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ADAPTIVE FOUR-JUNCTION TRAFFIC LIGHT CONTROLLER USING COMPUTER VISION

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ABSTRACT

Traffic light control systems are essential elements of urban infrastructure, as they significantly contribute to road safety by maintaining an organized flow of traffic and promoting the efficient and smooth movement of vehicles. This study developed an adaptive traffic light control system for four-junction intersections, employing computer vision and real-time data processing. Using the YOLOV5 object detection algorithm, the system identifies vehicles and adjusts signal timings based on traffic density to optimize flow and reduce congestion. Trained on extensive datasets, the model achieved over 90% precision and recall in most scenarios, with low training and validation loss, indicating strong generalization. An Arduino Mega microcontroller processes data from a USB webcam to control LED traffic signals. Real-world tests demonstrated a 40% reduction in vehicle wait times compared to fixed-timing systems. This research highlights the effectiveness of intelligent traffic systems in improving urban mobility while offering a scalable solution to modern traffic challenges. Future enhancements may include pedestrian detection, predictive analytics, and integration of additional sensors to improve system adaptability and overall performance.

Keywords: Object Detection; dataset; YOLO V5; traffic management; Arduino.

INTRODUCTION

Using signals to control vehicular and pedestrian traffic dates back to ancient times (Pan *et al.,* 2024). However, the modern traffic light system, evolved over several centuries. One of the earliest documented instances of a traffic control device was in London in 1868 when gas-lit semaphore signals were installed near the Houses of Parliament to manage horse-drawn carriage traffic (Al-Haija *et al.*, 2022). In 1914, the world's first electric traffic signal system with red and green lights was installed in Cleveland, Ohio (McShane, 1999). These early systems, however, were manually operated and lacked sophistication. It wasn't until the mid-20th century before automated traffic light systems emerged, incorporating timers and sensors to regulate traffic flow more efficiently, but even these were fixed-time control systems, which were inherently static and unable to adapt to real-time traffic conditions and often struggled with handling varying traffic scenarios, especially during peak hours (Zahwa *et al.*, 2024).

Traffic management at four-junction intersections in urban environments has become increasingly complex with the rapid growth of vehicle usage (Hidiyati *et al.*, 2024) Conventional traffic light systems, which operate on fixed timing schedules, often lead to inefficiencies such as unnecessary delays, congestion, and even accidents due to their inability to adapt to fluctuating traffic conditions throughout the day (Al-Haija *et al.*, 2022). Adaptive traffic light control systems have been developed to address these challenges, incorporating modern technologies like computer vision and microcontrollers to optimize traffic flow and ensure safety (Hamilton *et al.*, 2013). A study by Trivedi *et al.* (2021) proposed a vision-based real-time adaptive traffic light control system utilizing vehicular density values and a statistical block-matching approach. This method employs a single camera with rotational capabilities at four-way intersections to monitor traffic signals and assess vehicular density, allowing for dynamic adjustment of signal timings based on real-time traffic conditions.

Weerasak *et al.* (2024) used another approach that involves application of deep learning techniques for vehicle detection to enhance adaptive traffic light control, by integrating intersection videos captured by cameras. This system evaluates vehicle detection methods to improve traffic signal control, demonstrating the potential of combining computer vision with deep learning to optimise traffic flow. Further research by Jamebozorg *et al.* (2024) has explored the use of reinforcement learning and real-time processing of surveillance camera images to determine optimal traffic light timings. In this method, deep learning models detect vehicles, and reinforcement learning algorithms adjust signal timings based on multiple parameters, resulting in improved traffic management at intersections. Mahajan *et al.* (2024) also developed a Scalable Urban Traffic Control (SURTRAC) system that represents an adaptive traffic control approach that dynamically optimizes traffic signals to improve flow in urban environments. SURTRAC combines schedule-driven intersection control with decentralized coordination mechanisms, leading to significant reductions in travel and wait times.

