Journal of Transportation Engineering and its Applications
Volume 11, Issue 1, January-April 2026
ISSN: 3107-4499 (Online)

AI & Machine Learning for Traffic Prediction and Management

Tushar Thakur[1], Panjak Yadav[2], Abhinav Parasad[3]
Associate Professor, Students
Department of Civil Engineering
Green Valley Institute of Technology, Uttarakhand, India
Email: *Tusharthakur293@gmail.com[1], pankajy200@rediffmail.com[2], abhinavprasadt0@yahoo.com[3]*
DOI: *https//doi.org/10.5281/zenodo.19216254*

ABSTRACT

Rapid urbanization and growth of vehicles have created serious traffic congestion problems in cities across the world. Traditional traffic management methods are no longer sufficient to handle the dynamic and complex nature of modern transportation systems. Artificial Intelligence (AI) and Machine Learning (ML) techniques offer powerful tools for traffic prediction, congestion control, and real-time traffic management. These technologies can analyze large amounts of traffic data collected from sensors, GPS devices, cameras, and mobile applications to predict traffic flow and optimize transportation networks. This paper presents a detailed review of AI and ML applications in traffic prediction and management. Various algorithms such as Artificial Neural Networks, Support Vector Machines, Random Forest, Deep Learning models like LSTM and CNN, and Reinforcement Learning are discussed. The study also highlights data sources, system architecture, challenges, and future research directions. Tables are provided to compare different models and their performance. The paper aims to give a comprehensive understanding of how intelligent systems can improve urban mobility and reduce traffic related issues.

KEYWORDS: *Traffic prediction, Machine learning, Artificial intelligence, Intelligent transportation systems, Deep learning, Traffic management.*

INTRODUCTION

Traffic congestion is a major problem in both developed and developing countries. Increase in population, unplanned urban growth, and rise in number of vehicles have made traffic management very difficult. Long traffic jams lead to fuel wastage, air pollution, time delay and economic loss. Traditional traffic control systems based on fixed signals and manual monitoring are not capable to handle real-time traffic situations.

With advancement in Artificial Intelligence and Machine Learning, traffic systems can be made intelligent. AI models can learn patterns from historical and real-time data to predict traffic conditions. Machine learning helps to make decisions like signal timing adjustment, route diversion, and congestion control automatically.

AI-based traffic management is part of Intelligent Transportation Systems (ITS), which integrate sensors, cameras, GPS, communication networks, and computing systems. This paper reviews different AI and ML approaches used for traffic prediction and management.

NEED FOR AI IN TRAFFIC MANAGEMENT

Traditional traffic control systems were designed at a time when vehicle density was much lower and urban road networks were less complex. These systems generally operate on **static rules**, fixed-time signal plans, and manual supervision. In today's cities, where traffic conditions change every minute due to accidents, road works, weather variations, events, and peak-hour surges, such rule-based systems fail to respond efficiently. As a result, congestion, delays, and unsafe road conditions are frequently observed.

Limitations of Conventional Traffic Systems

1. **Fixed Signal Timing Irrespective of Traffic Load**

   Most intersections operate on pre-set signal timings based on historical averages rather than current traffic demand. Even when one lane is empty and another is heavily congested, the signal duration remains the same. This leads to unnecessary waiting time, long vehicle queues, and increased fuel consumption.

2. **No Real-Time Congestion Monitoring**

   Traditional systems lack integration with live data sources. Traffic police or control rooms

often rely on CCTV footage or public complaints to detect congestion, which is reactive rather than proactive. By the time congestion is noticed, it has already become severe.

3. **Poor Route Planning and Diversion Strategies**

   Drivers usually choose routes based on habit rather than current traffic status. Without intelligent guidance systems, vehicles keep entering already congested roads while alternative routes remain underutilized. Manual diversion plans are slow and inefficient.

4. **Delay in Emergency Response**

   Ambulances, fire trucks, and police vehicles often get stuck in traffic because signal systems do not prioritize emergency vehicles. Lack of coordination between traffic signals and emergency services increases response time and may cost lives.

5. **Lack of Prediction Capability**

   Conventional traffic management is reactive. It addresses congestion only after it occurs. There is no mechanism to forecast traffic build-up during festivals, bad weather, peak office hours, or special events.

How AI and ML Address These Issues

AI and ML introduce **intelligence, adaptability, and predictive capability** into traffic systems by learning from both historical and real-time data.

1. **Learning Traffic Patterns from Historical Data**

   Machine learning models analyze years of traffic data to understand daily, weekly, and seasonal patterns. For example, traffic on Monday mornings or during rainy evenings follows a predictable pattern. AI systems learn these trends and prepare the system accordingly.

