An AI-Based Adaptive Traffic Sign al Management System Using YOLOv5 for Real-Time Vehicle Detection and Emergency Priority Control

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***Abstract*—Fixed-time traffic signal systems fail to adapt to changing traffic conditions at urban intersections, leading to unnecessary delays and ineffective emergency handling. This paper proposes an AI-based adaptive traffic signal management system that adjusts signal timings using real-time vehicle density. A custom-trained YOLOv5 model is used to detect and count vehicles on each traffic lane from camera input. Based on the vehicle count, a decision logic module dynamically controls green signal duration to reduce waiting time. The system also provides emergency vehicle priority by temporarily overriding normal signal operation after a short warning phase. The proposed approach is implemented as a functional prototype and demonstrates reliable vehicle detection and adaptive signal control.**

***Index Terms*—Adaptive traffic control, computer vision, emergency vehicle priority, intelligent transportation system, YOLOv5**

I. INTRODUCTION

Traffic congestion at urban intersections is a major challenge due to the increasing number of vehicles and the continued use of fixed-time traffic signal systems [17]. Conventional traffic signals operate with predefined signal durations that do not adapt to real-time traffic conditions, often leading to inefficient signal utilization and increased waiting time. In fixed-time systems, lanes with very few or no vehicles may still receive full green signal duration, while congested lanes remain delayed. Similarly, when traffic density is low on all approaches, vehicles are forced to wait until the signal timer completes instead of allowing faster transitions. These limitations reduce traffic flow efficiency and contribute to fuel wastage and driver frustration. Another significant drawback of traditional traffic signal systems is the lack of emergency vehicle priority [27]. Ambulances frequently encounter red signals and are required to wait until the signal cycle ends, causing critical delays in emergency response. The absence of intelligent detection and control mechanisms makes such systems unsuitable for dynamic urban traffic scenarios.

To address these challenges, this paper proposes an AI-based adaptive traffic signal management system using a custom-trained YOLOv5 model for real-time vehicle detection and counting on individual lanes [2]. Based on the detected vehicle density, a decision logic module dynamically adjusts signal timings to improve traffic flow. The system also includes an emergency vehicle priority mechanism that temporarily overrides normal signal operation after a warning phase to ensure safe lane clearance. The proposed system is implemented as a functional prototype and demonstrates the potential of AI-driven traffic signal control [4].

II. RELATED WORK

a. Press Light: Press Light uses reinforcement learning with lane pressure to adapt traffic signal phases and reduce congestion. The method focuses on general traffic optimization and does not consider emergency vehicle priority [25].

b. Co Light Co Light enables coordinated signal control across multiple intersections using graph-based reinforcement learning. It improves network efficiency but lacks mechanisms for emergency vehicle detection or prioritization [26].

c. Emergency Vehicle Signal Preemption: Emergency vehicle preemption methods dynamically override signals to reduce response time while limiting traffic spillback. These approaches rely on GPS or V2I detection and do not use AI-based visual learning [27].

d. Vision-Based Emergency Vehicle Detection: Vision-based systems employ deep learning models to detect emergency vehicles from camera feeds and trigger signal overrides. Most solutions are rule-based and do not adapt signal timing based on traffic density [28]

III. PROPOSED METHODOLOGY

Problem Definition: Traditional traffic signal systems fail to adapt effectively to real-time traffic conditions and emergency situations, often causing delays for emergency vehicles at intersections. Existing adaptive methods focus mainly on normal traffic flow, while emergency vehicle preemption systems are mostly rule-based and lack intelligence. Hence, an integrated AI-based traffic signal system is required to detect emergency vehicles in real time, analyze traffic density, and dynamically prioritize emergency movement while maintaining overall traffic efficiency [17].

The proposed system follows a pipeline architecture consisting of four main stages: Data Acquisition, Preprocessing, Deep Learning–based Vehicle Analysis, and Decision-Based Signal Control.

A Data Acquisition- In this stage, real-time traffic video is captured using CCTV cameras installed at the intersection. The continuous video stream is processed to extract frames at fixed time intervals, which are used as input for subsequent traffic analysis and signal control.