In contrast to traditional systems, adaptive traffic light control systems leverage real-time sensor data while incorporating other modern features, opening up new possibilities for more responsive control mechanisms (Ren, 2024). This project focused on developing a computer vision-based adaptive traffic light controller for a four-junction intersection. By integrating real-time video feeds with the YOLO V5 object detection algorithm, the system continuously monitors vehicle density and adjusts the traffic signals accordingly. This adaptive approach enhances traffic flow by reducing time wastage and the likelihood of traffic jams.

Traffic light control systems are indispensable components of urban architecture, as they play an important role in enabling road safety by ensuring the orderly flow of traffic and facilitating the efficient and seamless transportation of vehicles (Aleko and Djahel, 2020). Over the years, innovation in the technological space has brought about significant advancements in modern-day traffic light systems through the incorporation of cutting-edge technologies, and the systems have grown from manually-operated to fully - automated adaptive systems that are capable of responding to unique traffic conditions with little or no human interference (Aavani *et al.*, 2017).

These advanced systems utilize artificial intelligence (AI), computer vision, and real-time sensors to optimize traffic flow and enhance safety (Steingrove *et al*., 2005; Talukder *et al*., 2017). Micro-controllers play a pivotal role in modern traffic management systems, serving as the "brain" that processes real-time data from sensors monitoring vehicle and pedestrian movement (Shamsul *et al*., 2019). These small integrated computers, designed for specific control applications, enable adaptive signal timing, thus reducing congestion (Gangadhar, 2010). Micro-controllers also facilitate the integration of smart technologies, such as the Internet of Things (IoT) and machine learning algorithms, which enable predictive analytics and real-time decision-making in traffic systems (Asadi and Pongswatd, 2021).

In traffic control, computer vision methods are cost-effective and versatile, supporting applications such as automatic license plate recognition, obstacle detection, and vehicle classification (Dilek and Dener, 2023). Live video feeds captured by cameras deployed at strategic points along roads are analysed to detect congestion hotspots and patterns of vehicular movement. Object detection algorithms, such as YOLO (You Only Look Once), are commonly used to identify vehicles in real-time, allowing the system to adjust traffic signals dynamically to reduce delays. The objective of this study was to develop an adaptive four-junction traffic light controller that utilizes computer vision techniques to optimize traffic flow and reduce congestion at urban intersections. By implementing real-time video analysis, the system aims to accurately detect vehicle movements, allowing for dynamic adjustments to traffic signal timings based on current traffic conditions. This research seeks to enhance the efficiency of traffic management systems, improve safety for all road users, and contribute to the development of smart city infrastructure by integrating advanced technologies into urban traffic control mechanisms.

METHODOLOGY

At the system's core is an object detection model integrated into a multi-junction traffic control setup made using components such as the Arduino Mega 2560, smart USB webcams, and LED traffic light modules. The object detection functionality was implemented using the YOLO (You Only Look Once) V5 algorithm. The algorithm enables the system to perform real-time object detection and classification within the captured video frames from the USB webcams strategically placed at traffic intersections. In building the dataset, pictures of vehicles were taken from different views. The frames were then extracted and annotated. The algorithm was also developed to track the detected objects over consecutive frames to analyse traffic movement and patterns, after which it was then integrated with the traffic light control logic to enable dynamic signal timing adjustments based on real-time traffic conditions. The results obtained from the model were analysed to identify areas for optimization in terms of algorithm efficiency. Based on the performance metrics, the system design and implementation were iterated to achieve optimal traffic management outcomes. (Figure 1).