2. **Predicting Congestion Before It Happens**

   Using time-series models like LSTM and GRU, AI can forecast traffic density for the next 15–60 minutes. Authorities can take preventive actions such as route diversion, signal adjustment, or public alerts before congestion builds up.

3. **Dynamic Signal Timing Adjustment**

   Reinforcement Learning and adaptive algorithms adjust signal durations based on real-time

vehicle count and queue length at intersections. If one road has more vehicles, green time is automatically extended, reducing waiting time and improving flow.

4. **Intelligent Route Guidance**
   AI-powered navigation systems integrated with GPS and mobile apps suggest alternate routes to drivers based on live traffic conditions. This distributes traffic more evenly across the network and reduces pressure on main roads.

5. **Effective Peak Hour Traffic Handling**
   During office hours, school timings, or public events, AI systems anticipate higher traffic load and modify traffic control strategies in advance. This ensures smoother flow during peak periods.

6. **Priority for Emergency Vehicles**
   Computer vision and sensor data can detect approaching emergency vehicles. AI-enabled signals can automatically turn green along the route, creating a "green corridor" for faster emergency response.

7. **Integration with Smart City Infrastructure**
   AI traffic systems can communicate with smart parking, public transport scheduling, weather monitoring, and surveillance systems, creating a holistic intelligent transportation network.

DATA SOURCES FOR TRAFFIC PREDICTION

Accurate traffic prediction using AI and Machine Learning mainly depends on the **quality, quantity, and variety of data** collected from the transportation network. Traffic is a dynamic phenomenon influenced by many factors such as vehicle volume, road condition, weather, human behavior, accidents, and special events. Therefore, AI models require **multi-source and real-time data** to understand these complex patterns.

Modern Intelligent Transportation Systems (ITS) collect traffic data from physical sensors, digital devices, communication networks, and even public inputs. These diverse data sources help in building reliable prediction models and improving traffic management decisions.

Road Embedded Sensors (Loop Detectors)

Loop detectors are one of the oldest and most reliable traffic data sources. These sensors are embedded beneath the road surface and detect vehicles passing over them using electro--magnetic signals.

- Measure vehicle count, speed, and occupancy
- Provide continuous and accurate data
- Useful for intersection and highway monitoring
- Limited to specific locations where installed

This data is very useful for time-series traffic flow prediction models like ANN and LSTM.

CCTV Cameras and Video Surveillance

Cameras installed at intersections and highways provide visual data. With the help of Computer Vision and CNN models, traffic parameters can be extracted.

- Vehicle counting and classification (car, bus, truck, bike)
- Estimation of traffic density and queue length
- Detection of accidents and rule violations
- Monitoring large areas in real time

Video data is rich but requires high computational power for processing.

GPS and Floating Car Data (FCD)

GPS devices in vehicles and smartphones generate location-based data known as Floating Car Data.

- Real-time vehicle position and speed
- Travel time estimation between two points
- Route choice behavior of drivers
- Identification of congested road segments

Navigation apps like Google Maps and Waze use this data for live traffic updates and route suggestions.

Mobile Applications and Crowd-Sourced Data

Users share traffic information through mobile apps either knowingly or unknowingly.

- Reports of accidents, roadblocks, construction work
- Sudden congestion alerts
- User feedback on road conditions

This data is very dynamic and helps AI systems to react quickly to unexpected situations.

Social Media and Public Feeds

Platforms like Twitter and local alert systems often report traffic incidents before official channels.

- Early detection of accidents or protests
- Information about public events affecting traffic
- Sentiment analysis for traffic conditions

Natural Language Processing (NLP) techniques can extract useful traffic insights from such text data.

Weather Sensors and Meteorological Data

Weather has significant impact on traffic speed and safety.

- Rain, fog, snow reduce visibility and speed
- Temperature affects road conditions
- Storm warnings help in traffic planning

AI models combine weather data with traffic data to improve prediction accuracy.

Drones and Aerial Monitoring

Drones are increasingly used for monitoring traffic in large urban areas and during events.

- Bird's eye view of traffic congestion
- Useful where camera installation is difficult
- Temporary monitoring during festivals or road works

Smart Infrastructure and IoT Devices

Smart traffic lights, connected vehicles, RFID tags, and IoT sensors continuously communicate data.

- Vehicle-to-Infrastructure (V2I) communication

- Real-time signal status and vehicle flow
- Automated data sharing across network

This enables faster decision making and adaptive control.

Table 1: Traffic Data Sources

Data Source	Description	Example Use
Loop detectors	Embedded sensors in roads	Vehicle count, speed
CCTV cameras	Video feeds for vehicle tracking	Traffic density
GPS devices	Location data from vehicles	Route tracking
Mobile applications	Crowd-sourced traffic information	Congestion reporting
Social media	Incident and event reporting	Accident detection
Weather sensors	Climate data	Weather impact
Drones	Aerial traffic monitoring	Large area coverage

These data are processed using AI models for prediction and decision making.

