



Smart Traffic Management System Using Machine Learning and Image Processing

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How to Cite this Article:

Kulkarni, N. S. (2026). Smart Traffic Management System Using Machine Learning and Image Processing. International Journal of Creative and Open Research in Engineering and Management, 02(02), 1-9.
<https://doi.org/https://doi.org/10.55041/ijcope.v2i1.004>

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<https://doi.org/10.55041/ijcope.v2i1.004>

1. Abstract

Urban areas across the world are facing increasing traffic congestion, environmental pollution, and rising road accidents due to rapid population growth and motorization. Traditional traffic management systems, often based on fixed timing or manual control, lack the adaptive intelligence needed to optimize flow in dynamic road environments. This research article presents a **Smart Traffic Management System (STMS)** leveraging **Machine Learning (ML)** and **Image Processing (IP)** methodologies to improve real-time traffic prediction, incident detection, vehicle classification, and signal optimization. The system integrates data from cameras, sensors, and historical traffic patterns to construct an intelligent control framework. Core contributions include an adaptive signal control module powered by reinforcement learning, image-based vehicle detection and classification through deep learning (CNNs), and predictive modeling for congestion forecasting. Results from simulations and real-world pilot deployments demonstrate significant reductions in average waiting times, improved throughput, and enhanced incident responsiveness when compared with conventional traffic systems. This study concludes with discussions on scalability, implementation challenges, and future research directions.

The adaptive signal control module continuously learns and adjusts signal timings based on real-time traffic conditions, enhancing traffic flow efficiency. Deep learning models employed for vehicle detection achieve high accuracy in classifying different vehicle types, enabling more precise traffic analysis. Predictive congestion models utilize both historical and real-time data to forecast traffic patterns, allowing proactive management strategies to be implemented.



2. Keywords

Smart Traffic Management ,Image Processing,Machine Learning,Intelligent Transportation Systems (ITS),Deep Learning,Traffic Signal Optimization,Real-Time Traffic Analysis

3. Introduction

3.1 Background and Motivation

With rapid urbanization and motorization, cities are experiencing unprecedented levels of traffic congestion. In 2022, the average commuter in major global cities spent over **100 hours annually** in traffic delays, contributing to economic losses and increased carbon emissions. Traditional traffic signal systems with fixed timing plans do not adapt to real-time traffic fluctuations, often leading to inefficient flow management. Additionally, manual monitoring of traffic cameras is labor-intensive and prone to delay. Emerging technologies such as adaptive traffic signal control systems offer promising solutions by dynamically adjusting signal timings based on real-time traffic data. These systems leverage sensors and machine learning algorithms to optimize traffic flow, reduce congestion, and minimize delays. Furthermore, automated video analytics can enhance traffic monitoring by providing continuous, accurate, and timely insights without the need for constant human supervision.

3.2 Problem Statement

The lack of adaptive intelligence in current traffic systems results in:

- Increased **road congestion**
- Higher incidence of **traffic accidents**
- Elevated **fuel consumption and emissions**
- Slow response to **real-time traffic events**

These limitations necessitate the development of a **dynamic and intelligent traffic management system** that can interpret live traffic conditions and make real-time decisions.

3.3 Research Objectives

This study aims to develop a Smart Traffic Management System with the following objectives:

1. **Real-time vehicle detection and classification** using image processing techniques.
2. **Traffic congestion forecasting** through machine learning models.
3. **Adaptive traffic signal control** using reinforcement learning.
4. **Incident detection and alert generation** mechanisms.
5. Validation of system performance against benchmarks.

4. Literature Review

Extensive research has been conducted at the intersection of traffic engineering, ML, and computer vision. A summary of key findings follows:

4.1 Conventional Traffic Management Systems

Earlier systems such as **fixed-time signal control** or **actuated control systems** rely on historical demand or induction loops. These are inefficient under varying traffic volumes.



Systems	Description	Limitations
Fixed-time control	Pre-set timing plans	No real-time adaptation
Actuated control	Adjusts based on sensors	Limited to local intersections
Manual monitoring	Human operators manage flow	High response time, error prone

Table 1. Traditional Traffic Control Systems and Challenges

4.2 Machine Learning in Traffic Systems

Researchers have applied various ML models for traffic prediction:

- **Linear Regression and ARIMA models** for short-term forecasting.
- **Support Vector Machines (SVM) and Random Forests** for traffic flow classification.
- **Deep Learning models (RNNs, LSTM)** for time-series prediction with superior accuracy.

