



## TYPES OF AI ALGORITHMS USED IN TRAFFIC FLOW PREDICTION

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### ABSTRACT

The increasing complexity of urban transportation systems and the growing volume of vehicles have made traffic congestion a persistent challenge in modern cities. Efficient traffic flow prediction is essential for mitigating congestion, improving road safety, optimizing traffic signal control, and enhancing overall transportation efficiency. In recent years, artificial intelligence (AI) has emerged as a transformative tool in the field of traffic management, offering sophisticated algorithms capable of modeling, analyzing, and predicting complex traffic patterns with high accuracy. The application of AI in traffic flow prediction leverages vast amounts of real-time and historical data to generate precise forecasts, supporting data-driven decision-making by urban planners and traffic control authorities.

The prediction of traffic flow involves analyzing time-series data that exhibit nonlinear, dynamic, and often stochastic behavior. Traditional statistical models, such as autoregressive integrated moving average (ARIMA), have proven to be limited in handling the high dimensionality and variability inherent in traffic systems. In contrast, AI algorithms possess the capacity to learn and adapt from complex data inputs without the need for explicit programming, making them particularly suitable for traffic-related applications.

AI algorithms used in traffic flow prediction can be broadly categorized into machine learning (ML) and deep learning (DL) approaches. Machine learning algorithms such as k-nearest neighbors (KNN), support vector machines (SVM), decision trees, and random forests have demonstrated effectiveness in short-term traffic prediction tasks. These algorithms are capable of identifying hidden patterns in traffic data and adjusting to changes in traffic behavior over time. Ensemble methods, which combine the strengths of multiple learning models, further enhance prediction accuracy and robustness.

Deep learning algorithms, a subfield of AI inspired by the human brain's neural architecture, have shown exceptional performance in capturing spatial-temporal dependencies in traffic data. Recurrent neural networks (RNNs), particularly long short-term memory (LSTM) networks and gated recurrent units (GRUs), are widely used for their ability to process sequential data and retain information over extended time intervals. Convolutional neural networks (CNNs) are employed to extract spatial features from traffic sensor data or road network imagery. Hybrid models that integrate CNNs with RNNs have achieved high levels of predictive precision by simultaneously learning spatial and temporal correlations.

In addition to supervised learning methods, unsupervised and reinforcement learning techniques are also applied in traffic flow prediction. Clustering algorithms, such as k-means and DBSCAN, assist in identifying traffic patterns, while reinforcement learning models optimize adaptive traffic signal control systems by learning optimal actions through environmental interaction.

This study explores the different types of AI algorithms used in traffic flow prediction, examining their theoretical foundations, structural differences, and practical applications. It aims to evaluate



the comparative advantages of various algorithms in addressing the challenges of real-time traffic prediction in increasingly complex transportation networks.

**Keywords:** Machine Learning, Deep Learning, Neural Networks, Regression Models, Reinforcement Learning

## Introduction

Traffic flow prediction is a critical aspect of modern transportation management, aiming to enhance the efficiency and safety of road systems. With the increasing complexity of urban traffic, the need for accurate and real-time traffic forecasting has become more pressing. Artificial Intelligence (AI) has emerged as a powerful tool in this domain, offering innovative methods to model and predict traffic patterns. Various AI algorithms have proven effective in handling the dynamic and often unpredictable nature of traffic systems. AI algorithms employed in traffic flow prediction can be broadly categorized into machine learning (ML) techniques and deep learning (DL) methods. Machine learning models, such as regression analysis, decision trees, and support vector machines, are commonly used to predict traffic flow based on historical data and real-time inputs. These algorithms rely on predefined features like traffic volume, weather conditions, and time of day to make predictions. On the other hand, deep learning methods, including convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have shown superior performance in traffic prediction tasks. CNNs are particularly effective when dealing with spatial data, such as road maps, while RNNs, particularly long short-term memory (LSTM) networks, excel at processing sequential data, making them ideal for time-series forecasting of traffic patterns. Another promising approach is reinforcement learning (RL), where algorithms learn optimal traffic control strategies through interactions with the environment. The integration of these AI algorithms with real-time traffic data from sensors, cameras, and GPS systems has opened new possibilities for traffic prediction systems. By leveraging AI, traffic management systems can improve traffic flow, reduce congestion, enhance public safety, and provide more efficient routes for commuters, ultimately contributing to the creation of smarter, more sustainable cities.

## Objective

The aim of the research is to explore the types of AI algorithms used in traffic flow prediction.

