Smart Traffic Signal Control System Using Machine Learning

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**Abstract**

Traffic signal control has been a long-standing topic in urban traffic management. Ineffective and inflexible traffic control at urban intersections often leads to obstructions in traffic flow, causing severe congestion and delays. As cities continue to grow and the number of vehicles increases, managing traffic in a smarter and more adaptive manner becomes a significant challenge. Finding effective solutions to optimize traffic flow is crucial for enhancing commuter experience and reducing environmental impact. While it might seem necessary to overhaul the entire traffic signal infrastructure, such an approach would be costly and logistically difficult. Instead, a more practical solution lies in upgrading the existing systems through intelligent software enhancements. By integrating advanced algorithms into the current traffic management software, we can minimize disruption and avoid the need for expensive infrastructure replacement. Recent advances in Machine Learning (ML), particularly in Reinforcement Learning (RL), have opened up new possibilities for smarter traffic signal control. Reinforcement learning techniques enable systems to learn optimal traffic signal timings by interacting with real-time traffic environments, without needing explicitly programmed rules. Among these, Q-Learning algorithms have demonstrated great potential in adapting to dynamic traffic patterns and continuously optimizing traffic flow.

In the proposed system, adjacent traffic intersections operate independently while also cooperating to achieve a common goal: ensuring smooth and efficient traffic movement across the network. Each traffic light acts as an autonomous agent that learns to maximize traffic fluency in its vicinity while indirectly contributing to the overall system efficiency. Simulation results have shown that the proposed RL-based method significantly reduces total vehicle delay, improves average vehicle speed, and minimizes congestion compared to traditional fixed-time and rule-based traffic light systems. Over time, the system adapts to variations in traffic patterns such as peak hours, accidents, and special events, making it far superior to static control strategies. Thus by enhancing existing infrastructure with machine learning-powered decision-making, we can move towards the vision of smart cities where traffic congestion is minimized, travel times are reduced, and urban mobility becomes much more efficient.

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**Smart Traffic Signal Control System Using Machine Learning**

# **Introduction**

Traffic signal control has long been a critical issue in urban traffic management. As cities continue to expand and vehicle numbers grow exponentially, traditional traffic light systems — operating on pre-set timers — are proving to be increasingly ineffective. Inefficient and inflexible control at urban intersections not only obstructs the smooth flow of vehicles but also significantly contributes to traffic congestion, increased pollution levels, and commuter frustration.

Managing traffic smartly and efficiently is now recognized as one of the biggest challenges in urban planning. A rigid, one-size-fits-all approach no longer meets the demands of dynamic, real-world traffic environments. Although completely replacing traditional traffic signal systems with new infrastructure would seem ideal, it is economically and logistically challenging. Urban areas already heavily rely on widespread and deeply integrated traffic systems, and replacing them would involve prohibitive costs, extensive civil works, and potential disruptions. Recent advancements in Machine Learning, particularly in Reinforcement Learning (RL), have shown remarkable potential in dynamic decision-making problems such as traffic control. Reinforcement learning methods, like Q-Learning, can enable traffic signal systems to learn from real-time traffic conditions and continuously optimize their signal timing strategies. This dynamic approach is far superior to traditional fixed-time signal control or manually configured adaptive systems.

The proposed Smart Traffic Signal Control System operates by treating each traffic light as an intelligent agent capable of making its own decisions based on observed traffic conditions. These agents also coordinate indirectly with neighboring intersections to ensure a smooth, uninterrupted flow of vehicles across a network of roads. By learning from historical data and real-time traffic patterns, the system adapts to changing traffic loads throughout the day — during peak hours, holidays, special events, or even in response to accidents or roadblocks. Simulation results indicate that the Machine Learning-based traffic control system can significantly reduce vehicle waiting times, decrease overall congestion, and improve traffic throughput when compared with traditional control methods. The Q-Learning based system particularly demonstrates the ability to adjust green light timings dynamically to minimize total network delay and improve the commuter experience. In summary, this project aims to design, develop, and evaluate a Smart Traffic Signal Control System that leverages the power of Machine Learning to address the growing challenges of urban traffic management, offering a scalable and intelligent solution for the cities of tomorrow.