MACHINE LEARNING TECHNIQUES FOR TRAFFIC PREDICTION

Traffic prediction is essentially a **time-series forecasting and pattern recognition** problem where the goal is to estimate future traffic parameters such as flow, speed, density, and travel time based on past observations. Machine Learning (ML) techniques are well suited for this task because they can capture **non-linear relationships**, handle noisy data, and learn complex patterns from historical traffic records.

Different ML models have been applied depending on the nature of data, size of dataset, and prediction requirement. Some models are suitable for small datasets and quick predictions, while others perform better with large historical datasets.

Artificial Neural Networks (ANN)

Artificial Neural Networks are inspired from the working of the human brain. ANN consists of input, hidden, and output layers where neurons are interconnected with weights. During training, these weights are adjusted to minimize prediction error.

In traffic prediction, ANN takes inputs such as:

- Historical traffic flow
- Vehicle speed
- Road occupancy
- Weather data
- Time of the day and day of the week

ANN is very effective because traffic parameters do not follow linear relationships. For example, small increase in vehicle volume may cause sudden congestion. ANN can learn such complex behaviors.

Advantages of ANN in traffic prediction:

- Handles non-linear and complex relationships
- Good performance with large historical datasets
- Can be trained for multi-variable prediction (speed, flow, density)
- Suitable for short-term traffic forecasting

Limitations:

- Requires large training data
- Training process can be time consuming
- Prone to overfitting if not properly tuned

ANN is widely used for **short-term traffic flow prediction at intersections and highways**.

Support Vector Machine (SVM)

Support Vector Machine is a supervised learning algorithm used for both classification and regression. SVM works by finding an optimal hyperplane that separates data points with maximum margin.

In traffic systems, SVM is used to:

- Classify traffic conditions (free flow, moderate, congested)
- Predict travel time and traffic speed
- Detect abnormal traffic patterns

SVM performs well when dataset is small or medium in size and when clear patterns exist in data.

Advantages of SVM:

- Effective for small datasets
- High accuracy in pattern classification
- Less chance of overfitting
- Works well with high dimensional data

Limitations:

- Not suitable for very large datasets
- Selection of kernel function is difficult
- Computationally expensive for large-scale problems

SVM is commonly applied in **traffic state classification and incident detection**.

Random Forest (RF)

Random Forest is an ensemble learning method that combines multiple decision trees. Each tree makes a prediction, and the final output is obtained by averaging or voting.

Traffic data often contains noise, missing values, and irregular patterns. Random Forest handles such issues effectively.

Applications in traffic prediction:

- Predicting traffic speed and volume
- Handling incomplete sensor data
- Identifying important traffic influencing factors

Advantages of RF:

- High prediction accuracy
- Robust against noise and missing data
- Less overfitting compared to single decision tree
- Provides feature importance analysis

Limitations:

- Requires more memory and computation
- Less interpretable compared to simple models

RF is suitable for **medium-term traffic forecasting** and data with uncertainties.

K-Nearest Neighbour (KNN)

KNN is a simple, instance-based learning algorithm. It predicts traffic conditions by comparing current data with similar past traffic situations.

For example, if current traffic parameters are similar to a past day at 9 AM, KNN assumes that traffic behavior will also be similar.

Advantages of KNN:

- Simple to implement
- No training phase required
- Works well when similar patterns repeat

Limitations:

- Computationally expensive for large datasets
- Sensitive to irrelevant features
- Performance depends on selection of 'K' value

KNN is useful for **quick prediction in small traffic datasets** and for similarity-based analysis.

DEEP LEARNING APPROACHES

Deep learning models are very powerful for time-series traffic data.

Convolutional Neural Network (CNN)

CNN is used for image-based traffic analysis from CCTV footage. It can detect vehicle count and traffic density.

Long Short-Term Memory (LSTM)

LSTM is a type of Recurrent Neural Network (RNN) suitable for time-series prediction. It remembers past traffic patterns and predicts future flow accurately.

Gated Recurrent Unit (GRU)

GRU is similar to LSTM but computationally faster. It is used in real-time traffic prediction systems.

REINFORCEMENT LEARNING FOR TRAFFIC SIGNAL CONTROL

Reinforcement Learning (RL) is used to optimize traffic signal timing. The agent learns best action (signal timing) by interacting with environment.

