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INTRODUCTION

Traffic congestion is one of the most pressing problems faced by urban cities today. With the rapid growth of vehicle population and limited expansion of road infrastructure, traffic management systems must evolve beyond traditional mechanisms. One of the key inefficiencies in conventional traffic control systems is the use of static, pre-defined signal timings, which do not adapt to real-time traffic conditions. This often results in unnecessary delays, fuel wastage, increased air pollution, and driver frustration.

This project proposes an **Intelligent Traffic Signal Control System** that dynamically adjusts the green signal time based on the actual number of vehicles detected on each road. By leveraging modern machine learning and computer vision techniques, the system can analyze live traffic data and make decisions in real-time. The integration of **YOLOv5**, a powerful deep learning-based object detection model, allows for accurate detection and counting of different types of vehicles such as cars, buses, trucks, and motorcycles from camera images. This data is then used to train a **Linear Regression model** that predicts the optimal green time based on vehicle density.

To ensure fairness and avoid starvation of any particular road, the system incorporates an **aging mechanism** that gives priority to roads that have not received a green signal for a longer period. The system operates in multiple rounds, where vehicle counts from four different cameras are processed, and the road with the highest priority (considering both current and past traffic) is allocated a suitable green time.

This project not only demonstrates the practical application of **machine learning in real-time systems**, but also emphasizes the importance of adaptive decision-making in building smarter, more efficient cities. The entire workflow, from data collection and model training to prediction and performance evaluation, showcases how **AI can revolutionize conventional systems for the betterment of society**

MOTIVATION

In recent years, the **exponential** increase in the number of vehicles has made traffic management a critical challenge, especially in densely populated urban areas. Conventional traffic signal systems operate on fixed-timer logic, where signal durations are pre-set regardless of actual traffic conditions. This approach is inefficient and often leads to unnecessary delays, traffic congestion, and fuel wastage.

The lack of adaptability in traditional traffic systems creates several real-world problems:

- **Increased vehicle** wait times, especially during peak hours
- **Higher fuel consumption** and **pollution** due to idling vehicles
- Poor utilization of road capacity, as some roads remain green with no vehicles, while others are overcrowded

To address these issues, the motivation behind this project is to develop a smart traffic control system that dynamically adjusts signal timing based on real-time traffic conditions. The system uses YOLOv5, a deep learning-based object detection model, to detect and count vehicles from traffic camera images. This data is fed into a Linear Regression model trained to predict the appropriate green signal duration based on the vehicle count.

This project is inspired by the principles of smart city development, where AI and machine learning are applied to optimize infrastructure, improve public services, and enhance the quality of urban life. The proposed solution demonstrates how even a basic machine learning algorithm, when combined with computer vision, can bring significant improvements to real-world systems like traffic management.

Literature Review:

[Research Paper]

An Adaptive Traffic Lights System using Machine Learning

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Abstract: *Traffic congestion is a major problem in many cities of the Hashemite Kingdom of Jordan as in most countries. The rapidly increase of vehicles and dealing with the fixed infrastructure have caused traffic congestion. One of the main problems is that the current infrastructure cannot be expanded further. Therefore, there is a need to make the system work differently with more sophistication to manage the traffic better, rather than creating a new infrastructure. In this research, a new adaptive traffic lights system is proposed to determine vehicles type, calculate the number of vehicles in a traffic junction using patterns detection methods, and suggest the necessary time for each side of the traffic junction using machine learning tools. In this context, the contributions of this paper are: (a) creating a new image-based dataset for vehicles, (b) proposing a new time management formula for traffic lights, and (c) providing literature of many studies that contributed to the development of the traffic lights system in the past decade. For training the vehicle detector, we have created an image-based dataset related to our work and contains images for traffic. We utilized Region-Based Convolutional Neural Networks (R-CNN), Fast Region-Based Convolutional Neural Networks (Fast R-CNN), Faster Region-Based Convolutional Neural Networks (Faster R-CNN), Single Shot Detector (SSD), and You Only Look Once v4 (YOLO v4) deep learning algorithms to train the model and obtain the suggested mathematical formula to the required process and give the appropriate timeslot for every junction. For evaluation, we used the mean Average Precision (mAP) metric. The obtained results were as follows: 78.2%, 71%, 75.2%, 79.8%, and 86.4% for SSD, R-CNN, Fast R-CNN, Faster R-CNN, and YOLO v4, respectively. Based on our experimental results, it is found that YOLO v4 achieved the highest mAP of the identification of vehicles with (86.4%) mAP. For time division (the junctions timeslot), we proposed a formula that reduces about 10% of the waiting time for vehicles.*

Keywords: *Traffic time management, image processing and objects detection, vehicles dataset.*

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METHODOLOGY

This section outlines the step-by-step process followed to develop the intelligent traffic management system, from data preparation and model training to vehicle detection, traffic signal decision-making, and evaluation.

