A Dual -Model deep Learning Framework for Dynamic Traffic Control and Emergency Vehicle Prioritization

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***Abstract*—Traffic jams are now a daily struggle, which is affecting economy, environment damage, fuel which leads to poor quality of life in modern cities. Traditional traffic signals are rely on fixed timer, systems often fail to handle the changing flow of urban traffic, it will not change even when roads are empty. To address this issue, we introduced an intelligent and real-time traffic management system that uses computer vision to monitor road traffic and optimize signal control, which is designed and implemented to work towards the solution of this problem. The system monitors live video feeds and uses the YOLOv8 object detection model to detect and observe vehicles which high accuracy. By calculating traffic density, a rule-based engine adjusts the signal timings dynamically which improves traffic flow and save time. A unique feature is designed in our system that detects ambulance in traffic, which was developed by trained YOLOv8 model on a custom dataset. When an emergency vehicle is detected, the system immediately turns into green light to clears its path. This ensures ambulances reach hospitals faster during peak hours. In this model, it improves the overall traffic flow and improves road safety and ensures emergency vehicle reach to their destination on time. So, the designed framework shows how deep learning models can improve the traffic jams flow.**

1. Introduction

The rapid development of cities brings opportunities, not to mention serious problems - and traffic overload is at the forefront. For countless commuters, endless delays have become the norm and are now burning up hours using more gas and poisoning nature [1]. Places like Delhi or Mumbai suffer gridlock every day making life in the city worse and slowing things down. Not only is it annoying, it strikes at the core of how well cities function - and how healthy they will be in the future.

As cities get smarter, tech's being used more to upgrade basic services. Instead of traffic lights in conjunction with timing systems, now experts held for systems which adjust themselves in function of the current activity on the road. This idea has lead us to the exploration of how AI can actually "see" the road with the computer vision in real time. These systems are able to observe, understand and respond to live traffic much faster and much more accurate, than traditional human controlled systems.

This paper presents an AI based system for the real time traffic management by monitoring and controlling the traffic. Our main goal was to develop an adaptive set-up to continuously adjust the set-up of its traffic signals depending on the number of vehicles recorded. We started by studying on already available city camera feeds, to understand the nature of a normal traffic flow. And another important part of this work is dealing with the gap in terms of a lack of emergency vehicles prioritization. By making and training a specific object detection model, it is possible to provide recognition of ambulance and taking immediate action for clearing ways for ambulance, i.e. making the traffic light as green.

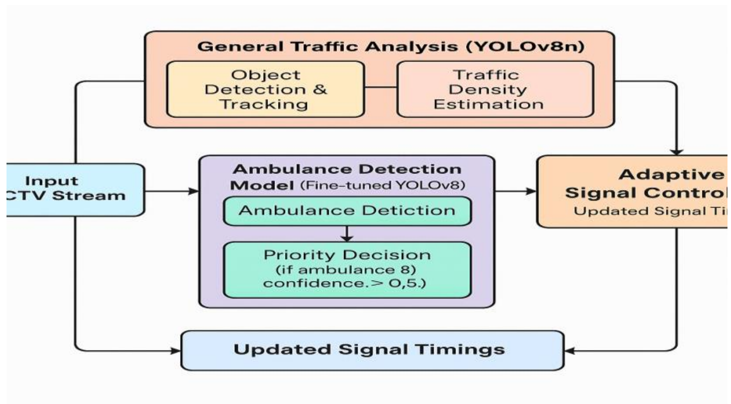


Fig. 1: YOLOv8-Based Ambulance Detection and Priority Signal Workflow

2. Literature Review

Through time, ways to manage traffic did get much better. Old setups were set schedules which relied on past info of flow times to determine light times. Easy to roll out - but they couldn't handle surprises such as crashes, busy commutes and big gatherings - so jams happened [2].

A big step forward came when signals also began to start using sensors buried in roads - such as SCATS - which are able to spot the cars and change the lights times on the fly. Even though they are better adapted than old timers, these systems are still in a state of catch up, they only react once jams have occurred instead of stopping them before they are able to move across the city streets [3].

Once computing capabilities got better, researchers started exploring the use of machine learning to explore traffic forecasting. In past methods people always have used different algorithms like used support vector machine (SVM) and Artificial Neural Net (ANN) algorithms to calculate the flow patterns of vehicles using the past collected data. If we consider the contemporary reports there was a study performed by Smith et al. using ANN to make a prediction of the traffic volumes that resulted in best improvements in signal coordination.

In the prevous years, the landscape has dramatically changed towards the Deep Learning and especially in Convolutional Neural Networks (CNNs). Frameworks such as YOLO (You Only Look Once) has actually made real-time object detection easy and possible. This lack includes the need for more flexible model.

3. PROPOSED METHODOLGY

This system is developed in Python language and is based on dual model architecture design and aims at both general and specific detection work. A generalist model is a model for day-to-day job of analyzing traffic, while a specialist model is dedicated to identifying high-priority emergency vehicles.

3.1. General Traffic Analysis For the main task of counting and tracking vehicles, we used the YOLOv8n model which is pre-trained on the COCO data-set, using ultralytics library. A schematic of the process is given in fig 1.

- Video Input: OpenCV library is used to have frames from a video source.
- Object Tracking: The frames being used object tracking for yolo v8n objects are fed to track() Function of yolo v8n model YOLOv8n is being used to detect and assign an id to vehicle which will help to find total count of objects in frames.
- Vehicle Counting: It picks out certain moving objects like cars or bicycles and counts number of different objects passing, using smart filter to do so; and then putting it all together without double counting.