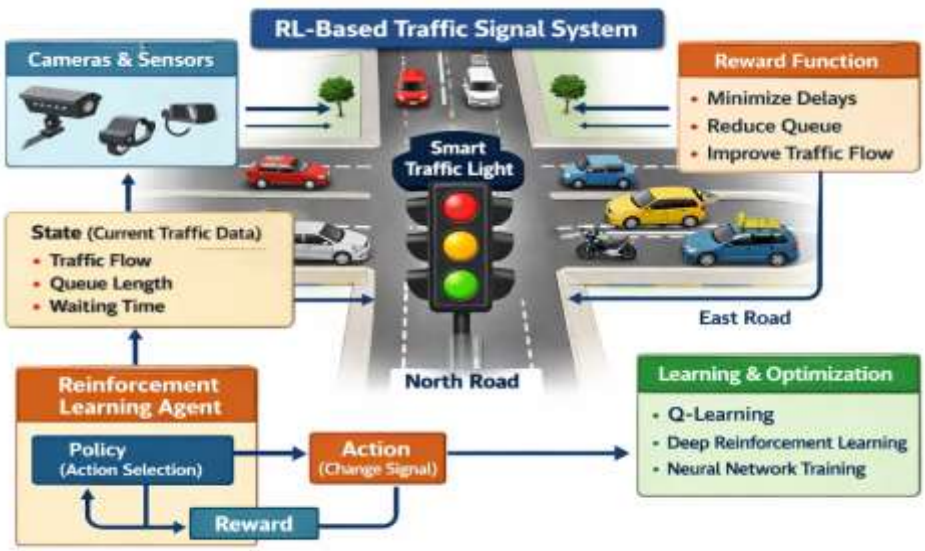

Figure 1: RL based Traffic Signal System

The system improves over time by maximizing reward (less congestion, less waiting time).

COMPARISON OF ML MODELS

Table 2: Comparison of ML Models for Traffic Prediction

Model	Accuracy	Data Requirement	Speed	Best Use
ANN	High	Large	Medium	Flow prediction
SVM	Medium	Small	High	Classification
RF	High	Medium	Medium	Robust prediction

Model	Accuracy	Data Requirement	Speed	Best Use
LSTM	Very High	Large	Slow	Time series
CNN	High	Image data	Medium	Density detection
RL	High	Real-time	Medium	Signal control

AI ARCHITECTURE FOR TRAFFIC MANAGEMENT

AI-based traffic management system has following layers:

- **Data Collection Layer** – Sensors, cameras, GPS
- **Processing Layer** – Data cleaning and storage
- **Prediction Layer** – ML/DL models
- **Decision Layer** – Signal control, route guidance
- **User Interface Layer** – Mobile apps, display boards

APPLICATIONS OF AI IN TRAFFIC MANAGEMENT

- Smart traffic signal control
- Accident detection and emergency routing
- Congestion prediction and avoidance
- Smart parking management
- Public transport scheduling
- Route optimization for vehicles

CHALLENGES IN AI TRAFFIC SYSTEMS

Despite advantages, some challenges exist:

- High cost of sensor installation
- Data privacy issues
- Requirement of high computing power
- Model training time
- Handling noisy and incomplete data
- Integration with old infrastructure

CASE STUDIES

Many cities like Singapore, London, and Barcelona have adopted AI traffic systems. These cities reported reduced congestion and improved travel time. Developing countries are also adopting smart traffic solutions slowly.

FUTURE RESEARCH DIRECTIONS

- Integration of AI with Internet of Things (IoT)
- Use of edge computing for faster processing
- Vehicle-to-Infrastructure (V2I) communication
- Autonomous vehicle traffic coordination
- Use of federated learning for privacy protection

DISCUSSION

AI and ML provide dynamic and adaptive traffic management. Deep learning models like LSTM show very promising results in prediction tasks. Reinforcement learning is useful for signal control. However, real implementation needs proper planning, data infrastructure, and government support.

CONCLUSION

Traffic congestion is a serious issue affecting daily life and economy. Traditional traffic management methods are insufficient for modern urban transportation systems. AI and Machine Learning techniques provide intelligent solutions for traffic prediction and real-time management. Various ML and DL models such as ANN, SVM, Random Forest, CNN, LSTM, and Reinforcement Learning have shown significant improvements in traffic flow prediction and signal optimization. Although challenges like cost, data privacy, and infrastructure exist, future research and technological advancements will make AI-based traffic systems more practical and effective. Adoption of these technologies will lead to smarter cities with better mobility and reduced congestion problems.

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Cite as:

Tushar Thakur, Panjak Yadav, Abhinav Parasad. (2026). AI & Machine Learning for Traffic Prediction and Management. Journal of Transportation Engineering and its Applications, 11(1), 14-27.

https//doi.org/10.5281/zenodo.19216254