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Optimized Adaptive AI-Driven Traffic Management with Emergency Vehicle Prioritization using YOLO-based Detection and Fuzzy Logic Control

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***Abstract*— The increasing pace of urban development, coupled with exponential growth in vehicle ownership has created unpredictable challenges in managing traffic flow at urban intersections particularly when emergency vehicles requires a rapid passage. Traditional traffic management systems which depend on a predetermined timing cycles that demonstrates the fundamental limitations in responding to dynamic traffic patterns that leads to a prolonged queue length, inefficient use of resources and increased pollution caused by vehicles waiting at signals with their engines running. This research introduces a smart and well-designed traffic management solution for four-way intersections that combines advanced computer vision capabilities through YOLOv8 which makes a human like decision reasoning implemented through fuzzy logic. This system processes a live camera feed to simultaneously monitor the vehicle density across the lanes, identifies the presence of emergency response vehicles and tracks the total waiting durations of each lane. These real time metrices are fed into a fuzzy inference engine that gives human judgment to dynamically determine signal priority, a guaranteed passage for ambulances and fire trucks while balancing congestion mitigation and preventing any lane from experiencing indefinite delays. This system has been trained with using a comprehensive dataset of 3,000 images of real time traffic scenarios and also by using the augmented variation images. Comparative analysis shows that our developed system over the fixed-time method systems in signals is of a measurable reduction in mean queue wait duration, enhanced intersection throughput and allowing faster passage for emergency vehicles. The system's inherent adaptability, low computational requirements and scalability makes it highly suitable for integration into modern smart city traffic systems.**

***Index Terms*— Adaptive Traffic Control, Computer Vision, Fuzzy Inference, YOLOv8.**

I. Introduction

The rapid urban growth has significantly changed the traffic patterns in cities, leading to a frequent vehicle accumulation at key junctions that often exceeds the capacity of existing road infrastructure [1]. The majority of the operational signal systems depends only on the static timing sequences or a pre-set phase schedules that do not adapt to real-time traffic conditions. Such rigidity results in several negative consequences including longer waiting times for road users, inefficient use of intersection capacity, imbalanced green-time allocation that may

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starve certain lanes and most importantly the emergency vehicles that are stuck in that congestion where every second or minute of delay can carry life or death situations. The AI which is a developing technology along with the machine leaning techniques has many possibilities to determine the automated vehicular monitoring using the vision-based technologies [7]. In the deep learning domain of object detection, the YOLO (You Only Look Once) versions of models which is known for its balance in finding the speed and also in detection accuracy plays a vital role in the transportation-related applications [17]. YOLOv8 which is a recent version, achieved a greater result in detection precision preserving the real-time operational capabilities [3]. Yet the system depends only on the vehicle count or traffic density is not enough to handle the uncertain situations, not treating all lanes fairly and may even fail to recognize the emergencies.

To bridge these limitations, this project brings up a solution in signal management framework for four lane intersections which helps the YOLOv8 with a fuzzy logic reasoning engine to combine different paths in a balanced way without any conflicts [4]. This system extracts multiple dynamic parameters from live video for a specific lane for the vehicle count, emergency vehicle detection status and total waiting time duration per lane. These information are fed into a fuzzy inference module. This framework enforces unconditional priority for emergency vehicles using a compensation logic to prevent any lane from suffering persistently ignored. By using this dynamic modulating signal approach, this system helps traffic move more smoothly and it treats all lanes fairly. By using this efficient approach system, it can be effectively used in modern smart city environments [9], [11].

II. Related Work

In the filed of intelligent traffic signal optimization has always been the subject of extensive academic inquiry with the researchers, investigating the different methodologies including the machine learning and different types of sensors. Convectional detection approaches such as inductive loops and infrared sensors are expensive to install and requires regular maintenance [1]. By contrast, camera-based systems that uses convolutional neural architectures are much better in identification of vehicles and offer greater deployment flexibility [10], [18].

Fuzzy logic has become a widely favoured control system in traffic management due to its natural capacity for encoding uncertainty and handling the nonlinear characteristics inherent in real traffic behaviour [4], [5]. However many existing frameworks concentrate mainly on density based metrics and ignore the important factors like giving priority to emergency vehicles and ensuring fairness across the lanes [16]. The existing YOLO based traffic systems have largely been directed towards congestion identification without including the adaptive signal timing mechanisms.