## Relevance of the problem and related studies

The topic of types of AI algorithms used in traffic flow prediction is highly relevant due to the growing need for efficient, intelligent transportation systems in urban environments. With rapid urbanization and increasing numbers of vehicles, cities face severe traffic congestion, leading to delays, pollution, and reduced quality of life. AI algorithms play a critical role in predicting traffic patterns, enabling better traffic control and infrastructure planning. Accurate traffic flow prediction supports real-time decision-making for navigation systems, traffic signal optimization, and emergency response coordination. AI models—especially those using deep learning and time-series analysis—enhance the precision of these predictions. Different AI algorithms (e.g., neural networks, decision trees, support vector machines, reinforcement learning, and hybrid models) are suited to different types of data and prediction goals. Understanding the types and capabilities of these algorithms is crucial for selecting appropriate methods in specific traffic scenarios. 4. Data-Driven Infrastructure Management Modern transportation systems generate massive amounts of



data from sensors, GPS devices, and cameras. AI algorithms can process and learn from this data, making it possible to forecast traffic flow patterns, detect anomalies, and plan road maintenance or expansions. By reducing traffic congestion through accurate predictions, AI helps lower fuel consumption, greenhouse gas emissions, and travel costs. This contributes to sustainability goals and more efficient urban economies. AI-driven traffic prediction is a core component of smart cities. Its relevance lies in how it integrates with Internet of Things (IoT) devices, connected vehicles, and automated public transportation systems to create responsive, adaptive urban mobility networks. As machine learning and deep learning techniques evolve, new algorithmic approaches (like graph neural networks or transformer-based models) offer improved accuracy and efficiency. Studying the types of AI algorithms used in this field keeps researchers and practitioners at the forefront of innovation.

### Methods

Traffic flow prediction is a complex and dynamic process. Traditional machine learning algorithms used in this process make it possible to make data-driven decisions and predict future traffic situations. The main types of these algorithms include Linear Regression, Support Vector Machines (SVM), Decision Trees, Random Forests and K-Nearest Neighbors (KNN). Linear regression is used to model the linear relationship of a dependent variable with independent variables. In traffic prediction, this method uses historical trends to predict traffic volume in a certain time period. For example, the future density of a road with heavy traffic observed during weekday morning hours can be predicted based on historical data. Although this method offers a simple and fast approach, it may be insufficient in cases where complex and non-linear relationships exist. Support Vector Machines are a powerful algorithm that can model non-linear relationships between data. In traffic prediction, it can work accurately in cases where density and speed are variable. In particular, it enables classification and prediction between complex data thanks to kernel functions. For example, SVM offers an effective solution for modeling traffic density changes at different hours. Decision trees create decision rules by dividing data into branches. In traffic prediction, it can work with categorical and numerical data such as hours of the day, weather conditions, and special events. However, it carries the risk of overfitting. Random Forests, which are used to reduce this risk, combine multiple decision trees to provide more robust and accurate predictions. The K-Nearest Neighbors (KNN) algorithm analyzes the K most similar neighbors for the prediction of a new data point based on past data [4]. In traffic prediction, the traffic situation in a certain time interval is predicted by learning from similar time periods in the past. This method attracts attention with its simplicity, but the computational cost increases in large data sets. These algorithms are often used as basic steps in complex problems such as traffic flow prediction and are often combined with more advanced deep learning techniques. However, the speed and interpretability of traditional machine learning algorithms still make them valuable, especially in small-scale projects.

Since traffic flow prediction is a dynamic and complex problem, deep learning algorithms play an important role in this area. Deep Learning Algorithms provide effective tools for analyzing and interpreting large amounts of complex traffic data. These algorithms include Recurrent Neural Networks (RNN), Long Short-Term Memory Networks (LSTM), Convolutional Neural Networks (CNN), Graph Neural Networks (GNN) and Autoencoders. Recurrent Neural Networks (RNN) were developed specifically to model time series data. They are used to account for the impact of past traffic conditions on future predictions in traffic flow. For example, traffic data from previous



