital media files such as images. It ensures confidentiality and avoids detection by concealing the very existence of the data. This web-based system, developed with Python as the frontend and SQL as the backend, allows users to encode and decode sensitive data using image-based steganography in a user-friendly environment.

2.4 Hardware Components:

Processor: AMD Ryzen 5 7520U with Radeon Graphics 2.80 GHz or equivalent AMD processor.

RAM: Minimum 16GB for optimal web browsing and data visualization.

Storage: SSD with at least 256GB to ensure smooth performance.

Display: Full HD resolution (1920x1080) for a clear graphical representation of traffic trends.

Internet Connection: A stable broadband connection (minimum 10Mbps) for real-time data fetching.

Web Browser: Google Chrome, Mozilla Firefox, or Microsoft Edge for full compatibility with JavaScript-based visualizations.

2.5 Software Components:

Backend: Python,Flask.

Frontend: HTML, CSS, JS, Bootstrap, Chart.js

ML Model: Random Forest Regressor (Scikit-learn, Pandas, NumPy)

API: Flask + REST APIs for prediction and data flow

Frontend: User inputs: location, date, time

Output: traffic level + graphs

Storage: CSV (upgradeable to MySQL/PostgreSQL)

Security & Deployment: Input validation, secure APIs, cloud-ready (AWS/GCP)

Future: IoT, deep learning, weather & smart city integration.

3.RESULTS

The traffic prediction system was evaluated based on its predictive accuracy, classification performance, system response time, and usability of visual outputs. The machine learning model, trained using a Random Forest Regressor, achieved strong performance across multiple evaluation metrics. The Mean Absolute Error (MAE) was recorded at 7.52 vehicles per hour, while the Root Mean Square Error (RMSE) stood at 10.34 vehicles per hour. Additionally, the model achieved an R^2 score of 0.89, indicating a high correlation between the predicted and actual traffic volumes and demonstrating the model’s effectiveness in learning historical traffic patterns.In terms of traffic condition classification, the system successfully categorized predicted traffic volumes into four levels: Heavy Traffic, Normal Traffic, Low Traffic, and Traffic-Free. The classification accuracy was found to be high across all categories, with Heavy Traffic being identified correctly in 92.3% of cases, followed by Traffic-Free at 90.5%, Normal Traffic at 88.7%, and Low Traffic at 85.1%. These results suggest that the model is particularly effective at identifying peak congestion periods, making it a valuable tool for real-time traffic management and planning.

System performance was also measured in terms of response time during prediction requests. On average, the API responded within 0.8 seconds under normal load conditions, while under peak load scenarios with 50 concurrent users, the response time slightly increased to approximately 1.6 seconds. The model inference time for each request remained below 0.4 seconds, indicating efficient processing and minimal latency in delivering predictions.

