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Reinforcement Learning for Adaptive Traffic Signal Timing in Range-Based TMS (Traffic Management System)

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Abstract- Conventional traffic signal control systems frequently fail to adapt to fluctuating traffic patterns, resulting in suboptimal traffic flow and heightened congestion levels. This project introduces an innovative solution that harnesses the capabilities of Reinforcement Learning (RL) to enhance traffic signal timing within a Range-Based Traffic Management System (RTMS). The RL agent is designed to optimize signal timing decisions. It receives feedback from the system, and there by reductions in congestion and enhancements in traffic flow. From a process of iterative learning, the RL agent refines its decision- making capabilities, resulting in progressively more efficient traffic signal management. Through this paper we tried to present a progress in the existing manual traffic control system.

Keywords- YOLO V8n, Reinforcement Learning (RL), Traffic Signal Control, Threshold, Range-Based Traffic Management System (RTMS), Computer Vision using AI, Real-Time Traffic Data.

I. INTRODUCTION

For decades, the conventional red, yellow, and green colour cycle of traffic lights has regulated traffic in cities. The conventional traffic control systems, which are normally based on pre-programmed timing plans or primitive car sensing methods,have indeed helped to bring some order to our roads. They provide a primitive framework for the regulation of complex interactions between motorist, pedestrians, and a variety of forms of transport. But as city centres experience heightened congestion and as our knowledge of traffic behaviour enhances, the natural limitations of such conventional systems come into sharper relief. This technique seeks to analyse these limitations through a human, setting out how their rigidity and inability to react in real-time can cause inefficacy, and potential safety issues for individuals making their way through our streets. In addition, the inability of conventional systems of traffic management to respond also worsens highway congestion. When traffic volume on a specific road exceeds expectations, fixed-time traffic signals continue to follow their pre-programmed cycles, causing unnecessary delays and the formation of long queues. The stop-and-go movement of traffic congestion also of a system that cannot respond to real-time conditions. Implementing predetermined algorithms in traditional systems restricts them to learn and adapt to changing traffic patterns. Urban expansion, changes in land use, and the addition of new transport infrastructure are influences that can make a great impact on traffic patterns over time. Fixed-timed signals without ongoing observation and modification become more inefficient, creating chronic congestion and operating ineffectiveness. A system centred on people would employ real-time examination of data and machine learning techniques to recognize these changing patterns and dynamically modify signal times to maximize traffic flow and reduce delays.

Fig.1. Conventional Traffic Pattern

The Evolution of Traffic Management and the Need for Intelligent Systems

Traditional traffic control is mainly based on fixed signal timing and primitive sensor technologies. For several decades, fixed cycles and simple loop detectors have played a significant role in determining the ebb and flow of urban streets. However, increasing traffic volume and variability necessitate a shift toward intelligent adaptive systems. The rhythmic cycles that used to govern traffic flows simply fell short against growing congestion, unforeseen events, and disparate land-use needs of the urban populace. This necessitates very significantly responsive and learning systems that can actually perceive changes in our dynamic road environments. Early attempts at dynamic traffic control consisted of threshold-triggered rule-based systems, which were a marked improvement over static time control. They represented a step forward from static timings, enabling some responsiveness to intermittent traffic volumes. An example is longer green times being called when a certain number of vehicles would be detected at the approach to an intersection. Yet, those systems were severely limited by their pre-programmed logic and could not respond to real-life situations that fell out of the bounds of their fixed rule sets.

The intervention of computer vision and machine learning gives birth to new possibilities in real-time traffic analysis and proactive control strategies that take traffic management away from simple detection and toward understanding traffic dynamics. Computer vision algorithms are applied to the video feeds for vehicle type identification, estimating queue lengths, tracking pedestrians and cyclists and even real-time incident detection; machine-learning algorithms can then analyse this rich data to identify patterns, predict future traffic state and optimally update signal timings

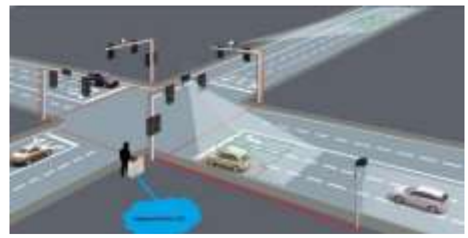

Fig.2. Virtual implementation of model

Hierarchical Traffic Density Classification: Moving Beyond Simple Counts:

Counting the vehicles is a good measure of traffic volume, but it may not provide a true reflection of how traffic congestion is operating. A high vehicle count on a multilane highway with large gaps between the vehicles is more beneficial for travel than the same high vehicle counts with vehicles packed together in stop-and-go traffic. To address this, a hierarchical classification of traffic density offers a more human-interpretable and actionable representation of the traffic situation. A three-level classification (low, medium, high) provides a clear and intuitive categorization of congestion levels.

