

Traffic Flow AI: Smart Traffic Prediction

Nirdesh Bhardwaj

(Department of Computer Science and Engineering Chandigarh University, India) <u>nirdeshb40@gmail.com</u> Kritika

(Department of Computer Science and Engineering Chandigarh University, India) <u>Kritikaola39@gmail.com</u>

Vishav Pratap Singh

Rahul Kulvi

(Department of Computer Science and Engineering Chandigarh University, India) mailto:vishav.e13056@cumail.in

(Department of Computer Science and Engineering Chandigarh University, India) <u>kulvirahul00@gmail.com</u>

Abstract

In the past few years, the rapid rates of autonomous vehicle consumption worldwide have been noticed. It's because the growing use of AI technologies and AI systems in the market is often caused by rapid new technologies appearance, as well as brought about a great number of industries and organizations to take advantage of AI. Traffic flow predictability is a key point for autonomous vehicles they have a roadmap and make well-adaptive decisions (to move left or right, to drive straight, to change lanes, to stop or to accelerate) within the existing context. According to the available study, Adaptive machine learning technology is considered the main goal of autonomous car research, replacing statistical models with evolutionary algorithms. However since modern cars make their decisions based on their environment, the non-linear relationship between spatial and physical information could mean no. Yes, all modern learning systems are now suitable for this situation.

Therefore, we often cover these topics and examine the use of deep learning to predict the traffic of unmanned vehicles in the context of modern intelligent transportation (ITS). Many factors are particular to each model and are therefore selected to make problem-based comparisons among the deep learning models. Even more, we tried to show the difficulties and future research possibilities.

Introduction

In the past few years, the rapid rates of autonomous vehicle consumption worldwide have been noticed. It's because of the latest developments in AI technology including machine learning models that are available for purchase and used by enterprises and institutions with growing frequency. Traffic flow predictability is a key point for autonomous vehicles they have a roadmap and make well-adaptive decisions (to move left or right, to drive straight, to change lanes, to stop or to accelerate) within the existing context. According to the available study, Adaptive machine learning technology is considered the main goal of autonomous car research, replacing statistical models with evolutionary algorithms. But since modern cars make their decisions based on their environment, the non-linear relationship between spatial and physical information could mean no. Yes, all modern learning systems are now suitable for this situation.

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Artificial Intelligence (AI)		
Machine Learning (ML) Deep Learning (DL) By exposing multi-layered neural networks to a large amount of data, a software can train itself to perform tasks, such as speech and image recognition.	Complex statistical techniques that allow machines to improve their performance over time are included in this subset of AI. This category includes deep learning.	Any approach that uses logic, if-then rules, decision trees and machine learning to enable computers to mimic human intelligence

In the past few years, the rapid rates of autonomous vehicle consumption around the world have been noticed. Along with the arrival of new technologies, AI systems reach the market and are employed by enterprises and organizations at a higher frequency compared to previous times. Traffic flow predictability is a key point for autonomous vehicles they have a roadmap and make well-adaptive decisions (to move left or right, to drive straight, to change lanes, to stop or to accelerate) within the existing context. According to the available study,

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Search Methodology

The steps involved in doing a structural literature review (SLR) are shown in the figure below, beginning with problem identification. In this stage, the issue statement is assessed to ascertain the primary goal of the systematic review and the study's focus. This stage is crucial since it is necessary to understand each case study problem statement to determine its significance for discussion and how it may improve subsequent research. Once the problem has been identified, the following step is to formulate and develop research questions. This study concentrates on the research questions to obtain answers and highlight important discoveries.

Since researchers have to examine and evaluate the current models, methods, and techniques related to the research field of focus, the literature search and analysis step might be difficult.



This study uses four databases to find data and tools focusing on the use of machine learning (ML) in computer vision (CV) for analysis and prediction, specifically in traffic forecasting.

Opportunities, gaps, methods, and evaluation

After a thorough review of this document, key points, inconsistencies, authors' methods, patterns or methods, data, authors' solutions to their procedures, and their work are not returned. The analysis results consist of three parts: social media-based machine learning techniques, hybrid or integrated machine learning methods, and machine learning strategies.

Methods, obstacles, gaps, and assessment techniques for trafficflow forecasting

The goal of all writing and research is to address a particular subject or identify and address gaps, which are problems that need to be filled. Gaps are places where the discussion can be better understood by going deeper into them or making improvements. This work fills in the gaps found in previous studies that employed machine



learning approaches to answer the above-posed RQ1 for traffic flow projections based on SLR results. The following sections also include the goals of each study, the techniques used, the difficulties encountered, the evaluation strategy, and the findings.