B. Preprocessing – In this phase, the extracted video frames are prepared for deep learning inference. Each frame corresponds to a specific traffic lane, enabling lane-wise analysis. Basic frame formatting is performed to ensure compatibility with the YOLOv5 model, while complex image transformations are avoided since feature extraction and normalization are handled internally by the detection network.

C. Deep Learning–Based Vehicle Detection and Counting - In this phase, a custom-trained YOLOv5 model is employed to detect vehicles from the preprocessed frames. The model is trained on a task-specific dataset to identify normal vehicles and emergency vehicles. It outputs bounding boxes and confidence scores for detected objects, which are filtered based on class and confidence threshold to obtain reliable lane-wise vehicle counts. The detection results serve as the primary input for adaptive signal timing and emergency vehicle prioritization [2].

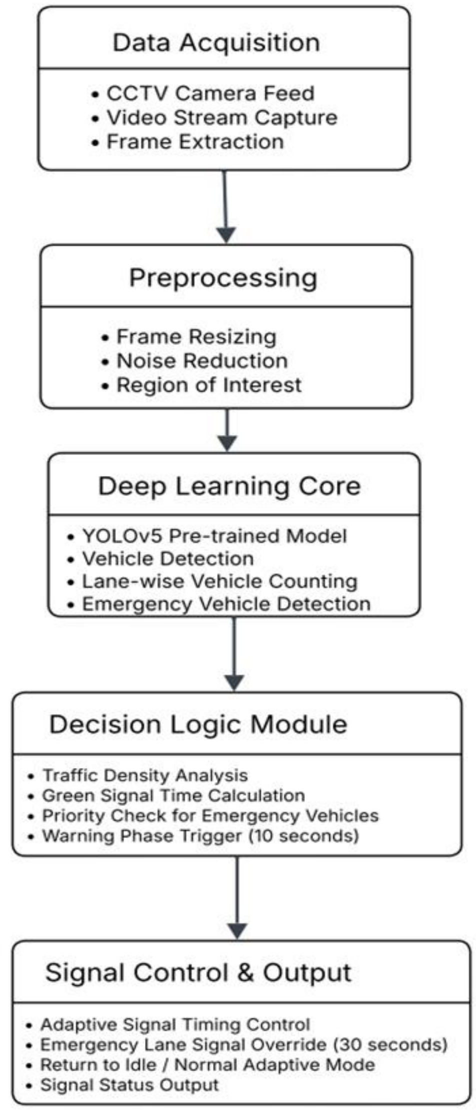

Figure 1 Architecture model.

Algorithm 1: Adaptive Traffic Signal Timing with Emergency Priority

Input:

Lane-wise vehicle images captured from CCTV cameras.

Output:

Adaptive signal timing for each traffic phase.

Steps:

1. Capture frames from each traffic lane at fixed time intervals.
2. Apply the custom-trained YOLOv5 model on each frame to detect density of vehicles and emergency vehicles.
3. Count valid vehicles in each lane after filtering by class and confidence threshold.
4. If an emergency vehicle is detected in any lane:
   - Trigger a warning phase for all lanes.
   - Assign green signal to the emergency lane for a fixed duration(30s).
   - Return the system to normal operation.
5. Else (no emergency vehicle detected):
   - Combine lane-wise vehicle counts into predefined non-conflicting traffic phases.
   - Calculate green signal duration for each phase based on vehicle count.
   - Ensure signal duration remains within minimum and maximum limits.
6. Apply the computed green signal timings sequentially to each phase.
7. Repeat the process continuously for real-time traffic control [2].

D. Decision Logic and Signal Control -The decision logic module controls traffic signal operation using lane-wise vehicle counts and emergency vehicle status obtained from the detection stage. The logic follows a rule-based approach to dynamically assign green signal duration while ensuring safe and conflict-free operation. Lane-wise vehicle counts are first aggregated to represent the current traffic density of the active phase. For the east–west direction, the total vehicle count is computed as:

$$V_{total} = V_{east} + V_{west} \quad (1)$$

where Veast and Vwest denote the number of detected vehicles in the east and west lanes, respectively.