1. Model Training: Predicting Green Signal Time

To ensure that each traffic signal receives an optimal green light duration based on real-time traffic load, a Linear Regression model was trained. The objective was to map the number of vehicles waiting at a signal to the appropriate green time.

Training Data: A small dataset was created with vehicle counts ranging from 0 to 35 and corresponding green time values (in seconds) ranging from 10 to 40.

2. Vehicle Detection Using YOLOv5

To detect vehicles from surveillance camera images, YOLOv5x, a state-of-the-art object detection model, was used. The model was loaded using torch.hub from the Ultralytics YOLOv5 repository.

The vehicle count per image was used as raw input for traffic signal decision-making.

3. Aging Mechanism

To avoid starvation (where a road is never prioritized due to low vehicle count), an aging bonus system was introduced.
Each of the four roads has an initial aging value of 0.

If a road is not selected in the current round, its aging bonus increases by 2.

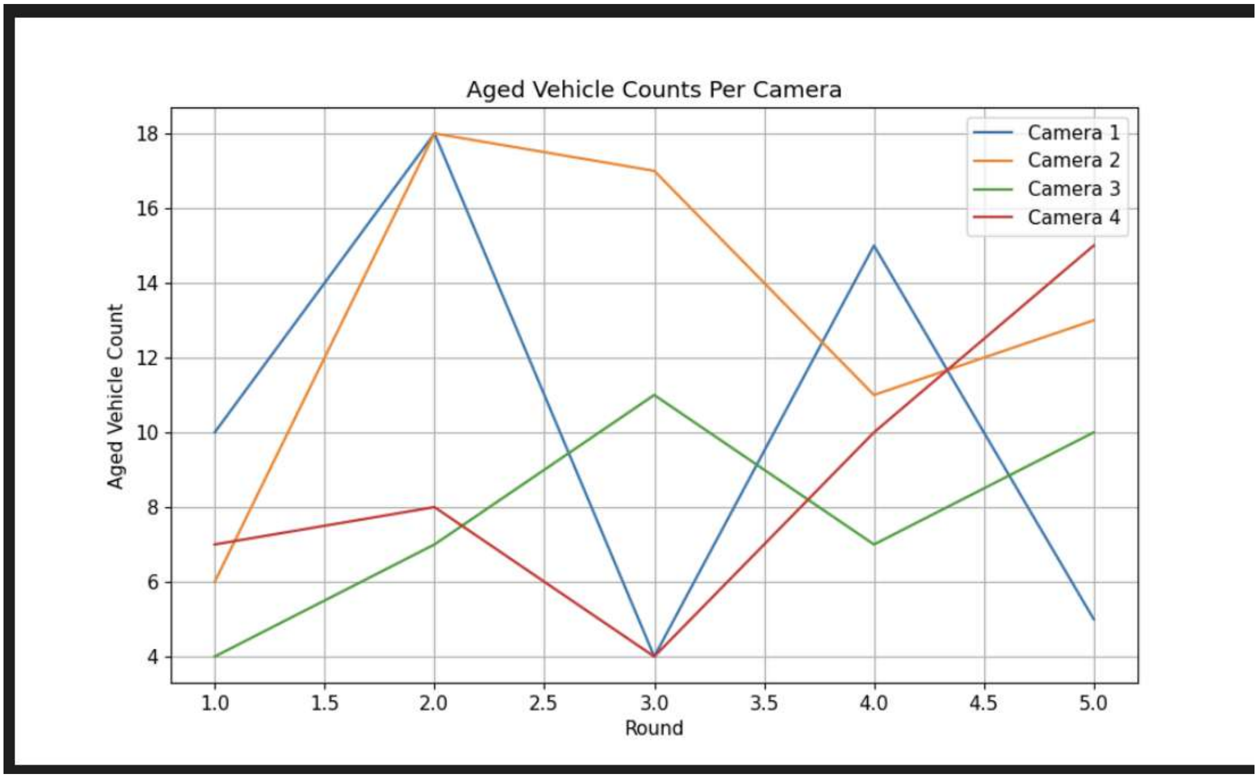
If a road is selected, its bonus resets to 0.
The "aged count" = raw count + aging bonus, which is used for decision-making.