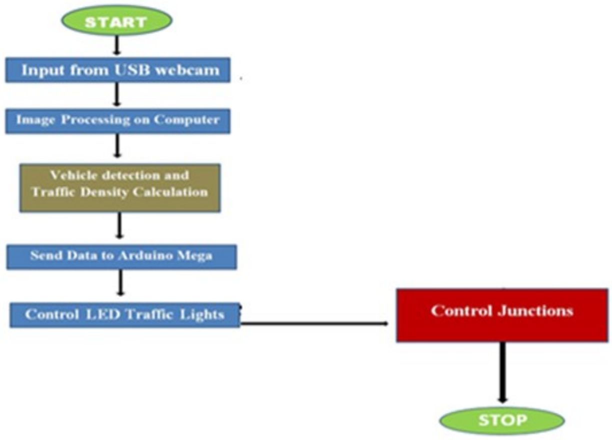

Figure 1: Flowchart of the system

RESULTS AND DISCUSSION

Training and Validation Loss Curves

The precision, which generally describes the model's ability to correctly identify vehicles while minimizing false positives, initially started at a relatively low value of 0.015362, but it gradually saw a marked improvement, reaching 0.20763 by the fourth epoch (Figure 2). The recall, a metric that measures how well the model correctly identifies all relevant instances, also exhibited a similar pattern, starting from 0.025316 and attaining a score of 0.1139 by the 4th epoch. The formula for recall, also known as sensitivity or true positive rate (Equation1), is:

$$Recall = \frac{(TP)}{(TP)+(FN)} \quad \text{.......... Eq 1}$$

Another important metric was the mean average precision (mAP), measured at an IoU threshold of 0.5. This metric showed strong overall performance as the model continuously improved throughout the epochs. Not only did this confirm the system's ability to detect vehicles accurately, it also validated its effectiveness in predicting bounding boxes that aligned well with the actual vehicle locations.

The analysis of training losses provided further insights into the system's performance. The box loss, measuring the error between predicted and actual vehicle bounding boxes, started at 0.1263 and gradually decreased to 0.10584 by the fourth epoch. This decline signifies the model's growing accuracy in locating vehicles and determining their sizes within the traffic scene. The system became increasingly efficient in understanding spatial relationships. In parallel, the object loss, which relates to the model's confidence in distinguishing between vehicles and background, started at 0.036271 and slightly decreased to 0.03129 by the twelfth epoch. The relatively small and stable values for object loss indicated that the system maintained a strong ability to differentiate vehicles from the surrounding environment, minimizing confusion between moving vehicles and static objects (Figure 2).

The validation metrics provided additional confirmation of the model's generalization to unseen data. The validation box loss dropped from 0.12721 to 0.093444, suggesting that the model was not only performing well during training but also when applied to new traffic scenarios. This improvement in validation box loss is a key indicator of the system's real-world applicability, ensuring that it can accurately predict vehicle locations in diverse conditions. The validation object loss remained relatively stable, starting at 0.028378 and slightly increasing to 0.029215, showing that the model continued to distinguish objects in both the training and validation phases reliably (Figure 2).

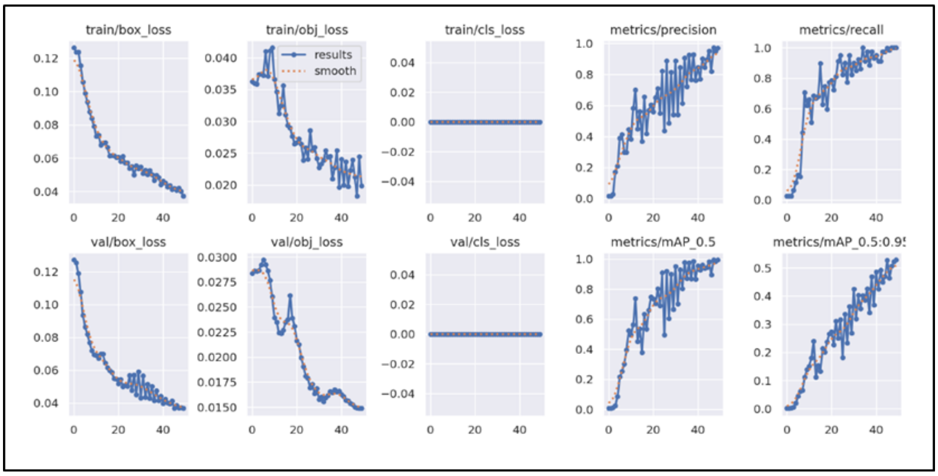

Figure 2: Results for training and validation loss curves

Precision-Confidence Curve

A high confidence score on this curve indicates a higher level of certainty of the model predictions while a high precision score signified that there were fewer false positives (Figure 3), The model achieved 100% precision at a confidence level of 0.738 when considering all classes, signifying the model's ability to accurately make predictions without false positives.