Reinforcement learning based approaches represent another options of explorations for adaptive signal control, especially in complex multi-lane environments [8], [15]. While these approaches shows good performance, they typically demand large training datasets and offer limits transparency in their control decisions. This study merges the deep learning with fuzzy logic to achieve both high accuracy in traffic control and clear making it an understandable decision-making for real-world implementation. By coupling the YOLOv8 based vehicle detection with a multi input fuzzy logic controller in this work, the system is specifically designed to prioritize the emergency vehicles while ensuring lane-fairness constraints across all competing traffic approaches [6], [20].

III. Proposed System Methodology

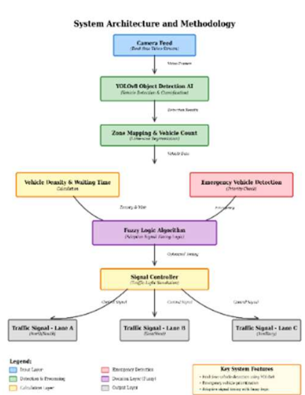

Fig. 1. System architecture and methodology

The architecture is composed of four main functional layers which are Traffic Data Acquisition, Traffic Analysis, Fuzzy Logic Detection System and Priority Score and Signal Acquisition. Fig 1 gives the clear representation of overall system architecture.

A. Traffic Data Acquisition

The videos are collected from the surveillance cameras which gives full coverage of a four-way intersection [1]. Each video frame is extracted and divided into lane – specific regions of interest to enable the parallel processing of all traffic approaches. This design enables the system to work on different types of intersection without changing the whole structure.

B. YOLOv8-Based Traffic Analysis

YOLOv8 detection engine [3] is used to analyse each lane image.

- It counts the number of vehicles in each lane
- Identifies the emergency response units

It calculated how long each lane has been waiting since its most recent green signal. This time-based metric plays a vital role in fair signal allocational and preventing low-
traffic lanes from being continuously ignored.

C. Fuzzy Logic Decision System

This fuzzy system [4] works based on three main input values. Using these inputs, it calculates the priority score for each lane. It uses the Mamdani Inference methodology combined with centroid defuzzification to convert the fuzzy result into a clear number [5], [8].

Vehicle Population Count: The traffic density at the intersection is represented three categories: Low, Medium, and High. The Low membership function will have high value when the vehicle density is less and decreases as the density increases. The Medium category has a triangular membership function centered at a moderate density value. The high membership function increases as the vehicle density increases. This fuzzy modelling approach enables gradual transitions between density levels [4].

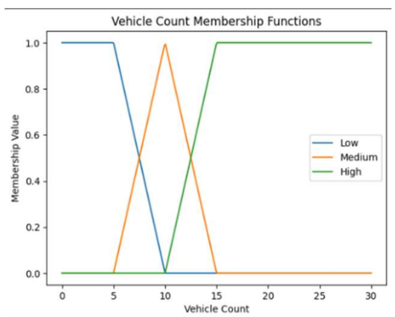

Fig.2 Vehicle count membership count

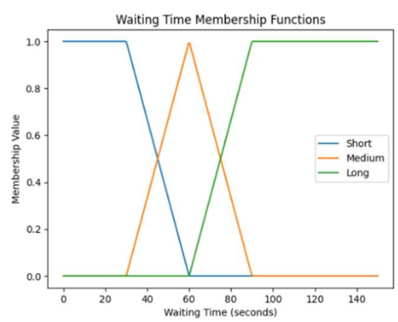

Fig. 3 Waiting time membership function

Emergency Vehicle Detection Flag: This is represented as a binary variable which indicates detection whether the priority vehicle is presented in that particular lane or not. When an emergency vehicle is detected, the system automatically assigns the highest priority to that lane within the fuzzy logic system [6], [20]. This feature ensures faster signal clearance for emergency vehicles, reducing response time and improving road safety.

Accumulated Waiting Duration: As depicted in Fig.3.3, the cumulative waiting time per lane is represented through three categories: Short, Medium, and Long. The Short function is mainly active when the waiting time is small. The medium category uses triangular from for moderate waiting time and the long function will get active as the waiting time extend. This fuzzy approach allows the waiting time to change smoothly from Short to Medium to Long instead of changing suddenly. It helps the system make stable and fair decisions, ensuring that all lanes get a balanced and equal chance to receive the green signal [13], [19].