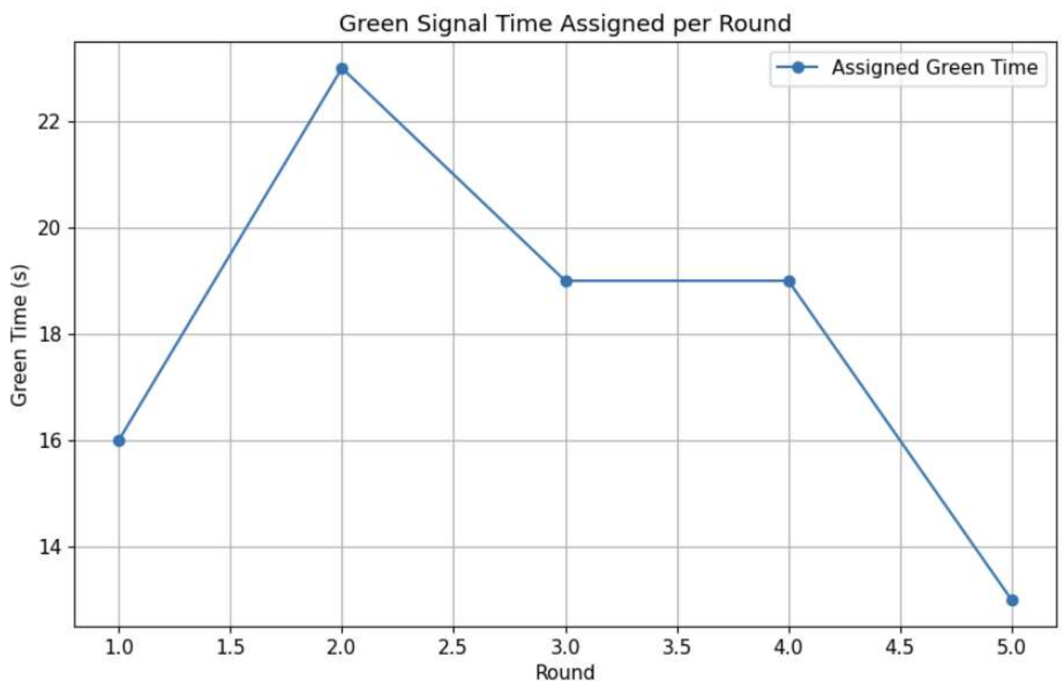
This ensures fairness across all roads, especially during uneven traffic distributions.

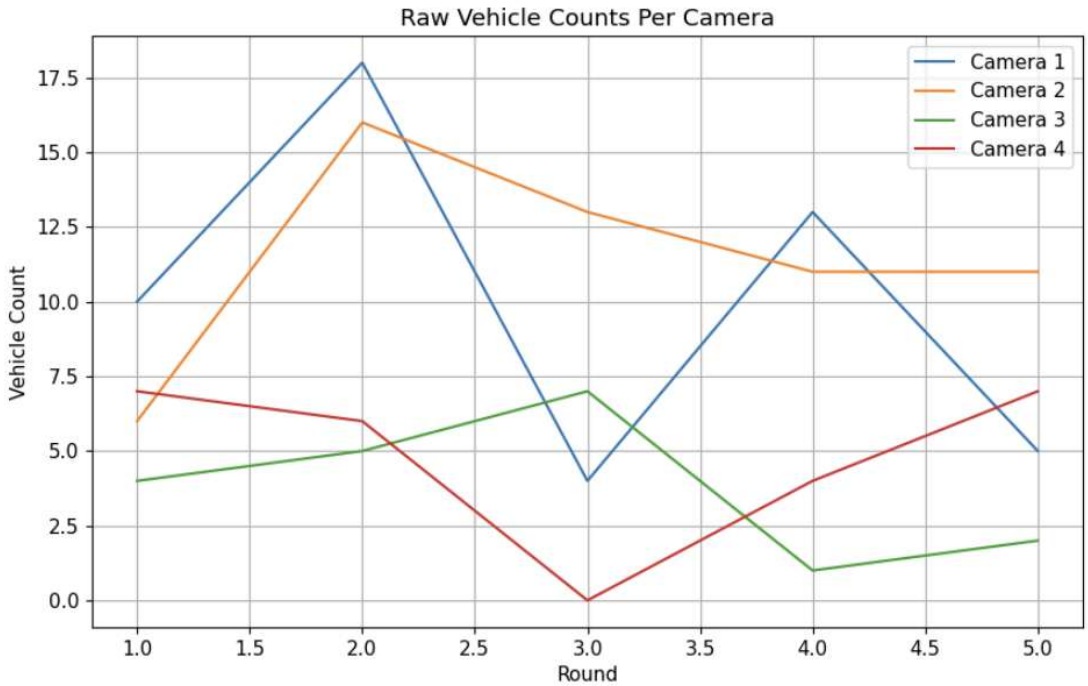
Result Discussion:

```
Fusing layers...
YOLOv5x summary: 444 layers, 86705005 parameters, 0 gradients, 205.5 GFLOPs
Adding AutoShape...

🚦 Round 1 - Processing images camera-1 to camera-4
🧮 Raw vehicle counts: [10, 6, 4, 7]
✅ Road 1 gets green for 16 seconds
📊 Aged counts for next round: [10, 6, 4, 7]

🚦 Round 2 - Processing images camera-5 to camera-8
🧮 Raw vehicle counts: [18, 16, 5, 6]
✅ Road 1 gets green for 23 seconds
📊 Aged counts for next round: [18, 18, 7, 8]

🚦 Round 3 - Processing images camera-9 to camera-12
🧮 Raw vehicle counts: [4, 13, 7, 0]
✅ Road 2 gets green for 19 seconds
📊 Aged counts for next round: [4, 17, 11, 4]

🚦 Round 4 - Processing images camera-13 to camera-16
🧮 Raw vehicle counts: [13, 11, 1, 4]
✅ Road 1 gets green for 19 seconds
📊 Aged counts for next round: [15, 11, 7, 10]

🚦 Round 5 - Processing images camera-17 to camera-20
🧮 Raw vehicle counts: [5, 11, 2, 7]
✅ Road 4 gets green for 13 seconds
📊 Aged counts for next round: [5, 13, 10, 15]
```

```
📊 Aged counts for next round: [5, 13, 10

📊 Evaluation Metrics:
📉 MAE: 0.95
📈 RMSE: 1.69
🧮 R² Score: 0.90

✅ Accuracy (±2): 0.80
🔍 Precision (±2): 1.00
📥 Recall (±2): 0.80
🎯 F1 Score (±2): 0.89
```