Based on the aggregated vehicle count, the green signal duration is calculated using a linear density-based rule:

$$T_g = T_{min} + \alpha \cdot V_{total} \quad (2)$$

where ‘Tg’ is the computed green signal time, ‘Tmin’ is the minimum allowable green duration, and ‘α’ represents the time allocated per detected vehicle. To ensure operational safety, the calculated green time is constrained within predefined minimum and maximum limits:

$$T_g = \min(T_{max}, \max(T_{min}, T_g)) \quad (3)$$

The system continuously monitors for emergency vehicles. If no emergency vehicle is detected, the dynamically computed signal timing is applied to the corresponding traffic phase. If an emergency vehicle is detected, normal adaptive signal control is overridden. An alert is issued to notify road users, and a fixed green signal duration is assigned to the emergency lane to allow safe and rapid clearance:

$$\text{If } E = 1 \Rightarrow T_g = T_{emergency} \quad (4)$$

where ‘E’ indicates the presence of an emergency vehicle and ‘Temergency’ is the predefined emergency clearance time. During this period, all other lanes remain red. Once the emergency phase is completed, the system resets and resumes normal adaptive signal operation [8].

IV. EXPERIMENTAL RESULTS

The experimental evaluation of the proposed system focuses on validating the performance of the custom-trained object detection model and the effectiveness of the adaptive traffic signal control mechanism. All experiments were conducted using a custom-trained YOLOv5 model integrated with the proposed decision logic for real-time traffic management [2]. The model was trained and evaluated using the Final_zara_traffic Dataset obtained from Kaggle, which contains approximately 4,600 annotated traffic images [20]. The dataset is designed for traffic scene analysis and includes a diverse range of vehicle types captured under varying road and lighting conditions. For this study, the dataset was organized into two main categories: normal vehicles and emergency vehicles.

Normal vehicles consist of four classes, namely car, bus, bike, and truck, while emergency vehicles consist of three classes, including ambulance, police vehicle, and fire truck [10]. This class separation enables the system to perform both general traffic density estimation and emergency vehicle prioritization. The dataset was used to train the detection model to accurately identify, classify, and localize vehicles in traffic scenes, forming the basis for subsequent signal timing decisions [2].

A. Model Training Performance The proposed YOLO-based model demonstrates strong detection capability for traffic analysis tasks. Experimental evaluation indicates an emergency vehicle detection accuracy of 90%, while vehicle counting accuracy under normal traffic conditions reaches 95%. These results confirm the model's effectiveness in distinguishing priority vehicles and reliably estimating traffic density. Performance is further analyzed using Precision, Recall, F1-score, Precision–Recall curves, and a confusion matrix.

a) F_curve analysis:

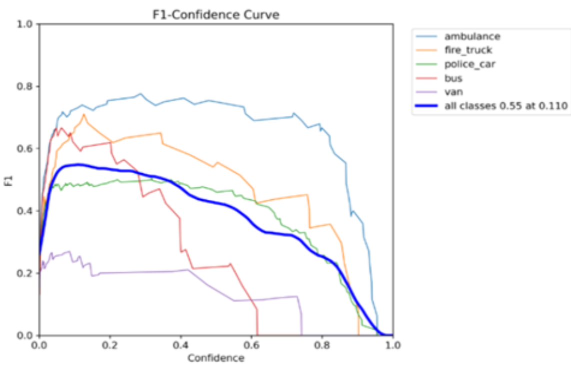

Figure 3 F _Curve

The F1-confidence curve evaluates the balance between precision and recall across different confidence thresholds. The model achieves a peak overall F1-score of approximately 0.55 at a confidence threshold of 0.11, indicating an optimal operating point for detection performance. Emergency vehicle classes exhibit relatively higher and more stable F1-scores, highlighting reliable priority vehicle detection. At higher confidence thresholds, the F1-score declines due to increased missed detections, reinforcing the selection of a lower threshold for real-time traffic signal applications.

b) PR_curve analysis:

The Precision–Recall curve illustrates the detection performance of the proposed model across varying