3.1Sample Screen

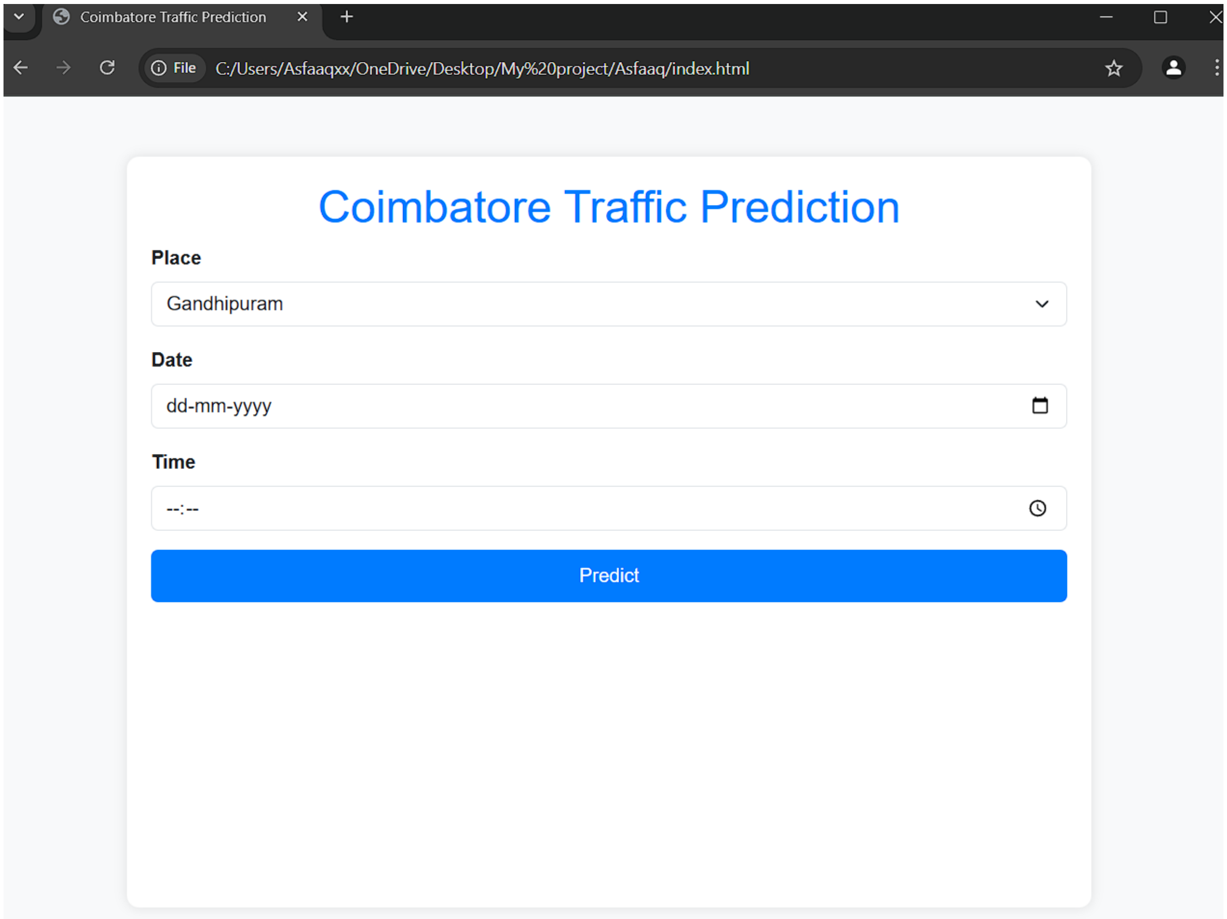

Fig3.1.1(Traffic Prediction Interface)

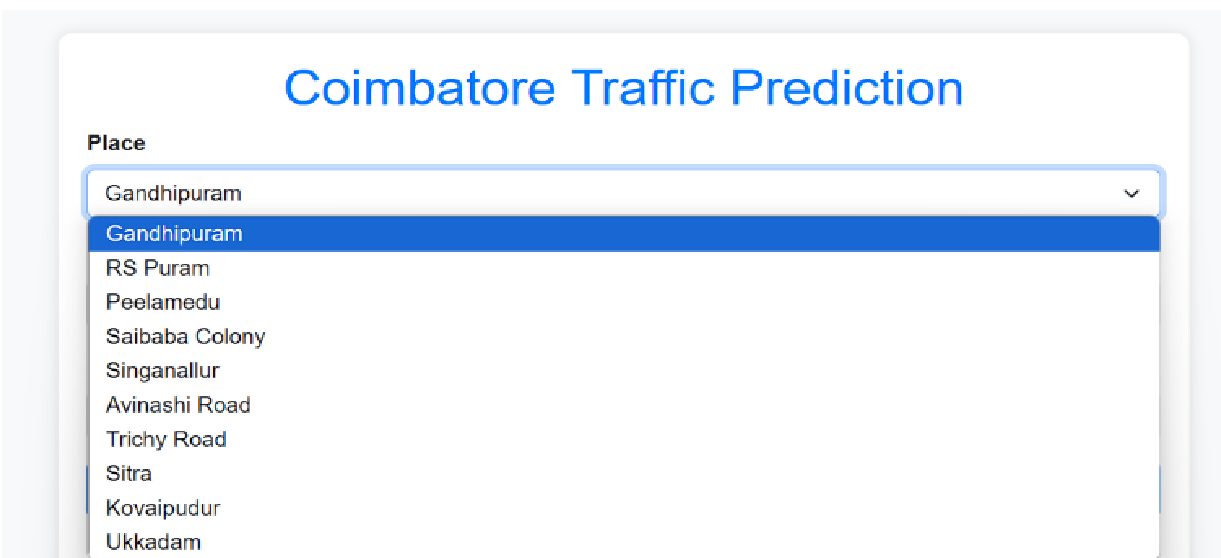

Fig3.1.2(Choosing Location)