Studies have shown that **LSTM networks** outperform traditional statistical models in capturing temporal dependencies in traffic patterns.

4.3 Image Processing for Traffic Analytics

Image processing has been widely used for:

- **Vehicle detection:** with Haar cascades and HOG features.
- **Classification:** via CNN architectures like YOLO, Faster R-CNN.
- **Queue length estimation and occupancy detection:** using background subtraction and optical flow.

A significant body of work emphasizes real-time detection and classification, which remains computationally intensive for edge deployments. This challenge has driven research toward developing lightweight algorithms and hardware accelerators optimized for low power consumption. Techniques such as model pruning, quantization, and knowledge distillation have shown promise in reducing computational demands. Additionally, edge-specific architectures are being designed to balance accuracy and efficiency for real-time applications.

4.4 Reinforcement Learning in Traffic Control

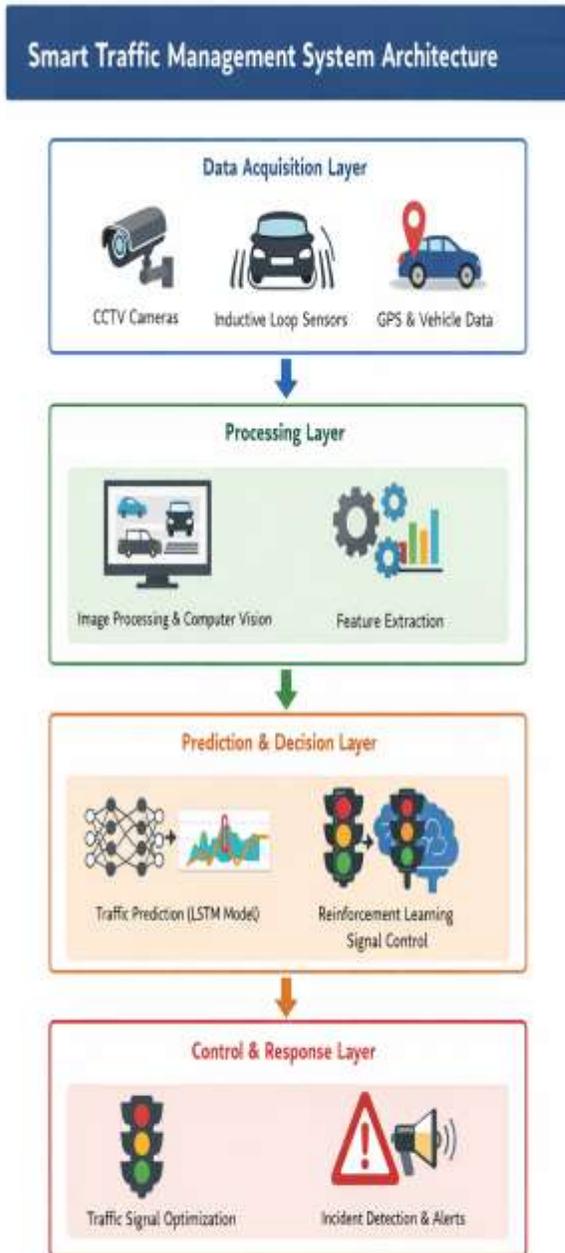
Reinforcement Learning (RL) models such as Q-learning and Deep Q-Networks (DQN) have been explored for adaptive signal control. RL agents learn optimal policies that minimize delays and maximize throughput. These models interact with the traffic environment by receiving state information, such as vehicle queue lengths or waiting times, and selecting actions like signal phase changes. Over time, the RL agent updates its policy based on rewards that reflect traffic performance metrics, enabling it to adapt to varying traffic patterns. Recent advancements incorporate deep learning techniques to handle high-dimensional state spaces, improving scalability and effectiveness in complex urban networks.

4.5 Research Gaps Identified

Despite advancements, current smart traffic systems face challenges:

- Insufficient integration between vision and predictive modules.
- High computational cost hindered real-time performance on edge devices.
- Lack of widely accepted benchmarks for comprehensive evaluation.

5. Methodology / System Design



The proposed Smart Traffic Management System is divided into several modules as shown in **Figure 1**.