D. Priority Score and Signal Actuation

The system gives each lane a priority score. The score is grouped into three categories: Low Priority, Medium Priority, and High Priority. This priority ranking is generated for each lane. The lane which gets the highest priority rank will receive the green phase. This fixed decision method ensures that only one clear signal decision is made, even when multiple lanes have nearly equal priority scores [8], [15].

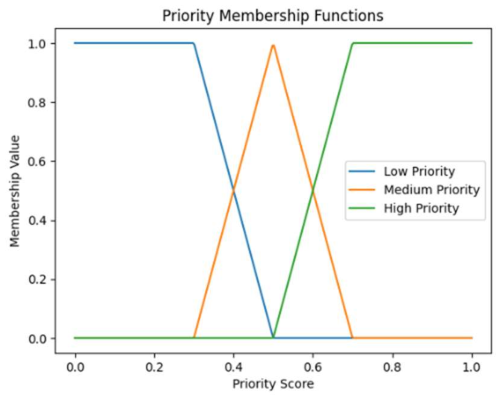

Fig.4 Priority membership functions

IV. Dataset Description

The model was trained and evaluated with a combined dataset of 3000 images
Consisting of bot real-world traffic recordings and augmented samples. The was deigned to cover a wide range of conditions including varying the levels of traffic density, diverse vehicles and specific scenarios including emergency response unit. To improve the model's generalization and robustness, standard data augmentation methods such as rotation, photometric adjustments and horizontal mirror transformations were applied [7], [10]. The dataset was divided into two using an 80:20 partition for training and evaluation.2,400 Images were allocated for training and the remaining 600 images were reserved for performance testing. The intentional inclusion of the augmented emergency vehicle was essential as the real
world dataset mostly contains the ordinary vehicles, which could weaken the model's ability to accurately detect emergency units under real world conditions [6], [20].

V. Mathematical Model

The equations form the computations of the signal control logic. The waiting time for a lane is expressed as:

$$W_i = T\_current - T\_last\_green$$

The normalized traffic density for a lane is measured as:

$$D_i = V_i / V\_max$$

The overall priority score for each lane is calculated as:

$$P_i = \alpha D_i + \beta W_i + \gamma E_i - \delta R_i$$

In the above expression, E_i represents the emergency vehicle presence and R_i denotes the recent lane release. The parameters α, β, γ, and δ are adjustable weighting coefficients that control, regulate, or determine the importance of individual factors of each input on the final priority decision. Signal assignment is subsequently performed as:

$$Selected\ Lane = arg\ max\ (P_i)$$

VI. Algorithm

The real time control system follows the procedural sequence mentioned below:
STEP 1: Capture video from the deployed surveillance cameras.
STEP 2: Using YOLOv8 vehicle detection in each lane is detected [3].
STEP 3: Identify and classify emergency vehicles presence in the detected lane [6].
STEP 4: Compute the vehicle count of each lane and accumulated waiting time.
STEP 5: Map the numerical inputs to the fuzzy membership values [4].
STEP 6: Apply the fuzzy inference rule to derive priority scores for each lane [5].
STEP 7: The green signal is released for the lane with the highest priority score.
STEP 8: Refresh all the related parameters after each evaluation and repeat the control cycle.

VII. Evaluation Metrics

Detection performance of the YOLOv8 model was evaluated using standard metrics widely employed across computer vision benchmarks [7], [10], are defined as follows:

$$Precision = TP / (TP + FP)$$

$$Recall = TP / (TP + FN)$$

$$mAP = (1/N)\ \Sigma\ AP_i$$

Here, TP, FP, and FN refers to true positives, false positives, and false negatives and AP_i denotes the average precision for object class i. The primary evaluation criterion is the mean Average Precision (mAP) computed at an Intersection over Union (IoU) threshold of 0.5.

VIII. Results and Discussion

The detection capabilities of YOLOv8 based model were evaluated against the metrics outlined in Section VII and the quantitative analysis outcomes is provided in Table I.