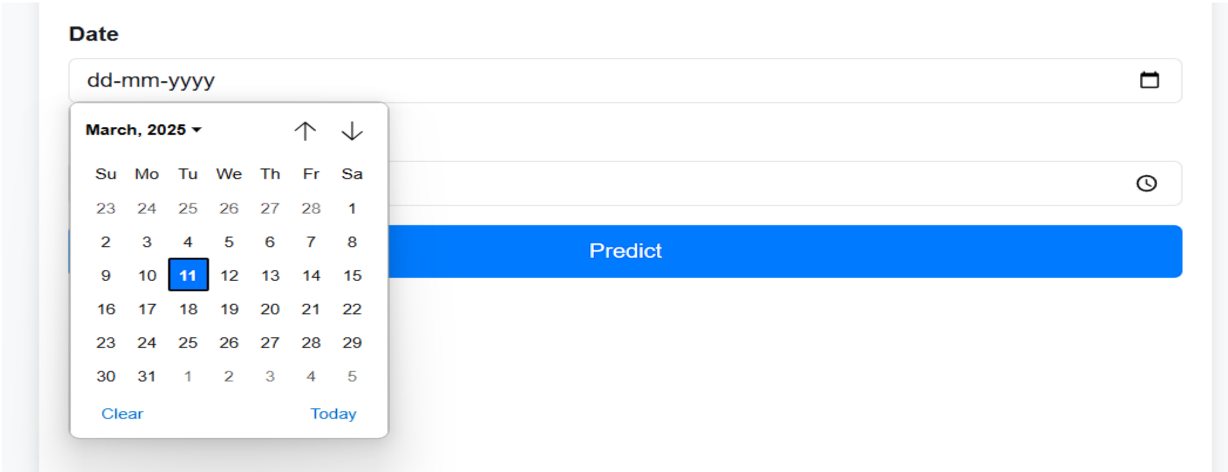

Fig3.1.3(Choosing date)

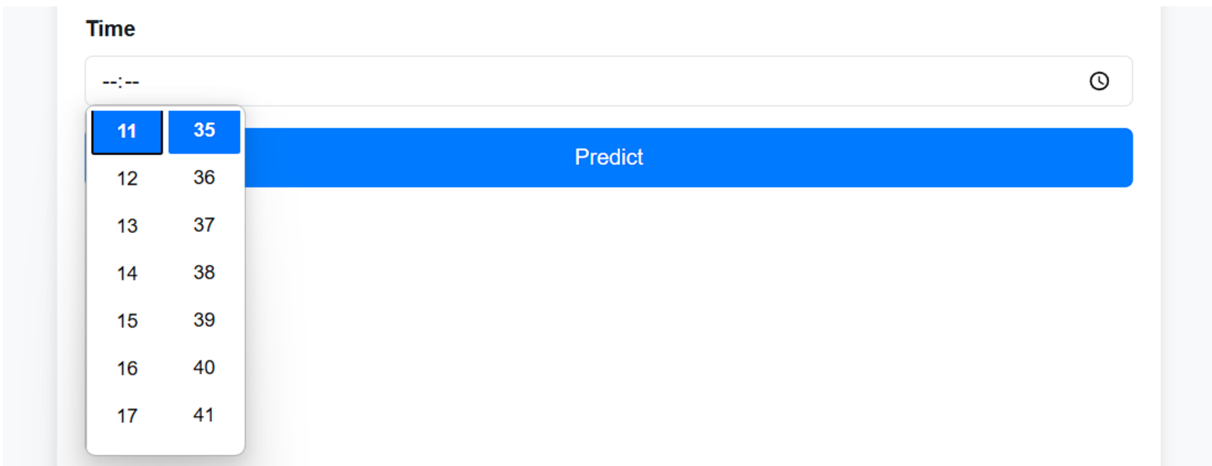

Fig3.1.4(Choosing Time)