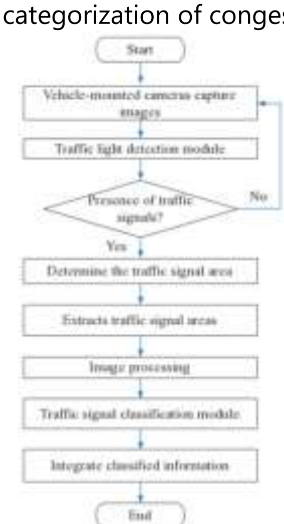

Fig.3. Working Mechanism of the system

- **Low Density:** Characterized by free- flowing traffic with ample spacing between vehicles, allowing for smooth movement. This translates to a comfortable and efficient driving experience for individuals.
- **Medium Density:** Indicates moderate congestion with reduced speeds and shorter inter-vehicle distances. Drivers may experience some delays but the overall flow remains relatively consistent. This level often signifies the onset of potential bottlenecks and requires proactive monitoring.
- **High Density:** Represents significant congestion with slow speeds, frequent stops and starts, and minimal spacing between vehicles. This directly impacts travel times and increase of traffic congestion.

This hierarchical classification, when derived from real-time analysis of lane-mounted camera feeds using YOLOv8, provides a more insightful understanding of the traffic situation than simple vehicle counts. It allows the traffic management system to respond not just to the number of vehicles but to the actual level of congestion experienced by road users.

The Strategic Advantage of Lane-Mounted Cameras:

The placement of cameras directly within the traffic lanes offers several key advantages for accurate and human-relevant traffic monitoring. Lane-mounted cameras provide a closer and more direct visual of single vehicles engaged with one another, unlike traffic cameras placed at height, or traffic cameras on road side, cameras mounted to lane, will allow for better accuracy of object detection since it can possibly reduce occlusion, distance will again enable the countdown fine granularity of inter-vehicle distance, also meaningful for calibration of traffic density. Because of being captured through the line of sight of driving itself, this will better portray what is a calculated activity of actual driving conditions or cue of congestion being experienced. This localized and detailed information is vital for implementing targeted and effective traffic management strategies.

Lane-mounted cameras provide a closer and more direct field of view of individual vehicles and their immediate interactions. This proximity significantly enhances the accuracy of object detection, particularly in complex and often challenging real-world conditions.

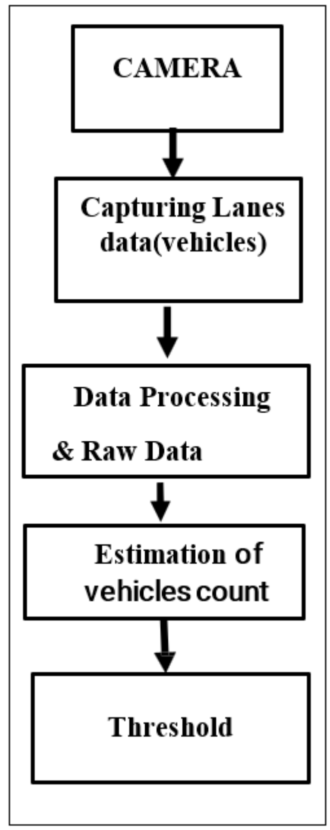

Fig.4. Humanizing the Flow: View of Traffic Counting

Integrating Yolov8, Hierarchical Density Classification

The synergistic integration of YOLOv8, hierarchical traffic density classification, and lane- mounted cameras holds significant promise for creating more human-centric traffic management systems. YOLOv8's real-time object detection capabilities can accurately identify and track vehicles within the field of view of the lane- mounted cameras. The extracted bounding box information and tracking data can then be used to calculate various parameters, such as vehicle speed, inter-vehicle distance, and occupancy within defined segments of the lane. These parameters, in turn, can be fed into a density classification algorithm to categorize the traffic flow into the three levels (low, medium, high) in real-time.