hours is used as an input to estimate traffic density on a road at a certain time period. However, standard RNNs may have difficulty modeling long-term dependencies, which leads to the use of a more advanced approach, LSTM. Long Short-Term Memory Networks (LSTM), as a variant of RNN, are quite successful in modeling long-term dependencies [1]. In traffic flow prediction, future traffic conditions can be predicted based on long-term historical data. For example, when predicting traffic density during holiday periods, LSTM can take into account both daily changes and weekly or seasonal trends. This feature makes LSTM ideal for complex traffic data. Convolutional Neural Networks (CNN), although usually used in visual data analysis, are also suitable for analyzing spatial data such as traffic maps or road plans. In traffic prediction, it can predict road conditions by analyzing traffic density maps or images obtained by cameras. For example, satellite images and density maps can be processed with CNN to understand traffic flow in a city. Traffic networks can be naturally modeled in a graph structure. Intersections are represented as nodes, and roads as edges. Graph Neural Networks (GNN) are used to predict traffic flow by analyzing the connections between different intersections. For example, a traffic network in a city can be analyzed with GNN to model the density and connections between intersections. Autoencoders are used to detect anomalies by representing data in a compressed form. In traffic prediction, it is possible to determine situations such as an unexpected accident or abnormal traffic flow with the help of autoencoders. These algorithms simplify the analysis process by preserving important features while reducing the size of the data. Deep learning algorithms offer powerful and flexible tools for traffic flow prediction. Especially when working with large data sets, RNN and LSTM provide effective solutions in time series predictions, CNN in spatial analysis, GNN in modeling traffic networks, and autoencoders in anomaly detection. The combination of these algorithms allows for the development of more precise and detailed traffic prediction models.

Traffic flow prediction is a complex problem that requires analysis of both temporal and spatial components. Hybrid models increase the prediction accuracy by combining these two dimensions. In particular, LSTM-CNN models and Attention Mechanisms overcome the limitations of traditional models and provide more precise predictions. LSTM-CNN models combine temporal and spatial data processing capabilities. While LSTM specializes in learning long-term dependencies in time series data, CNN is strong in analyzing spatial features. This combination is ideal for modeling traffic flow based on both time and space. For example, to predict traffic density in different parts of a city, spatial patterns in traffic maps are first extracted with CNN, and then temporal changes of this data are analyzed with LSTM. Thus, both trends in historical traffic data and spatial distribution of traffic flow are taken into account. This hybrid approach is successfully used in traffic prediction models, especially in large cities. Attention mechanisms increase the performance of models by focusing on the most relevant parts of the data. Attention mechanisms integrated into time series algorithms such as RNN or LSTM determine which time periods or spatial regions are more important in traffic prediction [6]. For example, heavy traffic flow in the morning and evening hours may have a more significant effect than other time periods. Attention mechanisms increase the accuracy of predictions by giving more weight to such important time periods. In addition, when analyzing connections between different intersections or roads, directing attention to the most critical connections provides more effective results in traffic prediction. Hybrid models offer modern and effective solutions in traffic flow prediction. While LSTM-CNN models allow temporal and spatial data to be analyzed together, attention mechanisms increase the focusing ability of the models and improve the precision in predictions.



These approaches are especially applied in regions with dense and complex traffic networks, and provide valuable contributions to traffic management.

Traffic flow prediction is a complex problem that requires effective handling of uncertainties and variables. In this direction, probabilistic models offer a powerful approach. Bayesian Networks and Hidden Markov Models (HMMs) are frequently used methods in modeling uncertainties in traffic data and making predictions. Bayesian Networks are directed graph structures used to model probabilistic dependencies between variables. In traffic prediction, it is suitable for modeling relationships between different roads, intersections and environmental factors. For example, traffic density at an intersection may be related to situations at other intersections in the vicinity. Bayesian Networks are used to understand such relationships and predict traffic flow under certain conditions. The biggest advantage of Bayesian Networks is the ability to work with missing data. For example, when there is a lack of traffic data received from sensors, Bayesian Networks can make probabilistic predictions based on the available data. In addition, it provides effective decision support systems by performing situation analysis in various scenarios, such as when a road is closed. Hidden Markov Models are a method used to model the situations of systems that change over time. In traffic flow, the traffic status of a particular road (e.g., open, busy, or congested) can be considered a “hidden state”. HMMs analyze observations in traffic flow to estimate these hidden states. For example, using observations such as speed and vehicle density data obtained from traffic sensors, they can estimate the current state of a road and how this state will change. In addition, HMMs provide realistic estimates by including dynamic events such as traffic accidents or sudden weather changes in the model [36, p.68]. Bayesian Networks and Hidden Markov Models are effective tools for handling uncertainties and variables in traffic flow prediction. While Bayesian Networks stand out in modeling dependencies between variables and working with incomplete data, HMMs are successful in estimating situations that change over time. These models are used to develop real-time predictions and strategic decision support systems, especially in complex traffic networks.