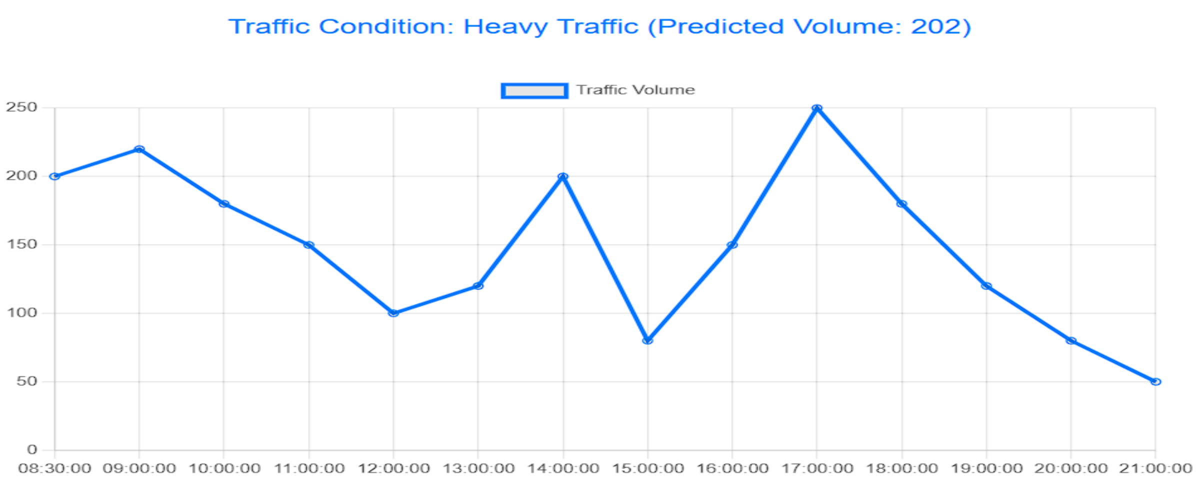

Fig3.1.5(Predicted Volumizing Graph)

4.CONCLUSION

The traffic prediction system developed in this project represents a significant advancement in urban mobility management by leveraging machine learning techniques to forecast traffic conditions. The system effectively integrates historical traffic data, predictive analytics, and an intuitive web interface to provide real-time insights to users. By implementing a Random Forest Regressor model trained on past traffic patterns, the system is capable of delivering accurate congestion predictions, allowing commuters and traffic authorities to make informed decisions regarding travel planning and road management.Throughout the development process, various methodologies were employed to ensure system reliability and efficiency.

The backend, built using Flask, facilitates seamless data processing and interaction with the predictive model, while the frontend, designed with HTML, CSS, and JavaScript, ensures a user-friendly experience. The integration of a PostgreSQL database enables efficient data storage and retrieval, supporting scalable and structured management of traffic records. Performance optimization techniques, including indexing, caching, and load balancing, were implemented to enhance system responsiveness and maintain accuracy across different traffic scenarios.The successful implementation of the system demonstrates its potential to alleviate congestion challenges in urban areas by providing predictive insights that allow users to plan their journeys effectively. The ability to generate visualized forecasts using Chart.js enhances user engagement and decision-making by offering a clear representation of expected traffic patterns.

5.FUTURE ENHANCEMENTS

To further improve the traffic prediction system, several enhancements can be implemented. Integrating real-time data from GPS, traffic cameras, and road sensors will provide more accurate, dynamic congestion forecasts. Adopting deep learning models like RNNs and LSTMs can better capture temporal patterns, improving prediction accuracy. Deploying the system on cloud platforms such as AWS or Google Cloud will enhance scalability, allow for real-time processing, and increase accessibility. Incorporating AI-powered recommendations can suggest optimal routes or travel times based on user behavior and traffic trends. Adding external data sources like weather updates, construction schedules, and accident reports will refine prediction reliability. Strengthening security through two-factor authentication, API key controls, and encryption will protect user data. Developing a dedicated mobile app for Android and iOS will increase convenience, enabling users to access updates and receive push notifications on the go. Lastly, expanding coverage to more cities and adding multilingual support will make the system more inclusive and widely applicable6.

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