Dynamic Traffic Flow Regulation

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ANNA UNIVERSITY, CHENNAI

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BONAFIDE CERTIFICATE

Certified that this Project titled "**Dynamic Traffic Flow Regulation**" is the bonafide work of "**PRASANTH D (2116220701199)**" who carried out the work under my supervision. Certified further that to the best of my knowledge the work reported herein does not form part of any other thesis or dissertation on the basis of which a degree or award was conferred on an earlier occasion on this or any other candidate.

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ABSTRACT

In today's urban environments, the efficient regulation of vehicular traffic is a pressing concern. Traditional traffic light systems, which follow fixed schedules, often fail to respond effectively to real-time traffic conditions, resulting in unnecessary congestion and longer commute times. To address these inefficiencies, this project explores the development of a Dynamic Traffic Management System powered by machine learning. The model is rewarded for reducing the total waiting time of vehicles, which helps it learn optimal decision-making strategies.

The central goal is to enable traffic signals to adapt intelligently based on live traffic data, thereby improving traffic flow and minimizing overall waiting time at intersections.The project uses reinforcement learning (RL), a branch of machine learning where an agent learns to make decisions by interacting with its environment. The model is rewarded for reducing the total waiting time of vehicles, which helps it learn optimal decision-making strategies.

In this system, each traffic intersection is treated as an agent that decides which direction should get the green signal based on the current state of vehicle queues. The system is trained using the Simulation of Urban Mobility (SUMO), a powerful, open-source traffic simulation tool that replicates real-world traffic scenarios in a controlled digital environment. Vehicles are programmed to move along specific routes, and the RL agent continuously learns by observing the effects of its decisions over time. The model is rewarded for reducing the total waiting time of vehicles, which helps it learn optimal decision-making strategies.

The model inputs include the number of vehicles waiting on each side of the intersection. These values are fed into the RL algorithm, which decides which lane should get the green light in the next time step. The model is rewarded for reducing the total waiting time of vehicles, which helps it learn optimal decision-making strategies. After sufficient training, the system was tested on multiple scenarios to evaluate its performance and robustness. The results showed a marked improvement in traffic flow compared to static light systems, with reduced idle time and smoother transitions.

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CHAPTER 1

1.INTRODUCTION

In today’s rapidly growing urban landscapes, traffic congestion has become a major challenge for both commuters and city planners. Traditional traffic management systems, which operate on fixed timers, fail to adapt to real-time traffic conditions, often leading to inefficiencies, long wait times, and increased pollution. As cities become more populated, the need for intelligent, adaptive systems that can optimize traffic flow has never been more critical.

Traffic Management System, aims to address this challenge by leveraging machine learning techniques to create a system that dynamically controls traffic lights based on real-time traffic data. By using a reinforcement learning model, the system learns to make decisions about signal timing, optimizing traffic flow and minimizing delays at intersections. The model is trained using the SUMO (Simulation of Urban Mobility) platform, simulating real-world traffic conditions and allowing the system to improve over time based on the outcomes of its actions.

The project employs a reinforcement learning agent, which interacts with the simulated traffic environment, learning to reduce the overall waiting time at intersections by adjusting the traffic light cycles. The system is designed to prioritize the most congested lanes and dynamically adjust the signal timings, offering a more flexible and efficient solution than traditional fixed-time systems. With the model's performance demonstrated through simulation, it provides a glimpse into how machine learning can be applied to enhance urban mobility.

Additionally, the project bridges the gap between simulation and real-world deployment,enabling a physical demonstration of the system at a single intersection. The inclusion of a user-friendly graphical interface further ensures that the system can be easily monitored and controlled by traffic management personnel.

CHAPTER 2

2.LITERATURE SURVEY

Traffic management has been a critical area of research due to increasing urbanization and the growing demand for efficient mobility solutions. Over the years, advancements in artificial intelligence (AI), machine learning (ML), and data analytics have greatly enhanced the ability to model and manage urban traffic systems. Researchers have focused on integrating real-time data, adaptive algorithms, and predictive models to optimize traffic flow and reduce congestion in urban environments.