The use of YOLOv8 allows for understanding of traffic conditions beyond simple vehicle counts. By accurately detecting and potentially classifying different types of vehicles (cars, buses, motorcycles), the system can gain a richer understanding of the traffic mix and its implications for flow. The hierarchical traffic density classification (low, medium, high), as discussed in the previous literature review, could be seamlessly integrated with YOLOv8's output to provide the RL agent with a more intuitive and actionable representation of the traffic situation.

Designed Hardware Prototype

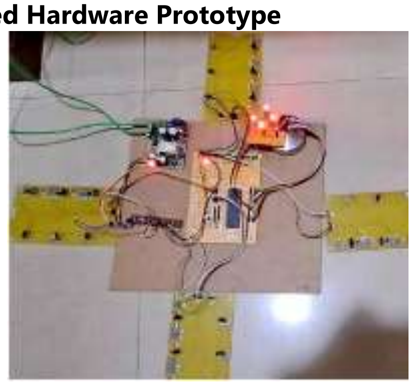

Fig.5.Basic Prototype

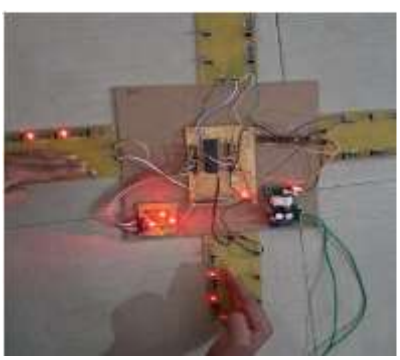

Fig.6. Multiple Lane traffic detection

- **Live Feed Analysis:** YOLO v8 processes live feeds from strategically placed CCTV cameras. It efficiently detects and classifies vehicles, gathering real-time data on traffic conditions.
- **Vehicle Detection and Counting:** YOLOv8 is capable of detecting and counting multiple types of vehicles (cars, buses, motorcycles, trucks) from static cameras or drones in real-time utilizing video streams. This information serves as a critical input to understand the amount and flow of traffic
- **Traffic Density Estimation:** YOLOv8 can estimate traffic density (low, medium, high) on a variety of road segments and intersections by considering the number of detected vehicles and their proximity to each other. This is important information to be used for flexible traffic controls.
- **Speed Estimation:** When combined with tracking algorithms (like Deep SORT) and camera calibration, YOLOv8 can contribute to estimating the speed of vehicles, aiding in identifying speeding violations and understanding traffic dynamics.
- **Vehicle Classification:** YOLOv8 can be trained to classify different types of vehicles, providing a more detailed understanding of the traffic composition. This can be useful for infrastructure planning and targeted traffic management strategies.

YOLO Models Comparison

For a given latency, YOLOv8 consistently outperforms the other YOLO versions in terms of accuracy.

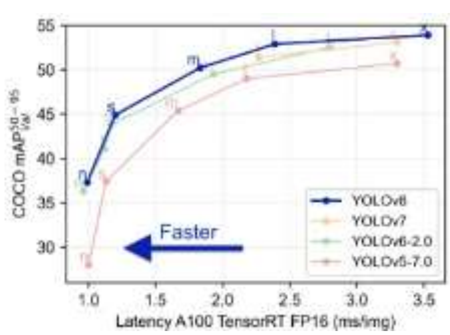

Fig.7.

- The trend indicates that newer YOLO models are more efficient in terms of parameter usage for a given level of performance.
- YOLOv8 generally achieves higher accuracy with fewer parameters compared to older versions like YOLOv7, YOLOv6- 2.0, and YOLOv5-7.0.

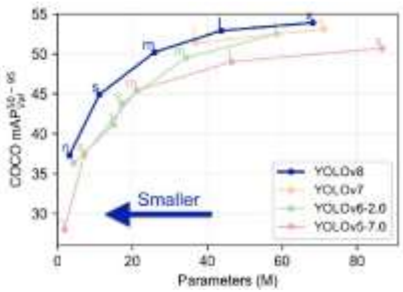

Fig.8.

II. RESULTS

Best model = YOLO("models/best.pt"):
This line indicates to load the pre-trained YOLOv8 architecture for object detection, "best.pt" shows the model to be loaded.