Recommendation Engine: rule-based engine that transforms the number of vehicles into the signal timing recommendation based on the predefined levels of "Light", "Moderate", "Heavy" traffic.

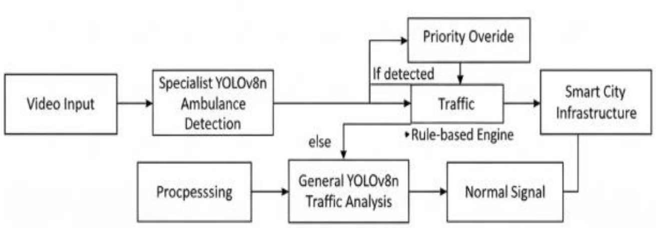


Fig 1: Dual Model Traffic Control Workflow 10.

3.2. Specialist Model for Ambulance Detection The YOLOv8n architecture received a fine-tuning that led to the creation of a specialist model for prioritizing emergency vehicles. In the training of the network, as shown in Fig. 2, the following steps were involved:

Data Collection The dataset of 738 images of ambulances was obtained from a publicly available repository called Roboflow universe [6].

Preparation and Annotation: Already bounding box annotated for the class "ambulance" dataset was organised, prepared and separated into train 88%, validation 7% and test 5% using Roboflow online platform.

Model Fine-Tuning: Training has been performed on Google Colab, using Tesla T4 GPU, for 50 epochs. The YOLOv8n model was a pre-trained state, whereas the best.pt was the last fine-tuned version which formed as the common ambulance detecter.

FIg 2 : Specialist Model Training Pipe Line

3.3. Integrating Systems with Master Control The final iteration ties up both the configurations as a sole seamless system. Note the general layout in the Figure 3 - this is the way it works:

The best.pt model is used to check for each image every if there is a emergency vehicle. If it spots one - it is confident of seeing one at greater than 0.5 - it switches into the high gear, which is to say: Put over the green light right away and start a countdown set to last twenty seconds.

If no ambulance shows up, the system switches back to usual rules of YOLOv8n which alter traffic on-the-fly.

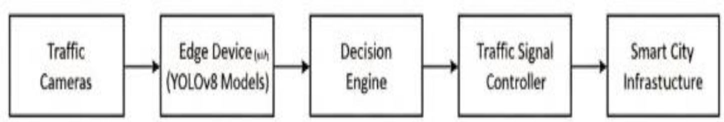


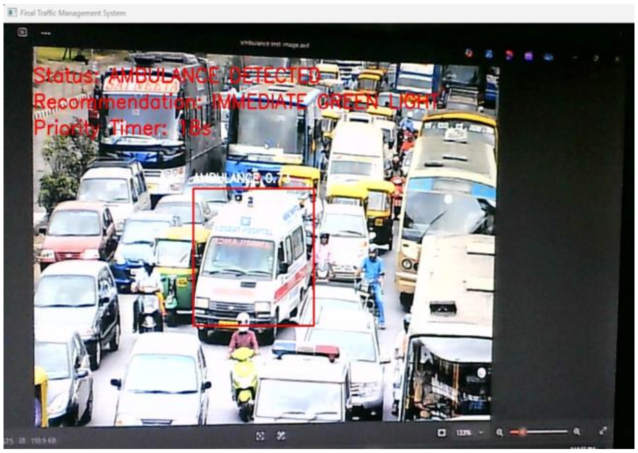
Fig 3 : Deployment Architecture

4. RESULTS AND DISCUSSION

The tuned ambulance detector worked fine: it had 89.8% precise, plus 72.4% recall when tested with validation data. With such high a precision, most of the alerts were correct: almost 9 out of 10 times, calls that it flagged as good were in fact ambulances. And for recall it has performed over 72% of real cases on test shots. That proves tweaking YOLOv8n with focused examples really make increase the accuracy with spotting emergency vehicles.

The two-part system combined worked exactly as planned when doing testing with a live stream from a camera. The main part detected running cars and changed the light times depending on the road busy-ness while the focused detector quickly flagged an emergency vehicle once it came into view immediately changing the light - green. That instantly reaction helped prove that the setup linked does what it's supposed to do.

The set-up was fine though - not to mention simple. A small and fast-size model was able to handle the smooth movement of vehicles: yolov8n.pt. On the other hand, tuned version of best.pt has coped very well with the spotting of an emergency - no lag. This is just about the right combination for use in a live application basically fast and reliable. For reactions that occur instantly at urban crossroads that mix helps out because every second counts.



5. Conclusion

The proposed study introduced an intelligent and two-tier system for city driving, where vehicles are tracked in motion and fast passage is given to ambulances. Instead of using only one approach, it makes use of advanced YOLOv8n model that detects congested traffic roads plus a custom developed tool that is specific for recognizing emergency vehicles. In such a way, the traffic lights would smoothly change according to the traffic but immediately open when rescue missions are on their way. This may be one such case where fine-tuning of advanced models such as YOLOv7 is paying off pretty well for certain applications even if not much data is there to train the models on.

The new setup will make travel within the city smoother while reducing dangers. After a while, crews are able to modify it to identify emergency vehicles such as ambulances or patrol cars. Switch from fixed rules to smarter logic can help provide better choices of the logic on the run. Running it on on-site local devices may speed up the testing process and may help more towns utilize the technology now.

References

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