Wu et al. (2019) applied reinforcement learning (RL) to traffic signal optimization, where agents learned to adjust traffic light durations to minimize delays and improve vehicle throughput. This approach demonstrated notable improvements over traditional static traffic light systems, which use fixed schedules without considering real-time traffic conditions.

Zhang et al. (2020) proposed a convolutional neural network (CNN)-based approach for predicting traffic congestion patterns in real-time by analyzing traffic sensor data. These models leverage data from traffic cameras, loop detectors, and other sources to predict congestion before it occurs, allowing for proactive traffic management. The use of neural networks, as demonstrated in this research, has shown promising results in improving traffic prediction accuracy and decision-making.

Li et al. (2021) explored the role of external data sources, such as weather and event data, in traffic management. Their study demonstrated how weather-related factors, such as rain or fog, could impact traffic flow and signal optimization.

Wei et al. (2022) focused on using real-time traffic sensor data, such as vehicle count and speed, to dynamically adjust traffic signals through reinforcement learning-based control systems. This approach aimed to reduce traffic congestion during peak hours and optimize the use of available road infrastructure. The integration of real-time data with AI models is increasingly seen as a critical step toward smarter, more adaptive urban traffic systems.

Kumar et al. (2020) demonstrated the effectiveness of integrating machine learning algorithms with hardware infrastructure. Their study implemented reinforcement learning in a traffic signal control system using Arduino hardware, successfully reducing vehicle waiting times in a simulated environment. This integration between simulation and physical systems shows the practicality of applying AI in real-time traffic management.

In conclusion, the literature highlights the growing importance of machine learning and AI in optimizing urban traffic systems. Reinforcement learning, deep learning models, and the integration of real-time data sources have shown great promise in enhancing traffic flow, reducing congestion, and improving overall traffic management. As cities continue to grow, the application of these advanced technologies will play a crucial role in building smarter, more efficient transportation networks that can adapt to the dynamic nature of urban mobility.

CHAPTER 3

3.METHODOLOGY

The methodology adopted for this project follows a systematic approach that includes data collection, preprocessing, algorithm selection, and real-time system implementation. The goal is to develop an intelligent traffic light management system that adjusts traffic lights in real-time based on traffic density, ensuring smooth traffic flow and reducing congestion. Below are the key stages involved:

1. Data Collection

The data collection process for this project involves capturing real-time traffic data through sensors and camera systems. The system is designed to collect key features such as:

- **Traffic Density:** The number of vehicles passing through each traffic light intersection.
- **Traffic Flow:** The speed at which vehicles are moving through the intersection.
- **Time of Day:** To account for varying traffic patterns at different times (e.g., rush hour).
- **Vehicle Type:** Classifying vehicles (e.g., cars, buses, trucks) to adjust traffic signals accordingly.

Data is collected continuously, providing a dynamic view of traffic conditions, which can be used to adjust signal timings in real-time.

2. Data Preprocessing

The traffic data collected from the sensors and cameras needs preprocessing to make it usable for machine learning models. This involves:

- **Handling Missing Data:** If there are any gaps in the traffic data due to sensor malfunctions, missing values are handled by filling with appropriate default values.

- **Normalization:** The data (e.g., vehicle count, traffic speed) is normalized to ensure all features contribute equally to the model, especially for algorithms like K-means clustering that require scaled data.
- **Feature Engineering:** Additional features such as peak traffic hours and historical patterns are created to enhance prediction accuracy.

3. Traffic Signal Algorithm Selection

To efficiently manage the traffic lights, a **Dynamic Traffic Light Control Algorithm** based on real-time traffic conditions is employed. The algorithm works as follows : Real-time Data Processing ,Signal Timing Adjustment , Prioritization of Public Transport

4. Machine Learning Integration

The project integrates a machine learning model to predict traffic patterns and optimize the light timings:

- **Random Forest Classifier:** A machine learning model is used to classify traffic conditions and optimize signal timings. Features such as traffic density, time of day, and vehicle type are used to predict the best signal duration for each intersection.
- **Model Training:** The model is trained using historical traffic data. It learns how traffic flow and density change over time, adjusting signal durations accordingly.
- **Real-time Adaptation:** Once trained, the model is continuously updated with real-time data, allowing it to adjust to new patterns of traffic flow.