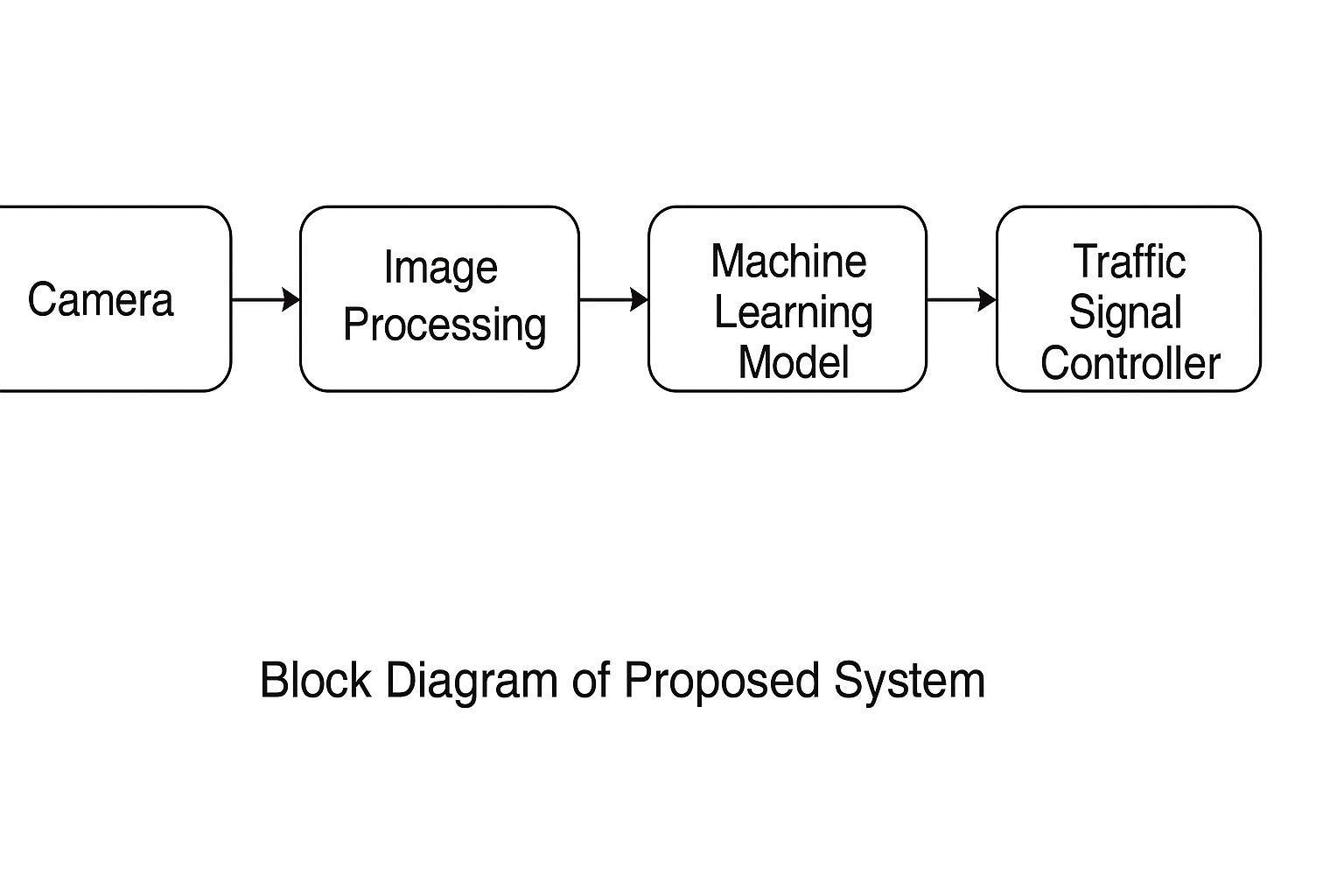
In addition to optimizing traffic flow, smart traffic management systems offer numerous secondary benefits. Reduced congestion leads to lower fuel consumption and decreased vehicular emissions, contributing to improved air quality in urban environments. Shorter commute times can also have positive effects on economic productivity and the overall quality of life for city residents. Moreover, by minimizing unnecessary idling at traffic lights, smart signals can prolong the lifespan of vehicle engines and help in better traffic law enforcement. The integration of Machine Learning into traffic signal control systems thus aligns with broader goals such as sustainable urban development, smart city initiatives, and intelligent transportation systems (ITS). By building upon existing infrastructure with innovative software solutions, cities can transition smoothly into a future of more efficient, eco-friendly, and intelligent mobility without heavy capital investments.