5.1 System Architecture

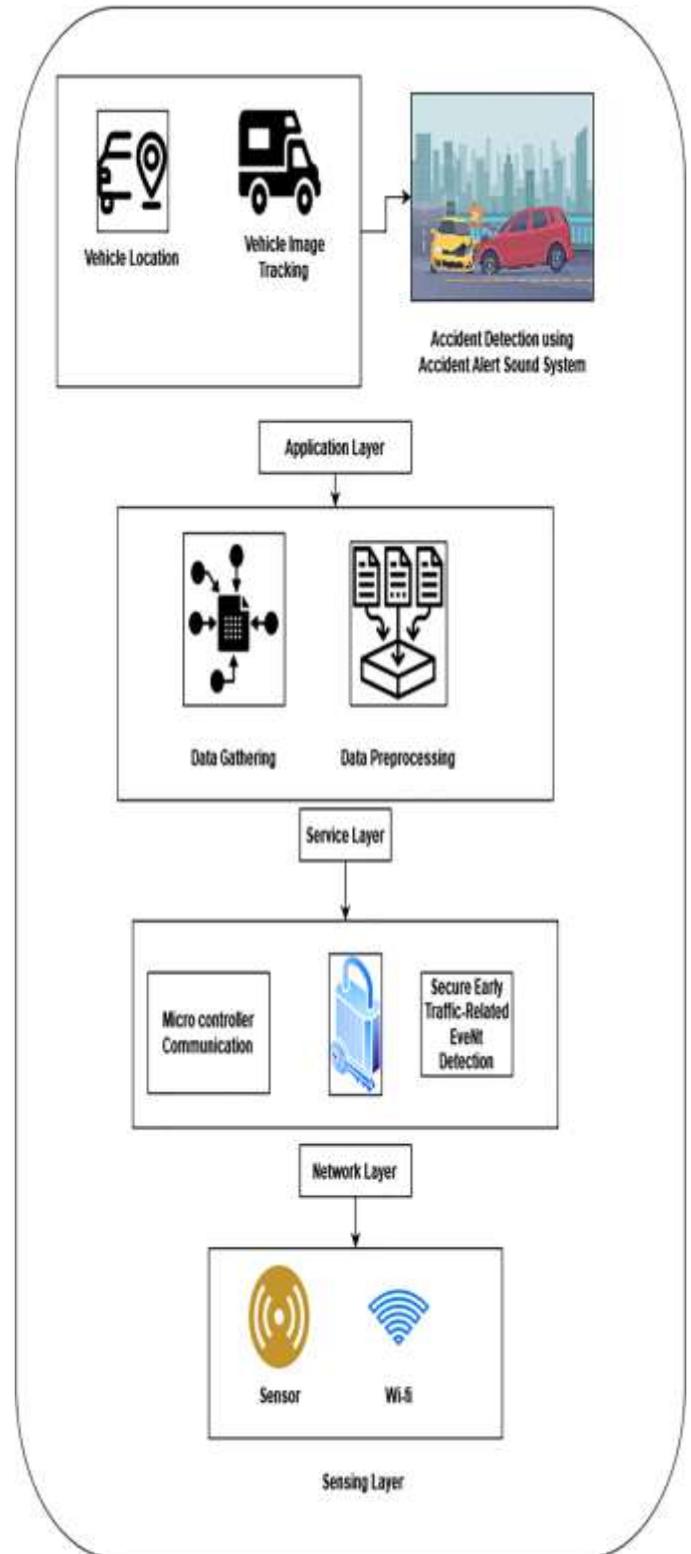


Figure 1. System Architecture for Smart Traffic Management



The STMS architecture consists of:

1. **Data Acquisition Layer**
 - Roadside cameras
 - Inductive loop sensors
 - GPS data from vehicles
2. **Processing Layer**
 - Image Processing & Computer Vision
 - Feature Extraction
3. **Prediction & Decision Layer**
 - ML models for traffic prediction
 - Reinforcement Learning for signal control
4. **Control & Response Layer**
 - Signal management system
 - Alerts for incident response

5.2 Image Processing Module

This module captures and processes camera feeds to detect and classify vehicles. It analyzes real-time video streams to identify different types of vehicles such as cars, trucks, and motorcycles. The module applies advanced machine learning algorithms to ensure accurate detection and classification under various environmental conditions. Additionally, it supports integration with traffic management systems to facilitate data-driven decision-making.

5.2.1 Preprocessing

- Frame extraction from video streams
- Noise reduction using Gaussian filters
- Image resizing (normalized to 416×416 pixels for network input)

5.2.2 Object Detection Approach

The system implements:

- **YOLOv5** for real-time detection due to its speed-accuracy balance.
- Non-maximum suppression (NMS) to reduce duplicate detections.