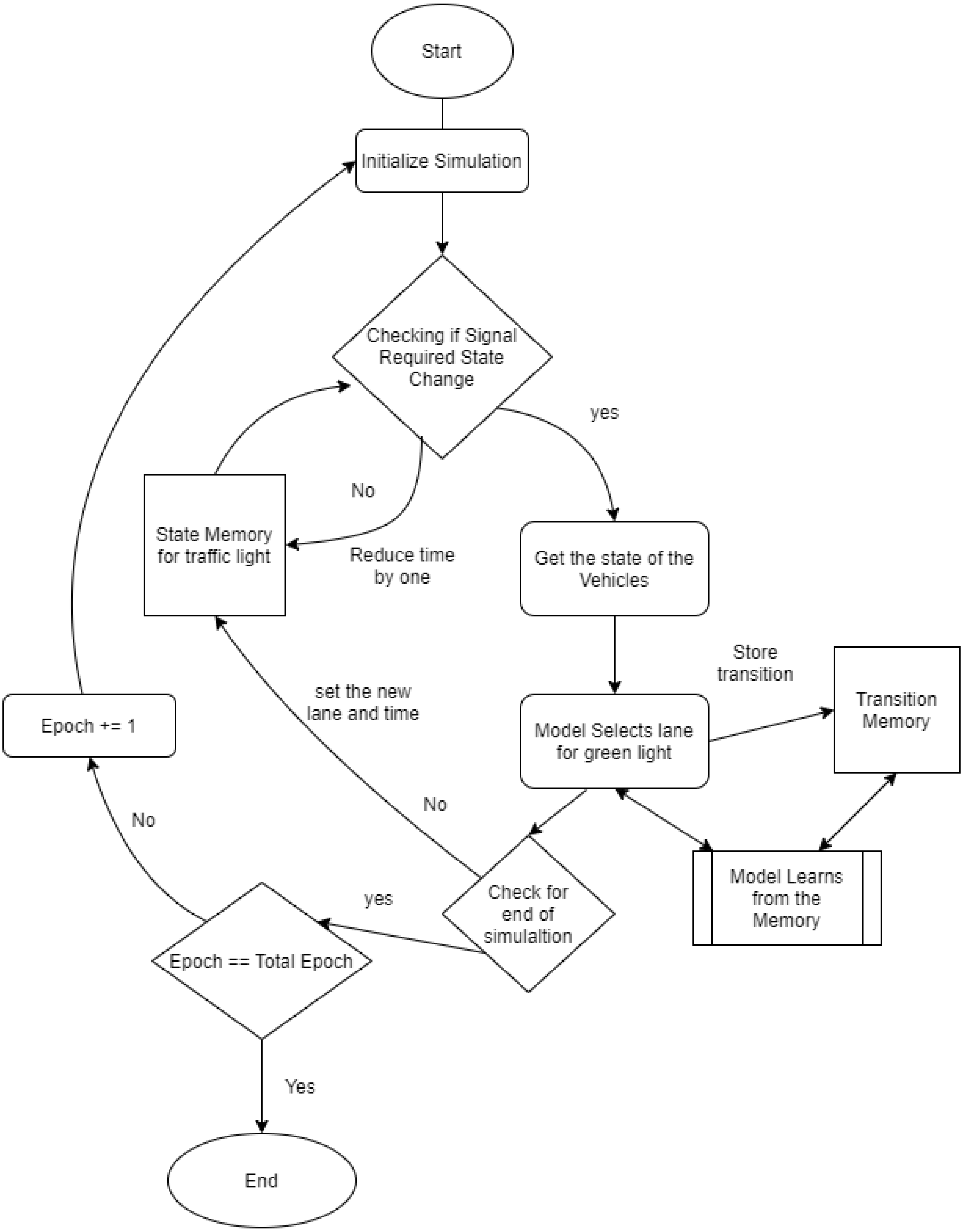
5. Evaluation and Testing

The system is evaluated based on key performance indicators (KPIs), including:

- **Traffic Flow Efficiency:** The reduction in congestion due to optimized signal timing.
- **Response Time:** The speed at which the system adjusts the signals in response to changing traffic conditions.