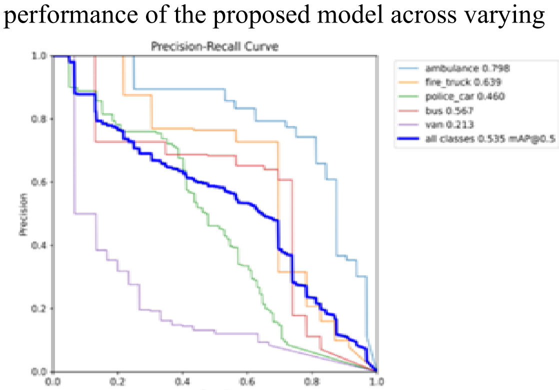

Figure 2 PR_Curve

recall levels. An overall mAP@0.5 of 0.535 is achieved across all classes, indicating consistent detection capability on the Zara Traffic Dataset. Emergency vehicle categories, particularly ambulances (0.798) and fire trucks (0.639), demonstrate higher precision across a wide recall range, validating the effectiveness of the model in identifying priority vehicles. Lower precision observed for certain normal vehicle classes can be attributed to visual similarities and dense traffic conditions. Overall, the PR characteristics confirm the suitability of the model for real-time traffic monitoring and signal control applications.

c) Confusion matrix analysis:

The confusion matrix provides a detailed class-wise evaluation of the proposed YOLO-based detection model.

Figure 4 Confusion matrix

Strong diagonal values indicate accurate recognition of key vehicle categories, with ambulance detection achieving the highest achieving the highest correct classification rate -(0.81), confirming reliable emergency vehicle identification. Moderate confusion is observed among visually similar normal vehicle classes such as buses and vans, primarily due to overlapping shapes and occlusions in dense traffic scenes. Additionally, misclassifications involving the background class highlight challenges posed by cluttered environments and partial object visibility. Overall, the confusion matrix demonstrates effective class discrimination, particularly for emergency vehicles, which is critical for priority-based traffic signal control.

B. Traffic Detection Results

This subsection presents qualitative detection results under normal traffic conditions, demonstrating the effectiveness of the YOLOv5 model in identifying and counting vehicles across different lanes. The detected vehicle density is used as a key input for adaptive traffic signal control.

i. Normal condition: Figure X illustrates an example output of the proposed YOLOv5-based vehicle counting system for the westbound lane of the intersection. Multiple vehicle classes, including cars, buses, and vans, are accurately detected using bounding boxes, enabling reliable estimation of vehicle density in real time. The same detection and counting procedure is applied independently to all incoming lanes, ensuring consistent traffic density assessment across the entire intersection. These vehicle counts serve as the primary input for adaptive signal timing, allowing the system to dynamically adjust green signal durations based on real-time traffic conditions.

Figure 5 Vehicle count (initial condition

Signal override logic: In normal traffic scenarios, vehicle density is estimated independently for all four incoming lanes using YOLOv5-based vehicle counting. The relative vehicle density across these lanes is jointly analyzed to determine adaptive green and red signal durations. Lanes with higher traffic density are allocated extended green times, while lower-density lanes receive shorter durations within predefined limits, enabling balanced and efficient intersection control compared to fixed-time signaling.

ii. Emergency vehicle: In the proposed system, emergency vehicle detection is restricted to lanes currently operating under a red signal, since priority intervention is required only for blocked approaches.

Figure 6 Emergency vehicle detection

Upon detecting an ambulance in a red-signal lane, the normal signal cycle is overridden and an immediate green signal is granted to the corresponding lane. This targeted priority mechanism ensures faster emergency vehicle clearance while minimizing disruption to traffic flow in lanes that are already active under green signals.

Signal override logic: When an emergency vehicle is detected in any lane currently under a red signal, an emergency override is immediately initiated. If the remaining red-signal duration of the detected lane exceeds 10 seconds, it is reduced to 10 seconds to prepare for priority clearance. Simultaneously, an audio announcement is broadcast to all approaches, informing road users about the approaching emergency vehicle and instructing all lanes to halt within the next 10 seconds.

After the preparation phase, the lane containing the emergency vehicle is assigned a dedicated green signal for a fixed duration of 30 seconds to ensure unobstructed passage. During this interval, all non-conflicting lanes remain halted to eliminate potential interference. This controlled green allocation prioritizes emergency clearance while maintaining intersection safety. Once the emergency phase concludes, the signal controller transitions back to its idle state and resumes normal adaptive traffic operation.

iii. Blocked Lane: Table.1 summarizes the relationship between vehicle density and adaptive green signal allocation under normal traffic conditions. It illustrates how different congestion levels are mapped to corresponding signal actions, enabling proportional and interpretable traffic signal control.

