AI-Powered Smart Traffic Management System for Urban Congestion Reduction

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ABSTRACT- This project showcases a real-time, AI-powered traffic signal management system that utilises intelligent signal control to enhance urban mobility and reduce traffic congestion. To dynamically control signal timings at intersections and monitor traffic density, the system integrates embedded electronics, computer vision, and machine learning. Traffic density is estimated in real-time by analysing live video feeds from cameras using deep learning models, such as YOLO (You Only Look Once), which are used for vehicle detection and counting. To monitor traffic patterns and gradually improve system accuracy, the data is processed and stored in a dedicated database. The system utilises heuristic algorithms or reinforcement learning techniques to optimise signal timings in real-time based on the number of vehicles. This system allows high-density lanes to have longer green lights. Hardware traffic lights are controlled by embedded controllers, such as Raspberry Pi or Arduino, based on AI-generated timing data. Additionally, for traffic monitoring and future scalability, the system provides a real-time web-based dashboard. In addition to reducing idle time and fuel usage, this project establishes the framework for smart city traffic infrastructure and enables the prioritisation of emergency vehicles.

Keywords- AI-powered traffic management, computer vision, deep learning, real-time signal control, smart city infrastructure.

I. INTRODUCTION

Traffic congestion is now a major problem in cities worldwide. This kind of congestion is primarily due to the exponential growth in urban populations and the rapid increase in car ownership. When it comes to managing dynamic and erratic traffic patterns, traditional traffic signal systems that rely on manually operated operations or preset timers are becoming increasingly ineffective. Longer waiting times, higher fuel consumption and an increase in the number of vehicles at each intersection are all frequently caused by these static systems. For evaluating the video feeds and calculating the levels of traffic pollution, deep learning models such as YOLO (You Only Look Once) are utilized [5]. There is an increase in demand for intelligent traffic controllers that can instantly adjust to shifting traffic patterns. This paper aims to develop an AI-based Real-Time Traffic Signal Management System that works with modern technologies such as computer vision, machine learning, embedded systems, and IoT. The primary objective of this work is to utilise real-time video feeds and sensors to measure density. Analysis shows that the system dynamically regulates the signal timing to optimise traffic flow and minimise waiting time at intersections. The paper integrates a centralised database, which can store both real-time and historical traffic data. It empowers the traffic management system to study past patterns for improving performance. Arduino boards or Raspberry Pis are an essential part of this kind of system to manage traffic lights based on AI-generated verdicts. The entire method is designed to be scalable and future-ready. It has the potential to integrate V2I communication, emergency vehicle detection, and smart city applications. This paper represents a significant step toward sustainable and intelligent urban transportation infrastructure.

II. LITERATURE SURVEY

An evaluation of existing work on AI-based traffic light management systems has been conducted. It clears the understanding of the current state of technology and identifies key areas that require innovation and improvement. These works shed light on the application of computer vision, embedded systems, and machine learning to the creation of intelligent traffic control systems. In a paper published in the Sindh University Research Journal by Zia et al. [1] developed an artificial intelligence-based smart traffic signal system. Their strategy utilised machine learning algorithms to optimise traffic light timing in response to current conditions. This effort laid the foundation for future studies on AI-powered traffic management systems, which verified notable decreases in traffic and vehicle idle time. The paper by Phand et al. [2] proposes a real-time traffic light optimisation model that combines AI and IoT technologies. Their method utilised artificial intelligence (AI) for dynamically adjusting traffic signal intervals. It focused on real-time data collection through sensors. To demonstrate how contemporary technologies can provide more effective transport infrastructure, the article focuses on enhanced traffic flow, improved emergency vehicle management, and adaptability in various metropolitan contexts. An open-source and working implementation of an AI-driven traffic control system can be found in Natnael-k's GitHub Project [3]. The repository contains applicable code and documentation that show how AI concepts may be converted into working software, even if it is not a peer-reviewed study. It gives students and developers a practical example.