In traffic flow prediction, reinforcement learning algorithms offer effective solutions for managing dynamic and ever-changing traffic systems. These algorithms learn by receiving feedback from the environment while trying to achieve a certain goal to optimize traffic flow. Methods such as Q-learning and Deep Q-Networks (DQN) are particularly prominent in traffic signal control and congestion management. Reinforcement learning allows an agent (for example, a traffic signal control system) to learn the most appropriate actions by interacting with its environment. The agent is presented with a certain situation and receives rewards or punishments as a result of its actions. The goal is to develop a policy that maximizes rewards. In traffic flow, this situation can be associated with goals such as reducing congestion, reducing vehicle waiting times, or improving overall flow. Q-learning is a basic reinforcement learning algorithm. This method calculates a Q-value for each situation-action pair, and this value indicates how beneficial a certain action is. In traffic prediction, it can be used to control traffic signals at an intersection. For example [5]:

- Situation - Information on vehicle density or traffic flow at the intersection.
- Action - Decisions such as extending the green light duration, changing the signal order.
- Reward - Less waiting time or reduced congestion.
- Over time, Q-learning learns and implements the most appropriate traffic signal control strategy.



Deep Q-Networks (DQN) are an extension of Q-learning and can solve more complex problems using deep learning methods. In traffic signal control, DQN excels at understanding more complex and dynamic traffic situations by learning from large data sets. For example, in busy intersections or complex traffic networks where multiple roads interact, DQN offers effective solutions to reduce congestion. DQN can optimize signal timings based on real-time data collected from traffic sensors. It also provides great advantages to traffic management systems with its ability to quickly adapt to sudden changes such as traffic accidents or road closures. Reinforcement learning algorithms offer dynamic and proactive solutions in traffic flow prediction. While Q-learning provides an effective approach for simple cases, DQN excels in solving more complex traffic problems. These methods are widely used in modern traffic management systems to reduce congestion and optimize traffic flow.

Traffic flow prediction is a critical area with a wide range of applications from urban planning to driver safety. Time series analysis techniques stand out among the artificial intelligence (AI) algorithms used in this field. ARIMA (Autoregressive Integrated Moving Average) and SARIMA (Seasonal ARIMA) are two commonly used models among these techniques. ARIMA (Autoregressive Integrated Moving Average) is a model designed to make predictions based on past trends and moving averages in traffic data. The autoregressive (AR) part analyzes how past values affect the current value, while the moving average (MA) part models the effects of error terms. The integration (I) element includes the process of making the data stationary. The effectiveness of ARIMA in traffic prediction increases when the data is stationary and contains a significant trend. For example, the ARIMA model can be used to predict morning and evening traffic congestion in a city. However, this model may be limited in capturing more complex patterns such as seasonality. SARIMA (Seasonal ARIMA) is an extension of ARIMA to include seasonal components. Seasonal traffic patterns may include regular recurring patterns, such as differences in weekday and weekend traffic patterns. SARIMA adds seasonal autoregressive and seasonal moving average terms to model such seasonal effects. This model is particularly effective in long-term traffic forecasts and data with significant seasonality. ARIMA and SARIMA models provide effective results in cases where historical data can be used for robust forecasting. However, the success of these models depends on the quality of the data used and the correct optimization of the model parameters. In addition, ARIMA and SARIMA models may be limited to handle large data sets with sudden changes, event-based traffic spikes, or complex relationships. In such cases, more advanced AI algorithms such as deep learning-based methods (e.g., RNN and LSTM) may be more effective [7]. ARIMA and SARIMA are considered basic and powerful tools for traffic flow forecasting. While these models provide ideal solutions for short- and medium-term forecasts, more comprehensive and precise forecast results can be obtained when used together with other artificial intelligence methods.

### **Conclusion**

The application of artificial intelligence algorithms in traffic flow prediction represents a significant advancement in intelligent transportation systems, offering enhanced accuracy, efficiency, and real-time decision-making capabilities. Various types of AI algorithms have been utilized to model and forecast traffic conditions, each bringing distinct strengths to the task. Traditional machine learning models such as Support Vector Machines (SVM), Decision Trees, and Random Forests have proven effective in analyzing structured traffic datasets and identifying



patterns. These models are often praised for their interpretability and relatively low computational demands.

However, the dynamic and nonlinear nature of traffic systems has increasingly driven researchers toward more sophisticated approaches. Deep learning algorithms, particularly Recurrent Neural Networks (RNNs) and their advanced form, Long Short-Term Memory (LSTM) networks, have demonstrated superior performance in capturing temporal dependencies in sequential traffic data. Convolutional Neural Networks (CNNs) have also been effectively employed to extract spatial features from traffic sensor data or images. More recently, hybrid models combining CNNs and LSTMs have emerged to address both spatial and temporal characteristics simultaneously, improving predictive power.