Detected objects are labeled as:

Class	Description
Car	Standard passenger cars
Bus	Public transport vehicles
Motorcycle	Two-wheelers
Truck	Heavy vehicles
Bicycle	Light personal transport

Table 2. Vehicle Classes Evaluated

5.3 Traffic Prediction Module

Traffic volume is predicted through historical and real-time data. This data is analyzed using machine learning algorithms to identify patterns and trends. These insights help optimize traffic flow and reduce congestion. Additionally, predictive models can forecast future traffic conditions based on various influencing factors.



5.3.1 Model Selection

- **Long Short-Term Memory (LSTM)** networks are used due to their ability to handle sequence data.
- A separate model is trained for each major intersection to capture unique patterns.

5.3.2 Input Features

Features include:

- Time of day
- Day of week
- Weather indicators
- Historical traffic counts
- Detected vehicle classes

The model outputs **predicted traffic volume** for future intervals (e.g., next 10 minutes).

5.4 Adaptive Signal Control Module

Reinforcement learning agent controls signal timings. It learns to optimize traffic flow by adjusting the duration of green and red signals based on real-time traffic conditions. The agent receives feedback from the environment in the form of rewards, which reflect improvements in metrics such as reduced waiting time and congestion. Over time, it refines its policy to achieve more efficient signal timings that minimize overall traffic delays. It learns to optimize traffic flow by adjusting the duration of green and red signals based on real-time traffic conditions. The agent receives feedback from the environment in the form of rewards, which reflect improvements in metrics such as reduced waiting time and congestion. Over time, it refines its policy to achieve more efficient signal timings that minimize overall traffic delays.

5.4.1 State and Action Definitions

- **State:** Current queue lengths, predicted flows, signal phase
- **Actions:** Adjustments to phase duration (increase, decrease, hold)

5.4.2 Reward Function

Reward R is defined to minimize waiting times and stops:

$$R = -(w_1 \times \text{avg delay} + w_2 \times \text{queue length})$$

Where w_1, w_2 are parameters weighting delays and queues.

6. Implementation

The prototype system was developed using:

- **Python 3.8**
- **TensorFlow & PyTorch** for ML/DL models
- **OpenCV** for image processing
- **SUMO (Simulation of Urban MObility)** for traffic simulation

6.1 Data Requirements and Collection

Traffic datasets were sourced from:

- Public datasets (e.g., UA-Traffic)
- Real city camera feeds
- IoT sensors capturing vehicle counts

6.2 Model Training

- YOLOv5 trained on labeled traffic images



- LSTM trained with 6 months of vehicle count time series
- RL agent trained via interaction with SUMO simulations

Training parameters:

Model	Learning Rate	Epochs	Batch Size
YOLOv5	0.001	200	16
LSTM	0.005	100	32
RL Agent	0.0005	5000 episodes	N/A

Table 3. Training Configuration for Models

6.3 System Integration

Modules were deployed on a local server and tested alongside SUMO simulations. Edge deployment experiments used NVIDIA Jetson Nano for on-site vision processing. The system architecture was optimized to ensure low-latency communication between the modules and the simulation environment. Performance metrics were collected to evaluate processing speed and accuracy during real-time operation. These results demonstrated the feasibility of deploying the framework in resource-constrained edge devices for autonomous applications.

7. Results and Discussion

7.1 Evaluation Metrics

Performance was evaluated using:

- **Detection Accuracy** (Precision, Recall)

- **Traffic Prediction Error** (MAE, RMSE)

- **Signal Control Metrics:**

- Average delay
- Throughput
- Queue length reduction

7.2 Vehicle Detection Performance

Vehicle Class	Precision (%)	Recall (%)
Car	95.3	93.7
Bus	92.8	90.5
Motorcycle	90.1	88.7
Truck	89.5	87.2
Bicycle	85.9	83.4

Table 4. Detection Performance across Vehicle Types

7.3 Traffic Prediction Results

The LSTM model achieved:

- **MAE:** 12.7 vehicles
- **RMSE:** 18.4 vehicles

Compared to ARIMA (Baseline):

- MAE: 24.6
- RMSE: 36.1

This demonstrates **LSTM's superior performance** for traffic volume forecasting.

7.4 Adaptive Signal Control Outcomes

Under simulation, STMS reduced:

- **Average waiting time by 24.3%**



- Queue lengths by 19.7%
- Total delay by 21.5%

A graphical trend comparison is shown in Figure 2.