The paper [4] by authors Kumar and Kaur (2021) presents their work in Procedia Computer Science. They are introducing an AI-based traffic signal control system for utilising IoT sensors to collect vehicle data from the road. This system uses intelligent decision-making algorithms. This algorithm is used for managing signal phases. It results in a better response. These systems offer effective traffic control compared to traditional systems. The research highlights the importance of integrating IoT with AI for effective real-time traffic management.

III. HARDWARE & SOFTWARE TOOLS

Fig1. RaspberryPi4

A. Hardware Components

a. Raspberry Pi is a cost-effective micro computer. This compact systme can manage real-time video analysis. It can control hardware signals through GPIO pins. It supports AI models such as YOLOv5, connects to cloud servers, and ensures efficient low-power operation.

Fig. 2 Traffic light LEDs

b. The Traffic Signal Light Module is a prototype LED traffic light. This prototype features Red, Yellow, and Green LEDs, controlled by either a Raspberry Pi or an Arduino. Used to simulate AI-based signal timing control.

c. USB Webcam Module: Captures real-time traffic video input for vehicle detection and density estimation using OpenCV and YOLO algorithms.

Fig. 3. USB Webcam

B. Software Components

a. Python Programming: Used for hardware interfacing, AI model execution, and traffic decision logic through libraries like RPi.GPIO, OpenCV, and TensorFlow.
b. YOLO v7 Algorithm: A fast, real-time object detection model used for vehicle detection and traffic density estimation, enabling adaptive control of green signal durations.

IV. METHODOLOGY

The AI-Integrated Smart Traffic Control System follows a modular design enabling real-time traffic analysis and adaptive signal optimisation. Using video input from webcams, YOLO detects and counts vehicles across lanes. This data is processed on a Raspberry Pi, which executes signal timing adjustments based on density using heuristic or reinforcement learning algorithms. The system continuously logs traffic data to a central database, enhancing long-term learning and predictive accuracy. Embedded controllers interface with traffic signal modules through GPIOs to apply AI-driven control decisions. A real-time dashboard displays traffic conditions and performance metrics for monitoring.

A. Flowchart: The system follows a structured workflow that enables real-time, AI-based traffic management, as outlined below:

a. **Start:** The system initiates automatically or upon user command, preparing to capture live traffic data from the surrounding environment.

b. **Camera Module:** A camera installed at traffic intersections continuously captures live video footage, serving as the primary input representing current road conditions.

c. **Vehicle Detection using YOLOv7:** Captured frames are processed through the YOLOv7 (You Only Look Once, version 7) deep learning model. The model identifies and localises vehicles using bounding boxes, classifying them as cars, bikes, buses, trucks, or emergency vehicles.

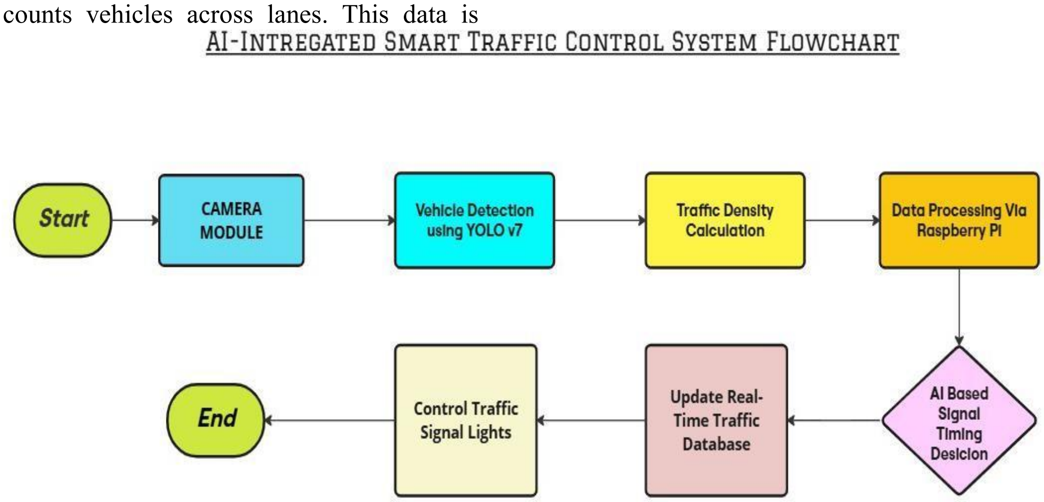

Fig. 4. Flowchart of the system

d. **Traffic Density Calculation:** Based on the detected vehicles, the system computes the effective traffic density for each lane, enabling the determination of congested directions requiring longer green light durations.

