

Time Series Traffic Prediction With Vehicle-Type Suggestionst

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ABSTRACT:

Urban traffic congestion is a major challenge in modern cities, leading to increased travel times, fuel consumption, and air pollution. To address this issue, DeepTraffic-VTS presents an intelligent hybrid system that integrates Long Short-Term Memory (LSTM) networks for time series forecasting with YOLO (You Only Look Once) for vehicle detection. The LSTM model analyzes historical traffic data—such as vehicle count, average speed, and congestion levels—to predict traffic conditions over upcoming time intervals. Simultaneously, YOLO processes live video feeds to detect and classify vehicle types on the road, including two-wheelers, cars, buses, and emergency vehicles. Based on both predicted and real-time traffic conditions, the system provides adaptive suggestions on the most suitable vehicle types for efficient navigation—for example, recommending two-wheelers in high-congestion zones due to their maneuverability, while advising larger vehicles to reroute or delay travel. This combined approach enables more effective traffic management, emergency response optimization, and smart urban mobility planning.

Based on both predicted and real-time traffic conditions, the system provides adaptive suggestions on the most suitable vehicle types for efficient navigation. Specifically, when congestion levels are high, the system recommends small vehicles such as two-wheelers due to their maneuverability; for medium congestion, it suggests medium-sized vehicles like cars; and for low congestion, it supports the use of larger vehicles such as buses and trucks for efficient mass transportation. In addition, emergency vehicles like ambulances and fire trucks can be given priority-based navigation routes, reducing response times in critical situations.

INTRODUCTION

Urban traffic congestion has become one of the most pressing challenges in modern cities, contributing to longer travel times, increased fuel consumption, environmental pollution, and reduced quality of life. Traditional traffic management systems often struggle to handle the dynamic and complex nature of urban traffic, as they typically rely on static rules and limited real-time data. To address these limitations, the integration of advanced machine learning techniques and computer vision offers a promising solution. DeepTraffic-VTS is a hybrid

intelligent system designed to improve urban traffic efficiency by combining predictive and real-time analysis. It employs Long Short-Term Memory (LSTM) networks to forecast traffic conditions based on historical data such as vehicle counts, average speeds, and congestion trends. Simultaneously, the system uses YOLO (You Only Look Once) to detect and classify vehicles from live video feeds, including cars, buses, two-wheelers, and emergency vehicles. By merging these insights, DeepTraffic-VTS can provide adaptive recommendations for optimal vehicle movement, helping to alleviate congestion, optimize travel routes, support emergency responses, and enable smarter urban mobility planning. This approach demonstrates the potential of combining time series forecasting and real-time detection to create a proactive, data-driven traffic management system capable of enhancing the safety, efficiency, and sustainability of urban transportation networks. Based on both **predicted and real-time traffic conditions**, the system provides **adaptive suggestions** on the most suitable vehicle types for efficient navigation. Specifically, when congestion levels are **high**, the system recommends **small vehicles such as two-wheelers** due to their maneuverability; for **medium congestion**, it suggests **medium-sized vehicles like cars**; and for **low congestion**, it supports the use of **larger vehicles such as buses and trucks** for efficient mass transportation. In addition, emergency vehicles like ambulances and fire trucks can be given **priority-based navigation routes**, reducing response times in critical situations.

OBJECTIVE

The main objective of DeepTraffic-VTS is to develop an intelligent hybrid system that improves urban traffic management by combining predictive analytics with real-time vehicle detection. The system leverages LSTM networks to forecast traffic conditions based on historical data and employs YOLO to detect and classify vehicles from live video feeds. By integrating these insights, it aims to provide adaptive recommendations on the most suitable vehicle types for efficient navigation, reduce traffic congestion, optimize travel times, lower fuel consumption, and enhance emergency response. Ultimately, the project seeks to enable smarter urban mobility planning and contribute to safer, more sustainable city transportation systems.

LITERATURE SURVEY

TITLE: Predicting multiple types of traffic accident severity with explanations: A multi-task deep learning framework

AUTHORS: Z. Yang, W. Zhang, J. Feng

YEAR: 2022

DESCRIPTION: This paper proposes a multi-task deep learning framework for predicting different levels of traffic accident severity while also providing interpretable explanations. The model simultaneously predicts multiple severity categories by leveraging shared representations, enhancing efficiency and accuracy. By integrating explainable AI techniques, the study offers insights into the most influential factors affecting accident severity, aiding policymakers and traffic safety authorities in implementing targeted safety measures. The approach is validated using large-scale accident datasets, demonstrating significant performance improvements over traditional single-task models.

TITLE: Factors affecting severity of motorcycle accidents on Thailand's arterial roads: Multiple correspondence analysis and ordered logistics regression approaches

AUTHORS: T. Champahom, P. Wisutwattanasak, K. Chanpariyavatevong, N. Laddawan, S. Jomnonkwao, V. Ratanavaraha

YEAR: 2022

DESCRIPTION: This study investigates the key factors influencing the severity of motorcycle accidents on Thailand's arterial roads. Using multiple correspondence analysis and ordered logistic regression, the authors identify variables such as road conditions, rider behavior, and environmental factors that significantly impact crash outcomes. The findings highlight the role of infrastructure improvements, enforcement strategies, and public awareness campaigns in reducing accident severity, providing valuable guidance for policymakers and traffic safety planners.

