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SMART CONTROL OF TRAFFIC LIGHT USING ARTIFICIAL INTELLIGENCE

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Abstract: This project presents a Smart Traffic Light Control System powered by Artificial Intelligence techniques to dynamically manage traffic signal timings based on real-time vehicle density, congestion levels, and environmental conditions. The proposed system uses computer vision and deep learning to detect and count vehicles at intersections, automatically adjusting green-phase durations to minimise waiting times and reduce overall traffic congestion. Machine Learning models trained on traffic-flow datasets enable intelligent, adaptive signal control that outperforms traditional fixed-timer systems. The system aims to improve road throughput, reduce fuel consumption, lower emissions, and enhance road safety across urban intersections.

Keywords: *Smart Traffic Light, Artificial Intelligence, Deep Learning, Computer Vision, Vehicle Detection, Adaptive Signal Control, YOLO, Convolutional Neural Networks, Traffic Management*

1.INTRODUCTION

Rapid urbanisation has led to an exponential increase in the number of vehicles on roads worldwide, resulting in severe traffic congestion, increased travel times, fuel wastage, and rising pollution levels. Traditional traffic signal systems operate on pre-programmed fixed timers that fail to adapt to dynamic changes in traffic density, leading to unnecessary delays even when roads are clear on one side while vehicles queue on another. This inefficiency demands an intelligent, adaptive solution.

Artificial Intelligence and Computer Vision offer a transformative approach to traffic signal management. By deploying cameras at intersections and applying real-time object-detection algorithms, the system can accurately count vehicles in each lane and dynamically compute optimal signal-phase durations. This project builds an AI-driven traffic light controller that continuously monitors intersection conditions and adapts signal timings to minimise cumulative vehicle waiting time across all lanes.

Unlike rule-based or sensor-loop systems, the proposed AI-based model uses deep learning to process visual data, enabling robust detection under varying lighting conditions, weather, and vehicle types. The system is designed to integrate with existing infrastructure with minimal hardware modification, making it a cost-effective and scalable upgrade for urban traffic management authorities.

2.LITERATURE SURVEY

Significant research has been conducted on intelligent traffic signal control using AI and image-processing techniques. Early approaches relied on inductive loop detectors embedded in road surfaces, which provided only basic vehicle-count data. Recent advances in computer vision have enabled far richer traffic analysis:

- **YOLO (You Only Look Once)** object-detection models deliver real-time, high-accuracy vehicle detection in video streams, making them ideal for fast-paced intersection monitoring.
- **Convolutional Neural Networks (CNN)** are widely used for image-based vehicle classification and density estimation, achieving state-of-the-art results on benchmark traffic datasets.
- **Reinforcement Learning (RL)** agents learn optimal signal-switching policies by interacting with traffic simulations, significantly reducing average waiting times compared to fixed-timer baselines.
- **Fuzzy Logic Controllers** have been applied to model imprecise traffic-flow parameters and generate smooth, adaptive phase-duration decisions without requiring explicit training data.
- **Support Vector Machines (SVM)** and **Random Forest** classifiers have been used for congestion prediction using historical flow data, informing proactive signal adjustments.

3. **Deep Q-Networks (DQN)** combine CNN-based state representation with Q-learning to optimise multi-intersection signal coordination in complex urban networks.

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4.PROPOSED SYSTEM

The proposed AI-based Smart Traffic Light Control System continuously captures video feeds from cameras mounted at each approach of an intersection. A YOLO-based object-detection model processes each frame in real time to detect and count vehicles in every lane. The vehicle counts are fed into an adaptive signal-timing algorithm that computes the optimal green-phase duration for each lane proportional to its current density, ensuring heavier-traffic lanes receive longer green phases dynamically.

The system follows a modular pipeline: video capture, preprocessing, vehicle detection, density estimation, signal-phase computation, and hardware actuation. A central controller aggregates data from all lane cameras, runs the timing algorithm, and sends switching commands to the signal hardware via a microcontroller interface. Emergency-vehicle detection is integrated as a priority override module that instantly grants a green phase to any lane occupied by an ambulance, fire engine, or police vehicle identified through visual classification.

The backend is built using Python with TensorFlow/Keras for inference, and OpenCV for real-time video processing. A simulation environment using SUMO (Simulation of Urban MObility) was used for initial algorithm development and benchmarking before hardware deployment. The system is deployable on edge devices such as NVIDIA Jetson Nano for low-latency on-site processing without cloud dependency.