Table 1 Density-based Signal Timing (normal condition)

Density	Congestion	Action	Time
Very low	Free flow	Normal Cycle	Minimum
Low	Light	Slight extension	Short
Medium	Moderate	Adaptive extension	Medium
High	Heavy	Priority allocation	Extended
Very high	Server	Maximum	Maximum

Table.2 summarizes the emergency vehicle priority control logic, detailing how red-lane emergency detection triggers signal overrides and timed green allocation before resuming normal operation.

Table 2 Emergency vehicle Signal Control

Condition	Lane status	Action	Time
None	Any	Normal Cycle	Density based
Detected	Red lane	Reduce red + alert	Preparation
Detection confirmed	Red lane	Green override	30sec
Clearance complete	-	Resume normal	Normal cycle

V. COMPARATIVE ANALYSIS

Under conventional fixed-time signal operation, traffic control relies on predefined timing cycles that remain constant regardless of real-time traffic demand. This lack of adaptability often results in inefficient signal utilization, congestion buildup, and increased vehicle waiting times, particularly during peak hours and emergency situations. In contrast, the proposed adaptive traffic signal management system continuously monitors lane-wise vehicle density and dynamically adjusts green and red signal durations to reflect current traffic conditions at the intersection.

This real-time responsiveness enables smoother traffic flow by prioritizing congested lanes and balancing queue clearance across all approaches. Furthermore, the integration of a targeted emergency override mechanism ensures significantly faster and uninterrupted passage for emergency vehicles when detected. By replacing static timing with density-aware and priority-driven control strategies, the proposed system demonstrates improved operational efficiency, adaptability, and reliability under both normal and emergency traffic scenarios.

VI. LIMITATIONS

Although the proposed AI-based traffic signal management system demonstrates effective performance under both normal and emergency traffic conditions, several limitations should be acknowledged:

1. Dataset-Specific Evaluation:

The system has been evaluated using a single publicly available traffic dataset, which may not fully represent the diversity of real-world traffic scenarios and intersection layouts [17].

2. Rule-Based Timing Strategy:

The adaptive signal control relies on predefined rule-based thresholds for green and red time allocation, which may restrict flexibility under highly dynamic traffic conditions [8].

3. Lack of Real-Time Field Deployment:

The validation is limited to simulated and offline experiments, without integration into live traffic signal infrastructure or real-world intersection testing [24].

4. Sensitivity to Environmental Conditions:

Vehicle detection and counting performance may be affected by adverse conditions such as low lighting, occlusions, or extreme weather, potentially impacting signal timing decisions [2].

VII. CONCLUSION & FUTURE WORK

This paper presented an AI-based traffic signal management system that integrates YOLOv5-based vehicle detection with adaptive signal timing to address congestion and emergency vehicle prioritization at urban intersections. By jointly analyzing vehicle density across all incoming lanes, the proposed system dynamically adjusts green and red signal durations, resulting in smoother traffic flow and improved intersection efficiency. A dedicated emergency override mechanism further enhances the system by enabling rapid clearance for ambulances through targeted red-time reduction and priority green allocation.

Experimental results demonstrate reliable vehicle detection performance and effective signal control under both normal and emergency traffic scenarios. Comparative analysis with conventional fixed-time signal systems highlights the advantages of real-time adaptability, responsiveness, and improved traffic handling.

As future work, the system can be extended through real-world deployment across multiple intersections, integration of learning-based signal optimization techniques such as reinforcement learning, and enhanced robustness to challenging environmental conditions. Additionally, incorporating vehicle-to-infrastructure (V2I) communication and city-scale coordination may further improve traffic efficiency and emergency response capabilities.

ACKNOWLEGEMENT

The authors would like to acknowledge the contributor of the Final_Zara_Traffic Dataset made publicly available on Kaggle, which was used for training and evaluation in this study. We also acknowledge Ultralytics, the developers of YOLOv5, for providing an open-source object detection framework that enabled efficient vehicle and emergency vehicle detection in this work.

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