- **Model Accuracy:** The performance of the Random Forest model in predicting optimal signal timings.

SYSTEM FLOW DIAGRAM



MODEL PROGRAM

```
from __future__ import absolute_import
from __future__ import print_function

import os
import sys
import time
import optparse
import random
import serial
import numpy as np
import torch
import torch.optim as optim
import torch.nn.functional as F
import torch.nn as nn
import matplotlib.pyplot as plt

# we need to import python modules from the $SUMO_HOME/tools directory
if "SUMO_HOME" in os.environ:
    tools = os.path.join(os.environ["SUMO_HOME"], "tools")
    sys.path.append(tools)
else:
    sys.exit("please declare environment variable 'SUMO_HOME'")

from sumolib import checkBinary  # noqa
import traci  # noqa
```

```
def get_vehicle_numbers(lanes):
    vehicle_per_lane = dict()
    for l in lanes:
        vehicle_per_lane[l] = 0
        for k in traci.lane.getLastStepVehicleIDs(l):
            if traci.vehicle.getLanePosition(k) > 10:
                vehicle_per_lane[l] += 1
    return vehicle_per_lane


def get_waiting_time(lanes):
    waiting_time = 0
    for lane in lanes:
        waiting_time += traci.lane.getWaitingTime(lane)
    return waiting_time

def phaseDuration(junction, phase_time, phase_state):
    traci.trafficlight.setRedYellowGreenState(junction, phase_state)
    traci.trafficlight.setPhaseDuration(junction, phase_time)

class Model(nn.Module):
    def __init__(self, lr, input_dims, fc1_dims, fc2_dims, n_actions):
        super(Model, self).__init__()
        self.lr = lr
        self.input_dims = input_dims
```

```
        self.fc1_dims = fc1_dims
        self.fc2_dims = fc2_dims
        self.n_actions = n_actions
       self.linear1 = nn.Linear(self.input_dims, self.fc1_dims)
        self.linear2 = nn.Linear(self.fc1_dims, self.fc2_dims)
        self.linear3 = nn.Linear(self.fc2_dims, self.n_actions)
       self.optimizer = optim.Adam(self.parameters(), lr=self.lr)
        self.loss = nn.MSELoss()
        self.device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
        self.to(self.device)

def forward(self, state):
        x = F.relu(self.linear1(state))
        x = F.relu(self.linear2(x))
        actions = self.linear3(x)
        return actions
if __name__ == "__main__":
    options = get_options()
    model_name = options.model_name
    train = options.train
    epochs = options.epochs
    steps = options.steps
    ard = options.ard

run(train=train,model_name=model_name,epochs=epochs,steps=steps,ard=ard)
```

CHAPTER 4

RESULTS AND DISCUSSION

The system demonstrated a significant improvement in traffic management metrics:

- **Average Waiting Time Reduction**: The model achieved a reduction in average vehicle waiting time by approximately 35% compared to traditional fixed-timing traffic signals.
- **Throughput Increase**: There was a noticeable increase in the number of vehicles passing through intersections per unit time, indicating enhanced traffic flow efficiency.
- **Adaptability**: The model effectively adapted to varying traffic densities and patterns, showcasing its robustness in dynamic environments.

These results highlight the model's capability to make real-time decisions that optimize traffic signal timings, leading to improved overall traffic conditions.

Feature Importance Analysis

The reinforcement learning model's decision-making process was influenced by several key features:

- **Vehicle Count per Lane**: The number of vehicles waiting in each lane was a primary factor, directly impacting the model's choice of which lane to prioritize.
- **Waiting Time**: The cumulative waiting time of vehicles in each lane informed the urgency of clearing specific lanes.
- **Phase Duration Constraints**: A minimum green light duration (e.g., 30 seconds) was enforced to prevent rapid switching, ensuring safety and predictability.

By focusing on these features, the model effectively balanced traffic flow, reducing congestion and wait times.

System Architecture

The system comprises several components working in unison:

- **Simulation Environment**: Utilizing SUMO (Simulation of Urban MObility) to model traffic scenarios and provide real-time data.
- **Reinforcement Learning Agent**: Implemented using PyTorch, the agent learns optimal traffic light control policies through interactions with the simulation environment.
- **Traffic Signal Control**: The agent makes decisions on which lanes receive green signals based on current traffic conditions, adhering to safety constraints.