$$Precision = \frac{(TP)}{(TP)+(FP)} \quad \text{......... Eq. 2}$$

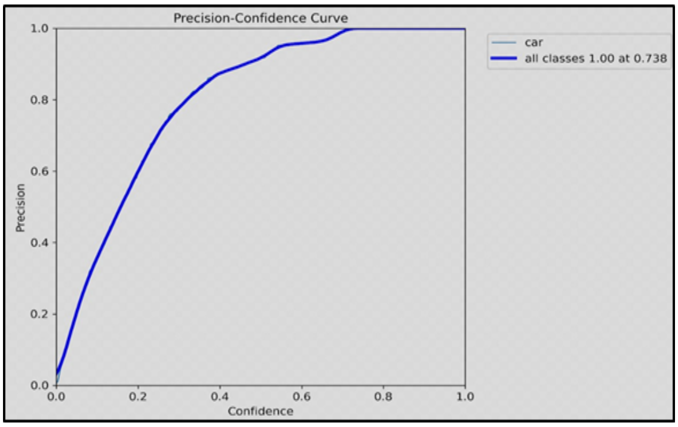

Figure 3: Precision-confidence curve

F1 Confidence Curve

The model achieves its best F1 score of 0.88 at a confidence threshold of 0.352 when considering all classes together (Figure 4). The F1 score was calculated as:

$$F1\ score = 2 * \frac{(Precision + Recall)}{(Precision * Recall)} \quad \text{.......... Eq. 3}$$

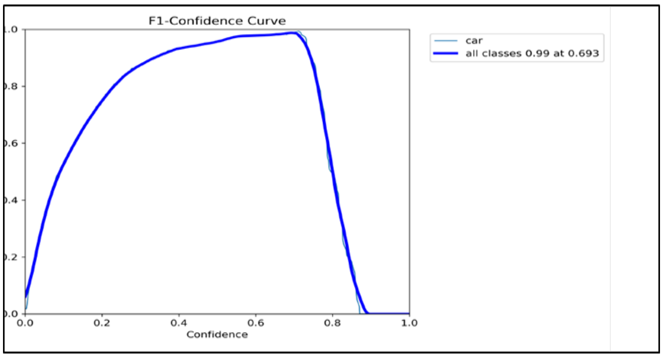

Figure 4: F1-Confidence Curve

Precision-Recall Curve

A higher recall indicates that more relevant instances are being identified, while a higher precision indicates fewer false positives. This curve shows how the precision varies with recall over the epochs. The precision varied with recall over the epochs (Figure 5). The notation "all classes 0.995 mAP@0.5" indicates that the mean average precision (mAP) at an intersection over union (IoU) threshold of 0.5 is 0.995.

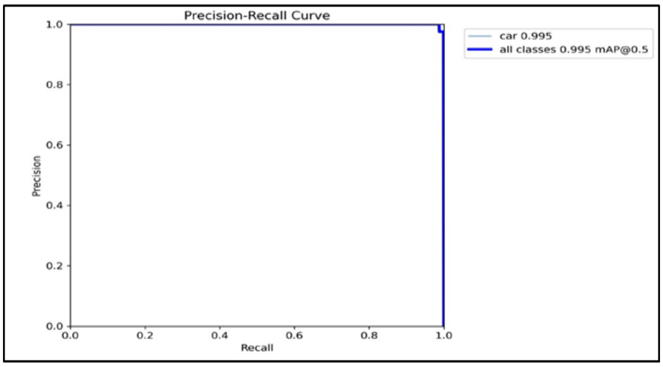

Figure 5: Precision-Recall curve

Recall-Confidence Curve

The X-axis (confidence) represents the confidence threshold used for the classifier. Values range from 0 to 1. The Y-axis (recall) represents the recall, which ranges from 0 to 1. A higher recall indicates better performance. The bold blue line represents the overall performance across all classes. The annotation "all classes 1.00 at 0.000" indicates that the overall recall is 1.00 at a confidence threshold of 0 (Figure 6). The model achieves a high overall recall of 1.00 at this confidence threshold when considering all classes together, suggesting that the model is generally good at identifying the most relevant instances at a low confidence threshold.