Threshold Definitions (Low_Threshold, Medium_Threshold, High_Threshold):
This reinforces the representations of thresholds based on the vehicle counts from the YOLOv8 detections or density indicators based on the counts.

Quadrilateral Definition (polygon):
Defines the area, the selected area to detect and evaluate the vehicle in a defined polygonal area selected for the traffic lanes of interest, so to restrict the area of concern for detecting vehicle in the camera's view.

Fig.9. Processing sample video frame

Left Lane: left1 (top, y=350-443), left2 (middle, y=443-536), left3 (bottom, y=536- 630).

Right Lane: right1 (top, y=350-443), right2 (middle, y=443-536), right3 (bottom, y=536- 630).

Coordinates: Adjusted to form quadrilaterals that account for perspective (narrower at the top, wider at the bottom). These are approximate and should be tuned to match the actual video's lane boundaries.

Regions: Each region shows its vehicle count and density (e.g., left1: 3 vehicles, medium) near its top boundary.

Traffic Lights:
Left Lane: Displayed at the top-left with a coloured circle (green or red) and text (e.g., Left Lane: Green (10.0 s) or Left Lane: Red (0.0 s)).

Right Lane: Displayed at the top-right with a similar circle and text

The image displays a live video feed of a multi- lane road with several vehicles present. Notably, each detected vehicle is enclosed in a bounding box with a label indicating the object detected (e.g., "vehicle 1.01"). This directly demonstrates YOLOv8's core functionality: its ability to accurately identify and localize objects of interest within the visual data. This real-time detection is the foundational layer upon which more advanced traffic analysis and control strategies can be built, as highlighted in our base paper review.

Fig.10. Low density Traffic

Fig.11. High density Traffic

Advantages and Future Directions:
While the integration of YOLOv8, hierarchical density classification, and lane-mounted cameras holds immense potential, several challenges need to be addressed. These include:

Computational Resources: Real-time processing of high-resolution video streams from multiple lane-mounted cameras requires significant computational resources. Efficient hardware and optimized algorithms are crucial for practical implementation.

Table:1 Comparison features of YOLO: v7 Vs v8

Feature	YOLOv7	YOLOv8
Architecture	Anchor- based	Anchor-free
Key Focus	High performance, efficiency	Versatility, user-friendliness
Strengths	High accuracy and speed, efficient training	State-of-the- art performance, user-friendly design, versatility
Weaknesses	Complex to customize, resource-intensive	Newer model
Training Model	Trainable bag-of-freebies	Advanced augmentatio n, optimized training
Accuracy	High	Improved, especially for small objects
Speed	High	Faster

Environmental Factors: Weather conditions such as heavy rain, fog, or snow can significantly impact the performance of object detection algorithms. Robust and weather-resilient systems are necessary.

Integration with Existing Infrastructure: Integrating these advanced systems with existing traffic control infrastructure can be complex and requires careful planning.

Scalability and Cost: Deploying and maintaining a large network of lane-mounted cameras can be costly. Cost-effective and scalable solutions are needed for widespread adoption.

Future research directions should focus on forward, traffic flow analysis, assessing the environmental impact, will assist in greener traffic planning. There will be seamless integration with connected vehicles to acquire rich real-time data. Mobile phone data will also capture pedestrian and cyclist movements. The deep learning mechanism will communicate with the existing traffic signals and variable message signs, whereas multimodal travel optimization will benefit from public transport data. Smart city infrastructure integration will give an overall urban perspective. Direct integration with emergency services will accelerate responses. With an emergence of autonomous vehicles, deep learning will ensure their safe coexistence. Future research will mainly focus on efficient architectures, robust algorithms for adverse weather, privacy-preserving techniques, low-cost deployments, and standard communication protocols. This integrated approach promises safe, efficient, and traffic mobility.

III. CONCLUSION

The integration of YOLOv8, a hierarchical three-level traffic density classification, and strategically placed lane-mounted cameras, such advancements in smart and human-friendly traffic management systems represents a significant step towards creating more intelligent and human-centric traffic management systems. The approach essentially portrays traffic in a real-time, high-definition, and clear way such that control actions are more responsive and anticipatory. Ultimately, this translates into reduced congestion, less travel time, increased safety, and simply a better experience of public transport.

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