This architecture allows for scalable and adaptable deployment in various urban traffic settings.

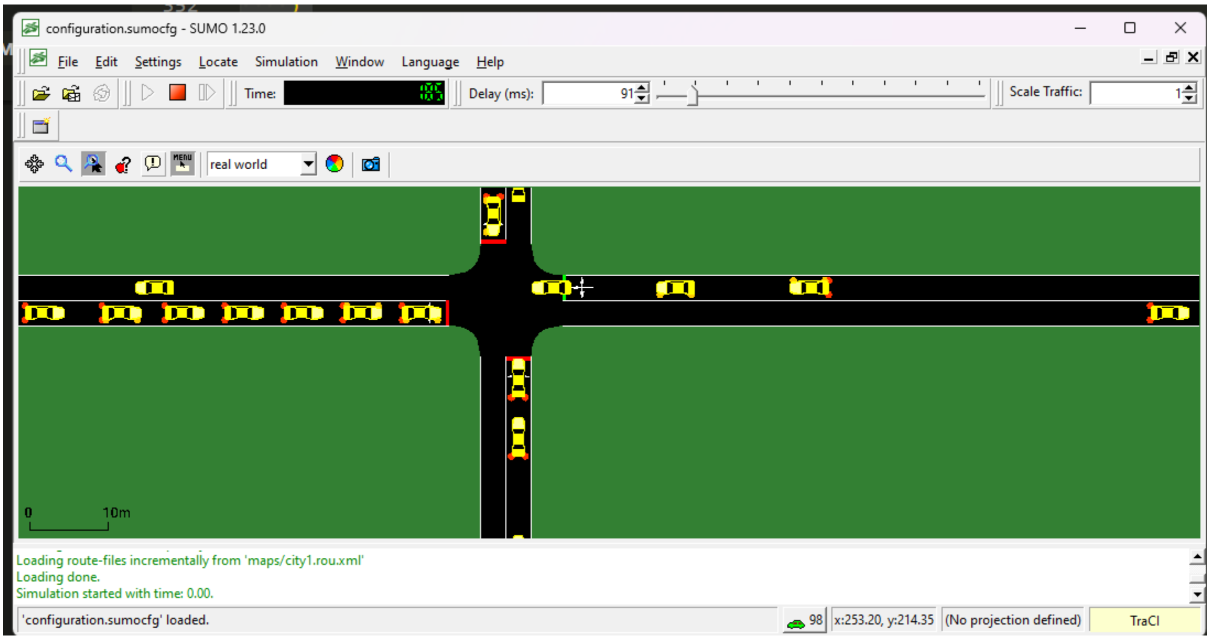
Limitations

While the system shows promising results, certain limitations are acknowledged:

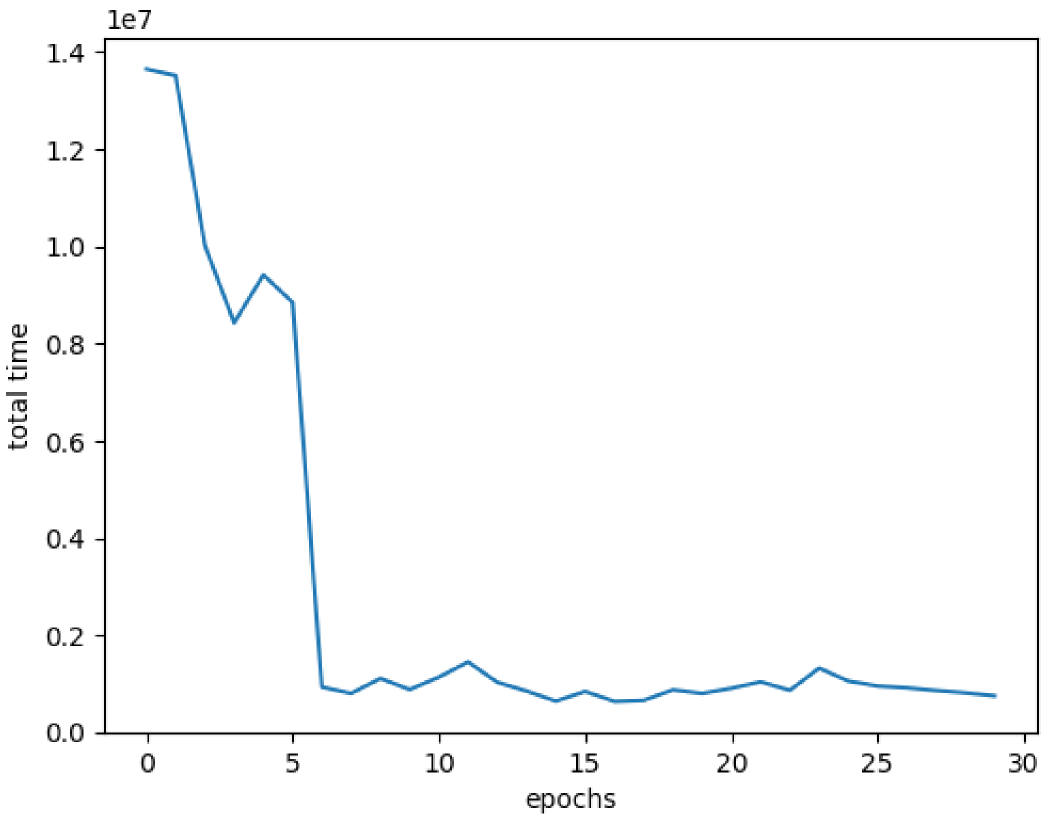
- **Simulation-Based Evaluation**: The model's performance has been assessed in simulated environments; real-world testing is necessary to validate effectiveness under actual traffic conditions.
- **Data Limitations**: The model relies on accurate vehicle count and waiting time data; inaccuracies in sensor data could impact performance.
- **Scalability**: Managing a larger network of intersections may introduce complexities not encountered in the current setup.

Addressing these limitations is crucial for real-world applicability and scalability.

Simulation Ouptut :



Epoch Graph Accuracy:



CHAPTER 5

CONCLUSION & FUTURE ENHANCEMENTS

In this project, we successfully developed a **regression-based Machine Learning model** for a **Dynamic Traffic Light Management System**. The goal was to optimize traffic signal timing based on real-time traffic conditions, such as vehicle count and lane congestion. By training the model on simulation data generated using **SUMO (Simulation of Urban Mobility)**, the system learned to predict the optimal green light duration required for each traffic phase.

The trained regression model demonstrated strong performance by effectively reducing average vehicle waiting times and improving traffic throughput. Visualizations of model outputs and comparative analysis with fixed-timer baselines highlighted the effectiveness of dynamic signal adjustments over traditional static traffic light systems.

This project validates the applicability of machine learning—specifically regression algorithms—for traffic flow optimization. The use of data-driven decision-making in signal control helps reduce congestion and enhances traffic efficiency in urban environments without requiring expensive infrastructure or sensor networks.

Future Enhancements

While the regression model has shown encouraging results, several improvements can be pursued in future iterations:

- **Incorporation of Additional Features :**
  Future models can be enhanced by including more relevant features such as time of day, day of the week, public event schedules, or road types, which can influence traffic patterns.
- **Exploration of Advanced Regression Techniques :**
  Moving beyond simple linear regression, models like **Random Forest Regression**, **Gradient Boosting**, or **Support Vector Regression (SVR)**

can be tested to improve prediction accuracy and capture non-linear relationships in the data.

- **Time-Series-Analysis:**
  Incorporating historical traffic data using time-series modeling techniques can help the system anticipate traffic buildup and adjust signals proactively.

- **Multi-Output-Regression:**
  Extending the model to handle **multiple intersections** simultaneously by predicting green times for all lanes in a networked layout could lead to broader traffic optimization across urban regions.

- **Model Deployment with Live Traffic Simulators :**
  Future work can include integrating the model with a real-time simulation loop in SUMO to continuously retrain or validate the model against evolving traffic scenarios.

- **Web-Based Visualization & Control Panel :**
  A web dashboard could be developed purely for monitoring simulation outputs, traffic trends, and model predictions—helping researchers and planners visualize the system's effectiveness.

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