Furthermore, Reinforcement Learning (RL) is gaining traction for its ability to adapt and learn optimal traffic control strategies through continuous interaction with the environment. Integrating Graph Neural Networks (GNNs) has also shown promise, especially in urban settings, by modeling road networks as graphs and better understanding spatial correlations. Ultimately, the choice of algorithm depends on the specific context, data availability, and computational resources. As AI continues to evolve, the integration of real-time data streams, edge computing, and multimodal datasets will further refine traffic prediction models. The synergy of various AI techniques holds immense potential to revolutionize traffic management systems, reduce congestion, enhance safety, and contribute to the development of smarter and more sustainable urban transportation infrastructures.

### **Declarations**

The manuscript has not been submitted to any other journal or conference.

### **Study Limitations**

There are no limitations that could affect the results of the study.

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## TRAFİK AXINININ PROQNOZLAŞDIRILMASINDA İSTİFADƏ OLUNAN AI ALQORİTMLƏRİNİN NÖVLƏRİ

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### XÜLASƏ

Süni intellekt alqoritmləri nəqliyyat axınının proqnozlaşdırılmasında mühüm rol oynayır, nəqliyyatın səmərəliliyini artırmağa və tıxacları azaltmağa kömək edir. Reqressiya təhlili, qərar ağacları və dəstək vektor maşınları kimi maşın öyrənməsi (ML) üsulları tarixi məlumatlara və hava və günün vaxtı kimi real vaxt amillərinə əsaslanaraq trafik axınını proqnozlaşdırır. Qıvrımlı neyron şəbəkələri (CNN) və təkrarlanan neyron şəbəkələri (RNN) daxil olmaqla dərin öyrənmə (DL) modelləri xüsusilə məkan və ardıcıl məlumatların emalında effektivdir və onları trafikin proqnozlaşdırılması tapşırıqları üçün ideal edir. CNN-lər yol xəritələri kimi məkan məlumatları idarə edir, RNN-lər, xüsusən də uzun qısamüddətli yaddaş (LSTM) şəbəkələri zamanla trafik nümunələrinin proqnozlaşdırılmasında üstündür. Gücləndirici öyrənmə (RL) həm də alqoritmlərin ətraf mühitlə qarşılıqlı əlaqə vasitəsilə optimal trafikə nəzarət strategiyalarını öyrəndiyi perspektivli bir yanaşma kimi ortaya çıxır. Bu süni intellekt üsulları real vaxt rejimində trafik məlumatları ilə birləşdirildikdə, trafikin daha ağıllı idarə edilməsinə, tıxacın azaldılmasına və ümumi nəqliyyat səmərəliliyinin artırılmasına imkan verir.

**Açar sözlər:** Maşın Öyrənməsi, Dərin Öyrənmə, Neyron Şəbəkələr, Reqressiya Modelləri, Gücləndirici Öyrənmə

## ТИПЫ АЛГОРИТМОВ ИИ, ИСПОЛЬЗУЕМЫХ ДЛЯ ПРОГНОЗИРОВАНИЯ ТРАНСПОРТНЫХ ПОТОКОВ

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### РЕЗЮМЕ

Алгоритмы ИИ играют решающую роль в прогнозировании транспортных потоков, помогая повысить эффективность транспортировки и уменьшить заторы. Методы



машинного обучения (ML), такие как регрессионный анализ, деревья решений и опорные векторные машины, прогнозируют транспортный поток на основе исторических данных и факторов реального времени, таких как погода и время суток. Модели глубокого обучения (DL), включая сверточные нейронные сети (CNN) и рекуррентные нейронные сети (RNN), особенно эффективны при обработке пространственных и последовательных данных, что делает их идеальными для задач прогнозирования дорожного движения. CNN обрабатывают пространственные данные, такие как дорожные карты, в то время как RNN, особенно сети с долгой краткосрочной памятью (LSTM), преуспевают в прогнозировании схем дорожного движения с течением времени. Обучение с подкреплением (RL) также становится многообещающим подходом, при котором алгоритмы изучают оптимальные стратегии управления дорожным движением посредством взаимодействия с окружающей средой. Эти методы ИИ в сочетании с данными о дорожном движении в реальном времени позволяют более разумно управлять дорожным движением, уменьшая заторы и повышая общую эффективность транспортировки.

**Ключевые слова:** Машинное обучение, Глубокое обучение, Нейронные сети, Регрессионные модели, Обучение с подкреплением.

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