e. **Data Processing via Raspberry Pi:** Raw and analysed data are transmitted to a Raspberry Pi, functioning as the system's central processing unit. It executes decision scripts and performs computations for signal control.

f. **AI-Based Signal Timing Decision:** An AI-driven timing algorithm determines the optimal signal duration based on learned traffic patterns. Emergency vehicles are prioritised with immediate green light allocation.

g. **Real-Time Traffic Database Update:** Traffic data are continuously updated and stored in a local or cloud-based database for analytics, trend observation, and predictive modelling.

h. **Traffic Signal Control:** The AI-generated output dynamically adjusts physical traffic lights in real time according to prevailing traffic conditions.

i. **Loop Continuation:** The system operates in a continuous feedback loop, enabling fully autonomous and adaptive traffic control without human intervention.

B. Data Collection/Input

Data acquisition forms the foundation of the AI-integrated traffic management system. Real-time video footage is captured from traffic intersections, pre-processed, and segmented into frames suitable for deep learning-based analysis.

C. Object Detection and Vehicle Recognition

The YOLOv7 architecture is employed for vehicle detection and classification due to its superior balance between speed and accuracy in real-time applications. Each frame is analysed to extract information such as vehicle type, position, and movement trajectory.

D. Vehicle Counting and Categorisation

Vehicles are counted and categorised to understand lane-wise traffic flow. Each vehicle type is assigned a weight factor based on its road occupancy, as shown in Table I.

TABLE I: Vehicle Weight Factors

Vehicle Type	**Weight Factor**
Bike	0.5
Car	1.0
Bus/Truck	2.0
Emergency Vehicle	5.0 (Priority)

This weighted approach provides a realistic measure of lane congestion rather than a mere vehicle count. Detection errors are mitigated using confidence thresholds (≥ 0.5) and frame-averaging techniques. Structured data is then passed to the density analysis module.

a. **Traffic Density Analysis:** Traffic density is computed as the effective load per lane, defined by:

b. **Effective Load Calculation**: The effective load for each lane is calculated using the following equation: The Effective Load (on Lane) = $\Sigma(V_i \times W_i)$ – (1)

In equation (1), Vi = Number of vehicles of type i and Wi = Weight factor, with respect to vehicle type i. Lanes get priority based on computed density and the presence of emergency vehicles. Density thresholds affect the optimised durations of signals with a minimum of 5s and a maximum of 25s.

E. Signal Timing and Control Logic

The signal module determines signal phases dynamically. Lanes with higher densities or emergency vehicles are granted extended or immediate green signals. The applied logic minimises congestion and enhances vehicular flow efficiency.

F. Visualisation and Output Display

Visualisation is implemented via Pygame. It provides an interactive graphical representation of traffic intersections that includes vehicles and signal lights. This module allows real-time observation of the AI's decision-making process and system responsiveness.

V. Simulation, Testing, and Performance Evaluation

a. Simulation: This paper represents an AI-based approach to urban traffic management system but it needs validation, which is done through a simulation. It was developed using various tools, including Python, OpenCV, YOLOv8, and Pygame. The simulation emulates real-time traffic conditions, vehicle detection, and adaptive signal control. The graphical interface shows the responses given by the system. This simulation can represent how the system is dynamically adjusting signal timings and prioritising varying vehicle densities emergency vehicles. This simulation interface gives a proof of concept. It demonstrates the effectiveness of AI in enhancing traffic flow and reducing congestion in urban scenarios. Fig. 5 illustrates categorised vehicle types, active signal control, and detected traffic conditions.

b. Final Output: A visually interactive simulation of the intelligent urban traffic signal system. It demonstrates how AI processes data and dynamically optimises signal's behaviour.