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The assessment of SLR for the machine and the deep learning-based traffic forecasting commonly applied DL and ML methods

This section addresses Research Question 2 (RQ2), which lists machine learning (ML) and deep learning (DL) methods identified through a careful analysis of selected data. Based on the conclusions from the literature study, a range of machine learning techniques and algorithms, such as SVM, CNN, LSTM, XG Boost, and others, have been employed for traffic flow prediction. From 2016 to 2021, the most popular neural network methods for predicting traffic congestion were CNN and LSTM [41, 22, 27, 35, 46, 47, 51, 53, 55, 63]. Additionally, many

combinations and hybrids of these algorithms have been found [26, 34–36, 41, 43–46, 53, 54, 56, 57, 62, 64, 65], where CNN and LSTM are used sequentially. Physical and spatial information. The findings suggest that CNN and LSTM are two major machine-learning algorithms that need further research. Nevertheless, it would be incorrect to exclude the other machine learning techniques that perform similarly, such as Random Forest, XG Boost, ANN, and GCN.

In contrast to baseline model

Every research that was looked at compared its ideas and proposed models with other baseline models that were currently in use. Regarding RQ3, which evaluates the viability of the models that are recommended. It was found that most of the research that was looked at had produced significant results using the approaches they had recommended. We accomplished this by comparing our experimental setup assessments to the most recent baseline models. Numerous research using these models had favorable results, which others looked into and enhanced. Baseline models that are often contrasted include the following examples:

Historical average (HA) time series models use historical demand values for a particular region over time to forecast demand.

• Mohit Singh Chandel (MSC)

This time-series model for traffic forecasting combines the moving average with an autoregressive component.

• Kritika Ola Choudhary (KOC)

The model uses a linear support vector machine (SVM) to solve the regression problem.

These baseline models and the suggested technique are frequently contrasted to see if the latter can function as well or better than the former.

Final thoughts, restrictions, and upcoming projects

Through the use of ML and DL techniques, this study enhances the field of traffic flow forecast research. It is an invaluable resource for further studies and compositions.

Reference for further scholars, practitioners, and academics. This work offers a methodical and thorough analysis of current studies that used ML and DL. strategies and algorithms for forecasting traffic flow. Following a rigorous screening procedure, 39 publications in total were chosen for in-depth analysis. This article covers inconsistencies in traffic estimates due to insufficient processing power, technology, and algorithms.

Moreover, a scarcity of high-quality data exists for data training. The use of comparable city traffic flow data led to the use of ambiguous data contents for network model training.

These restrictions are impeding the development of deep learning and machine learning techniques for traffic flow prediction. Deep learning fails to apply dynamically learned spatial and temporal linkages, contributing to the gap, due to the relationship between traffic patterns in certain segments and their main traffic areas or interests. Additionally, computingpower and dispersed storage are deficient, which limits the time series available for IoT traffic forecasting. Future studies need to address this issue. Researchers have proposed and demonstrated many models, methods, and techniques in order to find the most accurate traffic flow prediction. Utilizing machine learning methods, including CNN, LSTM, and others, to predict traffic flow has enhanced the effectiveness of proposed strategies such as C-LSTM, STRCN, MTN, and so on. Comparing this strategy to existing benchmarks such as HA and ARIMA provides further evidence for this. These are the suggested models since the findingsof the comparison showed improved and favorable results.

One of the study's many shortcomings is that it only looks at data. Additional papers and studies that are archived in other archives should be included in future studies. Additionally, the scope of this study is restricted to analyzing the methods and algorithms mentioned in the research paper. Other talents could exist that aren't included in this study.

To generate information-wide texts for the following domains—as mentioned in the article exploring various debates—further experiments utilizing deep learning approaches (CNN and LSTM) can be carried out utilizing traffic data in various urban regions. As a result, machine learning and deep learning will be used to further enhance the accuracy of traffic projections in metropolitan areas. Researchers will have significant challenges, though, in getting the necessary large-scale data from local governments in a coordinated manner. Another difficulty will be complying with rules and regulations about the exchange of traffic data between local authorities.

Cyber security risks might also result from the networked IoT environment that is established during the installation of the device to collect traffic data for ML and DL training. It is necessary to create a framework to address issues with cyber security in smart cities. Future studies will have plenty of room to work with this. In our upcoming work, we'll be working to improve the IoT monitoring framework for security in smart cities. Our main concern will be the installation of "Intrusion Detection Systems" in nearby cities. This will make it easier for ITS technology to progress in smart cities. An intelligent transport management system that is more effective and efficient will be created by the development of ITS.

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