5.METHODOLOGY

The working methodology of the system includes the following steps:

- **Data Collection:** Traffic video datasets including UA-DETRAC, VIRAT, and custom intersection footage were collected to train and validate vehicle-detection models under diverse conditions.
- **Data Preprocessing:** Video frames are extracted, resized to 416×416 pixels, and augmented with brightness variation, horizontal flipping, and noise injection to improve model robustness.
- **Vehicle Detection:** YOLOv5 is fine-tuned on the traffic dataset to detect cars, motorcycles, buses, and trucks. Non-Maximum Suppression (NMS) filters redundant bounding boxes for clean count output.
- **Density Estimation:** Per-lane vehicle counts from the detector are normalised and mapped to a congestion index (0–1 scale) representing relative lane load at each signal cycle.
- **Adaptive Phase Computation:** Green-phase durations are allocated proportionally to lane congestion indices within configurable minimum (15 s) and maximum (90 s) bounds, ensuring fairness and throughput.
- **Emergency Override:** A secondary classifier detects emergency vehicles using colour, shape, and siren-light patterns, triggering an immediate priority green phase for the affected lane.
- **Simulation & Evaluation:** The algorithm was evaluated in SUMO with 10,000 simulated vehicle trips. Metrics include average waiting time, queue length, throughput, and fuel consumption per cycle.
- **Hardware Interface:** A Raspberry Pi microcontroller receives phase commands via serial communication and drives relay modules connected to standard RGB traffic-signal LEDs for real-world testing.
- **Result Visualisation:** A real-time dashboard displays live camera feeds, vehicle counts per lane, current phase timings, and historical congestion heat maps for traffic-management operators.

The system was evaluated on a benchmark simulation with 4-way intersections over 8-hour traffic cycles:

Method	Avg. Waiting Time	Queue Length	Throughput
Fixed-Timer (Baseline)	62.4 s	18.7 vehicles	820 veh/hr
Fuzzy Logic Controller	48.1 s	13.2 vehicles	960 veh/hr
Reinforcement Learning (DQN)	37.6 s	9.8 vehicles	1,085 veh/hr
Proposed AI System (YOLO+Adaptive)	31.2 s	7.4 vehicles	1,190 veh/hr

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6.CONCLUSION

The developed Smart Traffic Light Control System demonstrates the effectiveness of Artificial Intelligence and Computer Vision in addressing one of the most pressing urban challenges — traffic congestion. By applying real-time vehicle detection using YOLOv5 and an adaptive phase-allocation algorithm, the system dynamically optimises green-phase durations based on actual lane density, achieving a 50% reduction in average vehicle waiting time compared to conventional fixed-timer systems.

The integration of emergency-vehicle priority override further enhances road safety by ensuring unimpeded passage for critical vehicles. The modular, edge-deployable architecture enables installation at existing intersections with minimal infrastructure changes, making the solution both technically robust and economically viable for municipal adoption. Simulation results validated strong improvements in throughput, queue management, and fuel efficiency across diverse traffic scenarios. In summary, this work contributes a practical, scalable, and deployable AI framework with significant potential to transform urban traffic management, reduce emissions, and improve quality of life in congested cities. The system provides a strong foundation for smart-city traffic infrastructure aligned with sustainable development goals.

7.FUTURE SCOPE

The system can be extended by integrating multi-intersection coordination using a centralised Deep Reinforcement Learning (DRL) agent that optimises signal plans across an entire urban corridor rather than isolated junctions. V2I (Vehicle-to-Infrastructure) communication can enable vehicles to broadcast their position and speed directly to the signal controller for finer-grained density estimation without reliance on camera-based detection alone. Future work may incorporate pedestrian and cyclist detection to ensure signal plans account for vulnerable road users, and integrate weather and visibility sensors to adaptively extend phases during fog, rain, or reduced-visibility conditions. Integration with city-wide Geographic Information Systems (GIS) and real-time navigation platforms such as Google Maps can enable predictive signal coordination based on anticipated traffic inflow from upstream routes. Explainable AI (XAI) techniques can be incorporated to provide traffic operators with transparent reasoning behind each phase-switching decision, building trust and enabling manual override when required. Deployment as a cloud-connected system with OTA (Over-the-Air) model updates will allow continuous improvement as new traffic patterns emerge, and federated learning across multiple cities can enable collaborative model training while preserving data privacy.

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