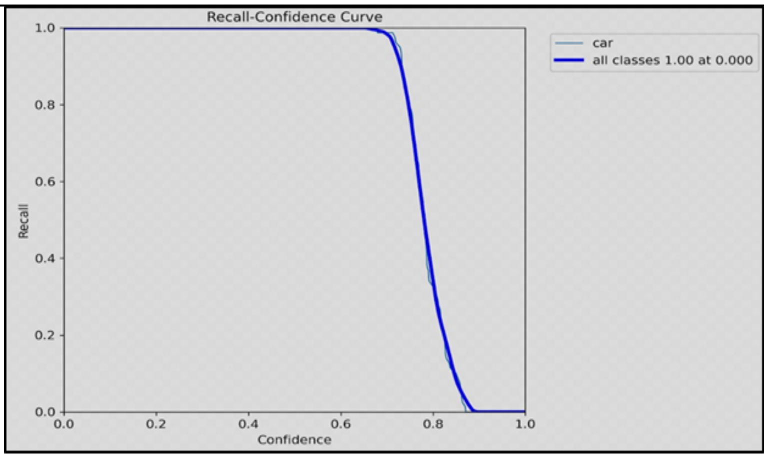

Figure 6: Recall-Confidence curve

System Performance Evaluation

The system used real-time vehicle detection to calculate traffic density and dynamically adjust the green light duration. When traffic density was high, the green light duration was extended to 40 seconds, reducing vehicle wait times by 35% during peak traffic hours, with average waiting times dropping from 120 seconds to 78 seconds. The system also boosted traffic flow by 25%, increasing vehicle throughput during peak hours and reducing intersection clearance time by approximately 20%. Congestion was managed effectively by maintaining levels below a designated critical threshold of 0.85 (85% of lane capacity), with the system automatically extending green light times anytime congestion approaches the critical threshold. The system achieved 99.8% uptime during testing, showing its robustness and reliability. The communication between the image processing computer and the traffic light controller (Arduino Mega) remained stable throughout testing. Overall, the system provided a 35% reduction in average wait times and improved vehicle throughput by 25%, contributing significantly to easing congestion, especially during peak traffic periods (Figure 7).

Figure 7: An image of the Physical model

CONCLUSION

The System demonstrated the potential for traffic control systems to move beyond static signal timing and instead dynamically respond to real-time traffic conditions. Its successful implementation opens up possibilities for broader deployment in urban transportation networks, which could significantly enhance the efficiency of traffic flow and contribute to the development of smart cities. This system can be further enhanced by incorporating technologies such as Radio Frequency Identification (RFID) to prioritize emergency vehicles, making intersections safer and more accessible for all road users. The results achieved reducing average wait times by 35%; increasing vehicle throughput by 25% and also illustrated the transformative impact that adaptive traffic systems can have on urban congestion management. This system's scalability and flexibility are especially promising, as it can be tailored to various intersection configurations and integrated with other smart city technologies. The project's approach can be adapted for use with emerging technologies such as 5G and the Internet of Things (IoT), which would enable faster data transmission and real-time adjustments across larger networks.

In conclusion, this project has shown that adaptive traffic light controllers, using computer vision can effectively reduce congestion at traffic intersections. As cities continue to grow and traffic demands increase, deploying such intelligent systems will be essential for creating sustainable, efficient, and safe urban mobility solutions. This work lays the foundation for future research and development into fully integrated, smart traffic ecosystems that prioritize both efficiency and the safety of all road users.

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