TABLE I: YOLOV8 DETECTION PERFORMANCE METRICS

Metric	Value (%)
Precision	92.4
Recall	90.1
mAP@0.5	91.7
Emergency Detection Accuracy	95.3

The model achieves 92.4% Precision and 90.1% Recall, corresponding to an mAP@0.5 of 91.7% and particularly the emergency vehicle detection rate is 95.3%. Which results the importance given to the life safety implications from this classification. These figures validate YOLOv8 as a robust detection for deployment in the real-world traffic settings [3], [10].
Fig. 8.1 represents a sample real world traffic scenario used during testing. Fig. 8.2 shows the corresponding output of the sample scenario from the YOLOv8 based detection module. Various vehicle categories including cars, auto-rickshaws, trucks, and motorcycles are accurately localized with bounding boxes and annotated class labels. The system also generates the total vehicle count per lane, validating its ability to perform robust detection and classification under authentic traffic conditions.

Fig.5 Real time image

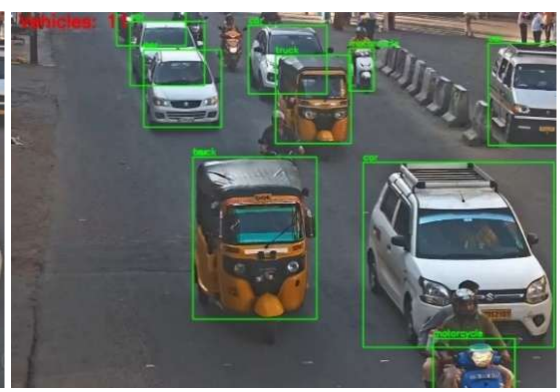

Fig.6 Detected image output

A systematic comparison between the fixed-time baseline and the proposed intelligent control method was classified into three operational parameters, summarized in Table II.

TABLE II: COMPARATIVE PERFORMANCE ANALYSIS

Parameter	Fixed-Time	Proposed
Avg. Waiting Time	High	Reduced
Emergency Clearance	Delayed	Immediate
Lane Starvation	Observed	Eliminated

The proposed system demonstrates definite advantages over the fixed time baseline across all evaluated parameters. The total eradication of lane starvation is a direct outcome of incorporating cumulative waiting duration into the fuzzy priority calculation [13], [19].
The capability of the system to provide immediate signal clearance for emergency vehicles is a strong practical utility for deployment in real world traffic settings [6], [20].

IX. Ablation Study

To evaluate the individual contribution of each system component to the overall performance, a structured ablation study was conducted. Three incremental system configurations were tested: (i) vehicle count alone, (ii) vehicle count in combination with waiting time, and (iii) the fully integrated system with emergency detection enabled.
Results indicate that systems operating only on vehicle count are susceptible to the lane starvation problem, as lower density lanes may be systematically bypassed [13]. The addition of waiting time as an input strongly improves distributional fairness in signal allocation [19]. Including emergency vehicle detection subsequently enables path clearance for urgent response scenarios [6]. The fully integrated configuration achieves the balance between the congestion reduction and equitable cross lane resource distribution, and it is clear that each component is most important to the overall architecture.

X. Conclusion

While this paper has introduced an intelligent traffic signal management syatem framework that works on emergency aware and adaptive operation through the combined deployment of YOLOv8 and fuzzy logic inference. The system enables real time signal timing adjustments in response to live traffic conditions and most importantly without any conditions prioritizing the emergency vehicles. The experimental validation demonstrates strong improvements in both operational efficiency and signal equity when compared to conventional fixed-timing baselines [1], [5], [16], confirming the readiness of the system for integration within present smart city transportation networks [9], [11].

Future Work

The current system demonstrates effective adaptive control system for four-way intersection junctions. In future with the enhanced merits the system can be deployed for multi- intersection junctions, by enabling corridor-level green-wave progression strategies [15], alongside with the existing fuzzy interface could yield high performance improvements when handling complex traffic scenarios [8].
Deployment on edge computing hardware, such as embedded GPU platforms, would lower processing latency and increases real-time system responsiveness. Integrating Vehicle-to-Everything (V2X) communication standards would enables direct data exchange with connected vehicles, for accelerating emergency vehicle access management [11]. Strong validation under challenging conditions including large-scale metropolitan deployments would provide an additional informations thorough characterization of system performance across operational environments.

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