Fig. 5. Simulation Interface

c. **Testing Conditions and Evaluation**: Testing of the system is a important phase for validating the reliability, effectiveness and real-time performance of the urban AI-Integrated Traffic Management System. This testing section outlines the operating environment, used tools, possible scenarios, and evaluation metrics used.

d. **Hardware Setup:** Laptop/PC with minimum i5 processor, 8 GB RAM, GPU (if using YOLOv8). USB camera or pre-recorded traffic video for testing input

e. **Software Used:** Python 3.x, OpenCV (for video processing), Ultralytics YOLOv8 or Haar Cascade (for object detection), Pygame (for GUI simulation), NumPy, time, and math libraries for backend processing

f. **Types of Testing Performed**

i. **Unit Testing**: Each module (e.g., detection, density calculation, signal control) tested independently. Debug print statements used for verification.

ii. **Integration Testing:** All modules combined and tested for data flow and synchronization. Ensured vehicle detection influenced correct signal allocation.

iii. **Real-Time Simulation Testing:** Live webcam and recorded traffic videos used as input. Frame-by-frame processing confirmed system responsiveness.

b. **Test Scenarios**

i. **Normal Traffic Condition:** Random mix of vehicles in each lane. Output: Signals dynamically adjust based on load.

ii. **Emergency Vehicle Scenario:** Ambulance icon inserted in one lane. Output: Lane given priority green signal.

iii. **Equal Load Scenario:** All lanes have the same density. Output: Fair and round-robin distribution.

iv. **No Traffic in a Lane:** Output: Lane skipped or minimum green time used.

TABLE II: Performance Metrics

Metric	**Description**	**Result**
Detection Accuracy	Correct identification of vehicles	>90% (YOLOv8)
Signal Allocation Time	Delay between input and response	<1 sec
Emergency Response Time	Time to detect and act on emergency	Immediate/Next Cycle
Simulation Stability	System lags or crashes	None observed
Real-Time Frame Rate	Frames processed per second	15–20 fps (YOLO with GPU)

VI. Conclusion

The Real-Time AI-Based Traffic Signal Management System presents an innovative and practical solution to the growing challenges of urban traffic congestion. By leveraging artificial intelligence, computer vision, and embedded systems, this project provides a dynamic approach to traffic signal control that adapts in real-time based on vehicle density and traffic flow. Unlike conventional fixed-timer systems, this intelligent system ensures optimal utilization of green signal time, thereby reducing vehicle idle time, fuel consumption, and environmental pollution. The system also lays a strong foundation for future smart city infrastructure. Its modular and scalable architecture allows integration of advanced features such as emergency vehicle prioritization, V2I communication, pedestrian detection, and traffic violation monitoring. Real-time data collection and AI-based decision-making ensure enhanced road safety, improved urban mobility, and better commuter experience.

References

[1] S. S. Zia, M. Naseem, I. Mala, M. Tahir, T. J. A. Mughal, and T. Mubeen, "Smart traffic light system by using artificial intelligence," *Sindh University Research Journal (Science Series)*, vol. 50, no. 4, pp. 639–646, 2018. DOI : 10.26692/sujo/2018.12.00104

[2] A. Phand, S. Bagade, N. Bandgar, and G. Wayal, "Real-time traffic light optimization using AI and IoT," *International Journal for Research in Applied Science and Engineering Technology (IJRASET)*, vol. 12, IV, 2024. DOI: https://doi.org/10.22214/ijraset.2024.60686

[3] Natnael-k, *AI-based traffic control system [Computer software]*, GitHub. URL: https://github.com/Natnael-k/AI-based-Traffic-Control-System--

[4] A. Kumar and R. Kaur, "AI-based traffic signal control system using Internet of Things (IoT)," *Procedia Computer Science*, vol. 192, pp. 5154–5163, 2021. URL: https://www.sciencedirect.com/science/article/pii/S18770509221025187

[5] Leveraging deep learning for traffic management using existing system. (2025). *Journal of Data Analytics and Artificial Intelligence*, 4(1), Article 52. https://doi.org/10.46632/jdaai/4/1/52