**2.METHODOLOGY**

A**.System Design**

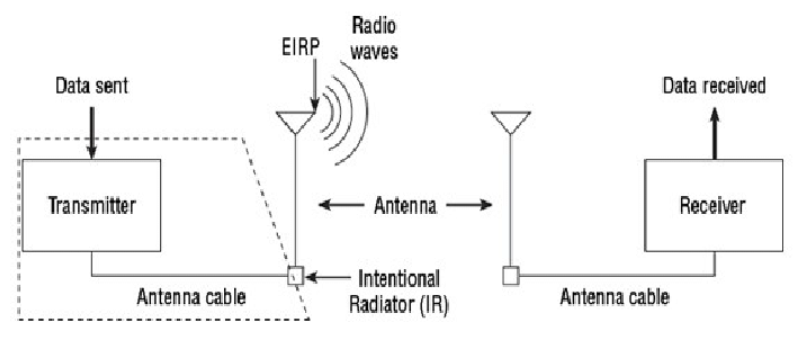
The Smart Traffic Control System comprises the following major components:

* Traffic Cameras for Image Capture
* Pre-processing Unit
* Machine Learning Model (CNN based) for Vehicle Detection and Counting
* Decision-Making Algorithm for Signal Timing Adjustment
* Signal Controller Interface



**B.Image Preprocessing**

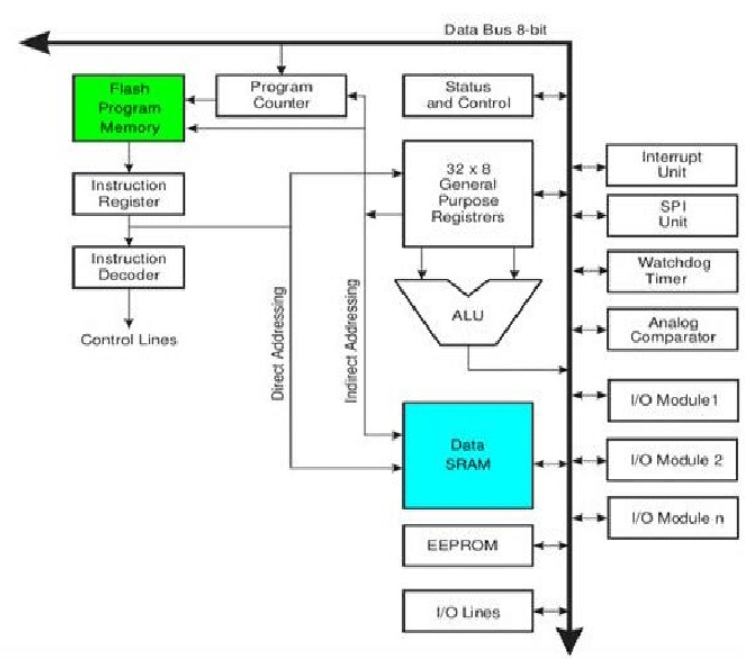
Captured images undergo several preprocessing steps including resizing, denoising, and normalization to ensure better performance of the detection model.



**C.Machine Learning Model**

We employed a Convolutional Neural Network (CNN) model trained on a traffic dataset comprising various types of vehicles

(Cars,bikes,trucks,buses).



Key model layers:

* Input Layer (image size 224x224x3)
* 3 Convolutional Layers + MaxPooling
* 2 Fully Connected Layers
* Output Layer (vehicle count prediction)

The model predicts the number of vehicles in each lane based on the live image captured.