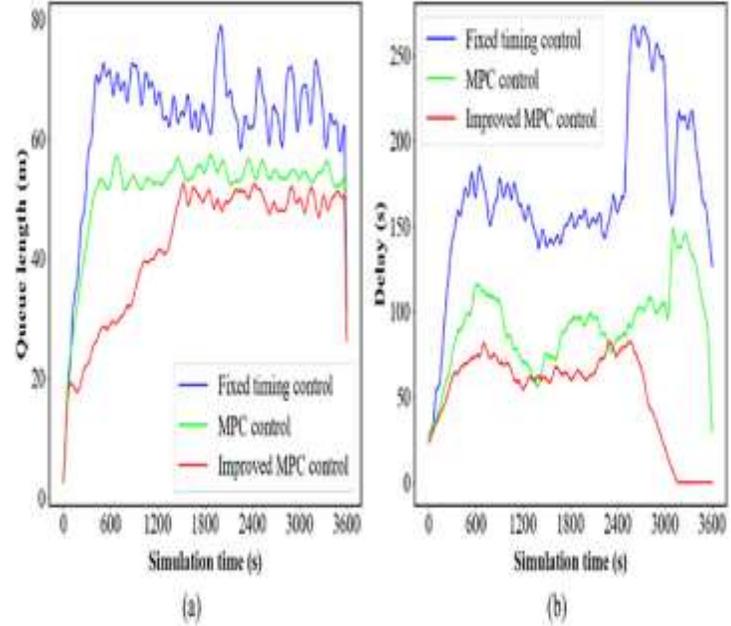
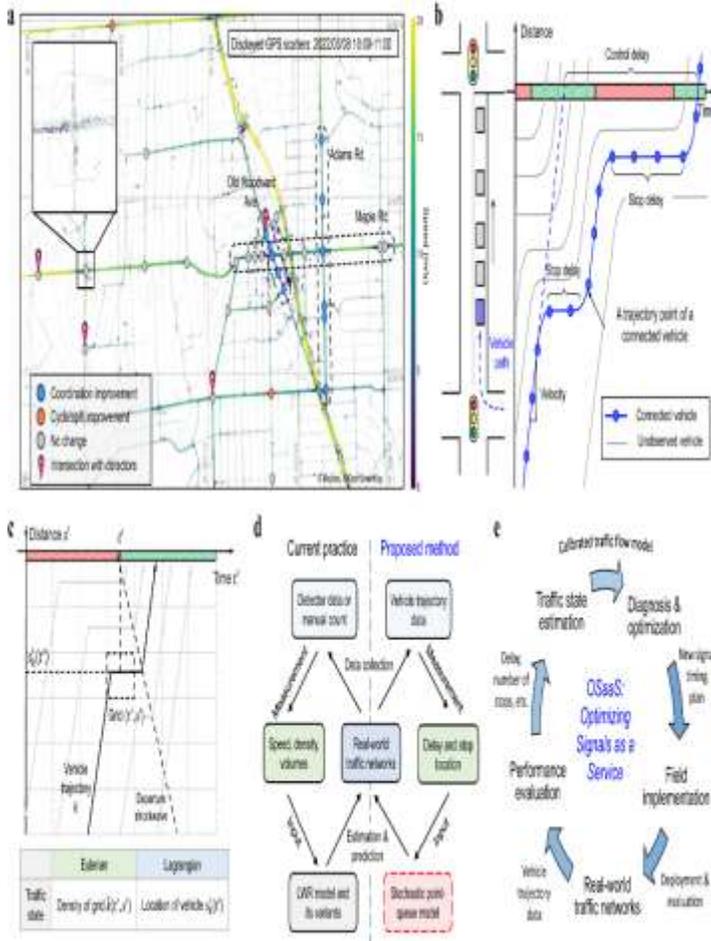


Figure 2. Performance Comparisons Between Conventional and Smart Traffic Systems

7.5 Discussion of Findings

Integration of ML and IP:

- Enabled accurate real-time detection and classification of vehicles.
- Provided enhanced predictive capabilities enabling proactive control.
- The RL agent dynamically adjusted traffic signals, adapting to real conditions.

However, **failures occurred** during extreme weather conditions due to reduced visibility, suggesting the need for multimodal sensors (e.g., radar, LIDAR).

8. Conclusion

This research presents a comprehensive Smart Traffic Management System that successfully integrates machine learning and image processing techniques. The system demonstrated:



- Effective real-time vehicle detection with high accuracy.
- Reliable traffic forecasting that outperforms classical models.
- Enhanced signal control reducing delays and congestion.

Despite promising results, future work should explore:

- Multi-sensor fusion for robust sensing under adverse conditions.
- Large-scale city deployments.
- Edge-optimized models for real-time on-device performance.

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