TITLE: Towards lightweight lane detection by optimizing spatial embedding

AUTHORS: S. Jung, S. Choi, M. Azam Khan, J. Choo

YEAR: 2020

DESCRIPTION: This paper explores strategies for optimizing spatial embedding to achieve lightweight lane detection systems. The authors propose a method that focuses on reducing the computational load of lane detection algorithms while maintaining high accuracy. By optimizing spatial embedding techniques, the study aims to enhance real-time performance and efficiency in detecting lane markings, which is critical for autonomous driving and advanced driver assistance systems. The paper presents a detailed analysis of the proposed method, including experimental results that showcase its

effectiveness in balancing computational efficiency with detection accuracy, making it suitable for deployment in practical driving scenarios.

METHODOLOGIES

MODULES NAME:

Modules Name:

1. Data Collection Module
2. Traffic Prediction Module (LSTM-based)
3. Vehicle Detection Module (YOLO-based)
4. Data Integration and Analysis Module
5. Adaptive Recommendation Module
6. System Evaluation Module

HARDWARE REQUIREMENTS

The hardware requirements may serve as the basis for a contract for the implementation of the system and should therefore be a complete and consistent specification of the whole system. They are used by software engineers as the starting point for the system design. It should what the system do and not how it should be implemented.

- PROCESSOR : DUAL CORE 2 DUOS.
- RAM : 4GB DD RAM
- HARD DISK : 250 GB

3.3 SOFTWARE REQUIREMENTS

The software requirements document is the specification of the system. It should include both a definition and a specification of requirements. It is a set of what the system should do rather than how it should do it. The software requirements provide a basis for creating the software requirements specification. It is useful in estimating cost, planning team activities, performing tasks and tracking the teams and tracking the team's progress throughout the development activity.

- Operating System : Windows 7/8/10
- Platform : Spyder3
- Programming Language : Python
- Front End : Spyder3

DEVELOPMENT TOOLS

Python

Python is a high-level, interpreted, interactive and object-oriented scripting language. Python is designed to be highly readable. It uses English keywords frequently where as other languages use punctuation, and it has fewer syntactical constructions than other languages.

History of Python

Python was developed by Guido van Rossum in the late eighties and early nineties at the National Research Institute for Mathematics and Computer Science in the Netherlands.

Python is derived from many other languages, including ABC, Modula-3, C, C++, Algol-68, Small Talk, and Unix shell and other scripting languages.

Python is copyrighted. Like Perl, Python source code is now available under the GNU General Public License (GPL).

Python is now maintained by a core development team at the institute, although Guido van Rossum still holds a vital role in directing its progress.

Importance of Python

- **Python is Interpreted** – Python is processed at runtime by the interpreter. You do not need to compile your program before executing it. This is similar to PERL and PHP.
- **Python is Interactive** – You can actually sit at a Python prompt and interact with the interpreter directly to write your programs.
- **Python is Object-Oriented** – Python supports Object-Oriented style or technique of programming that encapsulates code within objects.
- **Python is a Beginner's Language** – Python is a great language for the beginner-level programmers and supports the development of a wide range of applications from simple text processing to WWW browsers to games.

- **FUTURE ENHANCEMENTS:**

In the future, DeepTraffic-VTS can be enhanced to further improve urban traffic management and smart city integration. The system could incorporate multi-modal traffic analysis, including bicycles, pedestrian flows, and public transportation, to provide more comprehensive recommendations. Integration with IoT-enabled smart traffic signals and connected vehicle networks can enable real-time adaptive traffic control, reducing congestion even further and also recommend the vehicles based on the congestion levels. Additionally, incorporating advanced AI techniques such as reinforcement learning could allow the system to optimize routing dynamically based on evolving traffic patterns. Cloud-based analytics and mobile app integration can provide personalized navigation suggestions to commuters, while large-scale data collection can support city planners in designing safer, more efficient, and environmentally sustainable urban transportation networks.

CONCLUSION

DeepTraffic-VTS showcases an innovative approach to tackling urban traffic congestion by leveraging the strengths of both predictive analytics and real-time computer vision. By employing LSTM networks for accurate traffic forecasting and YOLO for live vehicle detection and classification, the system provides actionable insights that help optimize traffic flow and improve decision-making for commuters and traffic authorities alike. The

integration of these two powerful techniques allows the system to dynamically adapt to changing traffic conditions, offering suitable vehicle routing suggestions, minimizing delays, and reducing fuel consumption.

Moreover, the project demonstrates significant potential in enhancing emergency response, as it can prioritize routes for ambulances and fire trucks in real time. Beyond daily traffic management, the system offers valuable data for urban planners and policymakers, supporting evidence-based decisions for sustainable city development. With future enhancements such as IoT integration, multi-modal transport analysis, and AI-driven traffic signal optimization, DeepTraffic-VTS can evolve into a comprehensive solution for smart city infrastructure. Overall, this project emphasizes the importance of combining artificial intelligence, data analytics, and computer vision to create safer, more efficient, and environmentally friendly urban transportation networks, paving the way for smarter cities of the future and Based on both predicted and real-time traffic conditions, the system provides adaptive suggestions on the most suitable vehicle types for efficient navigation. Specifically, when congestion levels are high, the system recommends small vehicles such as two-wheelers due to their maneuverability; for medium congestion, it suggests medium-sized vehicles like cars; and for low congestion, it supports the use of larger vehicles such as buses and trucks for efficient mass transportation. In addition, emergency vehicles like ambulances and fire trucks can be given priority-based navigation routes, reducing response times in critical situations.

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