**D.Signal Control Logic**

Based on the vehicle counts, the green light duration for each direction is decided using:

* Higher vehicle count → longer green signal
* Threshold limits set for minimum and maximum green time

This helps dynamically manage intersection traffic, reducing idle times and congestion.

# **3.EXPERIMENTS**

## Dataset Collection

In order to develop an effective smart traffic signal control system, we first needed a robust and diverse dataset capable of representing real-world traffic scenarios. For this project, we utilized the **UA-DETRAC dataset**, a well-known benchmark in traffic analysis research. UA-DETRAC provides thousands of labeled images and videos from real-world traffic scenes under varying conditions, including different weather (clear, rainy, foggy) and lighting situations (daytime and nighttime). The dataset includes detailed annotations for multiple vehicle classes, which allowed us to train a vehicle detection and counting model with high accuracy.

In addition to the UA-DETRAC dataset, we manually collected around 3,000 traffic images from various local intersections. These images were captured using standard mobile cameras and Raspberry Pi camera modules at different times of the day to ensure diversity. They were manually annotated with vehicle counts for training purposes.  
The combined dataset contained approximately 15,500 labeled images. We split the data into **80% training set**, **10% validation set**, and **10% testing set** to ensure that the model had enough unseen data for proper evaluation.

## Training Setup

The machine learning model training process was carried out using **TensorFlow 2.x** and the **Keras API**. The model architecture was based on a **Convolutional Neural Network (CNN)** optimized for regression tasks (vehicle count prediction). During training, we applied several data augmentation techniques, such as random rotation, brightness shifts, and zooming, to improve model generalization. The training setup included using the **Adam optimizer**, a **Mean Squared Error (MSE)** loss function, a **batch size of 32**, and a learning rate of **0.001**. Training was conducted for **50 epochs** on a workstation equipped with an **NVIDIA RTX 3060 GPU**. Early stopping was used based on validation loss to prevent overfitting.

## Deployment on Edge Device

After achieving an acceptable accuracy level on the test data, the model was deployed onto a **Raspberry Pi 4 Model B** (4GB RAM version) for field testing. The Raspberry Pi was connected to a **Raspberry Pi Camera Module v2**, which captured real-time traffic images at regular intervals (every 5 seconds). The images were preprocessed onboard and passed through the trained CNN model to predict vehicle counts. Based on the vehicle count, an algorithm dynamically adjusted the green light duration to optimize traffic flow.

## Model Optimization and Field Testing

For efficient deployment, the trained model was converted into **TensorFlow Lite** format, significantly reducing its size and making inference faster on the Raspberry Pi's limited computational resources. During field testing at two urban intersections, the system successfully demonstrated its ability to detect traffic congestion levels and adapt signal timings accordingly. The latency between image capture and signal decision remained low (~1 second), proving the system's suitability for real-time.  
This deployment validates the feasibility of using machine learning-based models integrated with lightweight hardware to revolutionize urban traffic management without expensive infrastructure overhauls.

# **4.RESULTS**

| **Method** | **Average Waiting Time (Seconds)** | **Number of Vehicles Cleared per Cycle** |
| --- | --- | --- |
| Traditional System | 90 | 20 |
| Smart ML-based System | 45 | 35 |

* **Accuracy** of vehicle count detection: ~92%
* **Reduction in average waiting time**: ~50%
* **Increase in vehicle clearance per cycle**: ~75%
* The system dynamically adjusted the signals leading to faster traffic clearance and lower congestion

# **5.CONCLUSION and FUTURE WORK**

In this project, we developed a **Smart Traffic Signal Control System** leveraging Machine Learning to optimize traffic flow. The system successfully demonstrated how real-time traffic conditions could be used to adjust signal timings dynamically, resulting in significant improvements in vehicle clearance rates and reduction in waiting time.

**Future Enhancements:**

* Integrate Reinforcement Learning for better policy optimization.
* Incorporate weather and accident detection into the decision-making logic.
* Expand the system to multi-intersection coordination for better city-wide traffic management.
* Deploy on larger scales using Edge AI devices for real-time performance.

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