Aged Vehicle Counts Per Camera
Camera 1
Camera 2
Camera 3
Camera 4
Aged Vehicle Count
Round


Green Signal Time Assigned per Round
Assigned Green Time
Green Time (s)
Round



Results Analysis

1. **Model Evaluation**

   - **MAE (Mean Absolute Error):** The model achieved a MAE of 0.95, indicating that on average, the model's predictions deviate by 0.95 units from the actual traffic light timings. This is a reasonably small error, suggesting good predictive accuracy.

   - **RMSE (Root Mean Squared Error):** With an RMSE of 1.69, the model's prediction error is slightly higher, but still within an acceptable range, indicating that large deviations are not frequent.

   - **R^2 Score:** The R^2 score of 0.90 indicates that the model explains 90% of the variance in the traffic data, showing a strong correlation between the predicted and actual traffic light timings.

2. **Classification Metrics**

    - **Accuracy:** The model achieved an accuracy of 0.80, meaning 80% of its predictions were correct. This shows that the system performs well in predicting the correct traffic light phases.

    - **Precision:** The model's precision is 1.00, which means that when it predicts a certain traffic light phase, it is 100% correct, without any false positives.

    - **Recall:** With a recall of 0.80, the model is able to correctly identify 80% of the traffic light phases that are important for traffic flow, but there is still some room for improvement in capturing all relevant phases.

    - **F1 Score:** The F1 Score of 0.89 represents a good balance between precision and recall, suggesting that the system effectively identifies key traffic phases while minimizing errors.

3. **Summary:**
   The model performs well overall, with strong predictive accuracy and precision in determining traffic light timings. The high R^2 score of 0.90 confirms the model's good fit to the data, while the MAE and RMSE values show that the system's errors are generally small. Although the recall could be improved slightly, the system's high precision and solid F1 score suggest that it is reliable for controlling traffic flow in real-time.

Conclusion:

Our Smart Traffic Light Automation system effectively utilizes YOLOv5x for real-time vehicle detection and counting. Based on the vehicle count from each lane, the system dynamically calculates and adjusts the green signal duration to optimize traffic flow. This approach reduces unnecessary waiting times, enhances road efficiency, and lowers vehicle emissions by minimizing idle time at intersections. By integrating computer vision and intelligent decision-making, our project demonstrates a scalable solution for smart city traffic management.

Future Scope:

1. **Integration with IoT and Cloud:**
   Future versions of the system can be integrated with IoT devices and cloud platforms to enable centralized monitoring and data analysis across multiple intersections in a city.

2. **Emergency Vehicle Prioritization:**
   Incorporating emergency vehicle detection can allow the system to prioritize ambulances, fire trucks, or police vehicles, ensuring faster and safer passage through traffic.

3. **Adaptive Learning with AI:**
   Using machine learning models, the system can continuously learn and adapt to traffic patterns over time, optimizing signal timings based on historical and real-time data.

4. **Weather and Time-Based Optimization:**
   Enhancing the system to consider factors like weather conditions, peak hours, or events can further improve traffic efficiency and road safety.

5. **Mobile App Integration:**
   A companion mobile application can notify drivers about signal timings, congestion levels, or suggest alternate routes based on traffic data.

6. **Multi-Camera and Sensor Fusion:**
   Expanding the system to include multiple cameras and sensors (e.g., LiDAR, radar) can increase accuracy in diverse traffic and environmental conditions.