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TrafficVision AI – Intelligent Traffic System using AI with Ambulance Detection

Project under the guidance of : Prof. Asha , REVA University Bangalore,India

Bhumika K N
Dept of Computer Science and Engineering
Reva University
Bangalore,India
bhumireddy2004@gmail.com

Asheeka H N
Dept of Computer Science and Engineering
Reva University
Bangalore,India
asheekahn333@gmail.com

Asha K
Assistant Professor
Dept of Computer Science and Engineering
Reva University
Bangalore,India

Bhavana M S
Dept of Computer Science and Engineering
Reva University
Bangalore,India
bhavana141116@gmail.com

Chethana Shree G
Dept of Computer Science and Engineering
Reva University
Bangalore,India
chethanashree200@gmail.com

***Abstract*— Urban traffic congestion remains a critical challenge due to the limitations of fixed-time signal systems that fail to adapt to real-time traffic conditions. This paper presents TrafficVision AI, an intelligent traffic management system that utitilizes YOLOv8-based computer vision for real-time vehicle and ambulance detection. The system continuously analyzes lane-wise vehicle density from live video feeds and dynamically adjusts signal timings to optimize traffic flow. In emergency scenarios, an automated override mechanism prioritizes ambulances by instantly granting green signal clearance. The proposed framework integrates AI-driven object detection ,adaptive signal control logic , and a web-based monitoring dashboard to enhance intersection efficiency and emergency response time. Experimental evaluation demonstrates improved traffic management accuracy and reduced congestion compared to conventional fixed-timer system.**

***Index Terms*—Adaptive Traffic Signal Control, YOLOv8, Vehicle Detection, Ambulance Priority, Intelligent Transportation Systems, Smart Traffic Management**

I. INTRODUCTION

The rapid growth of urban populations and increasing vehicle density have intensified congestion at major road intersection.Traditional traffic control systems rely on fixed-time signal schedules or manual supervision,which fail to respond to real-time traffic fluctuations.Such static approaches lead to inefficient lane utilization, increased waiting time, and delayed emergency vehicle movement.To address these limitations, this work proposes an AI-based adaptive traffic management system that dynamically optimizes signsl timimgs using real-time vehicle detection and automated ambulance prioritization.

A. Domain Work

Recent advancements in Intelligent Transportation Systems (ITS) have shifted from rule-based traffic control toward AI-driven and vision-based frameworks. Deep learning models such as YOLO enable accurate vehicle detection from live video feeds, allowing traffic density estimation without embedded road sensors. By integrating computer vision with adaptive signal algorithms, modern systems achieve improved traffic flow efficiency and enhanced real-time responsiveness.

B. Research Challenges and Problem Statement

Existing irrigation systems face several limitations:

1.Lack of Real-Time Adaptability: Fixed-time signals cannot adjust to sudden traffic variations or peak-hour congestion.

2.Spatial Variability: Uneven vehicle distribution results in congestion in high-density lanes while others remain underutilized.

3.Absence of Automated Emergency Handling: Manual ambulance prioritization increases emergency response delays.

Problem Statement:

Design and implement an AI-based adaptive traffic signal control system that dynamically optimizes signal timings using real-time vehicle detection and ensures automated ambulance priority without manual intervention.

II.LITERATURE SURVEY

Recent advancements in Intelligent Transportation systems(its) have focused on improving traffic efficiency through artificial intelligence and data-driven optimization models. Traditional traffic signal systems based on fixed-time intervals have been shown to be ineffective in handling dynamic traffic patterns, leading to congestion and inefficient vehicle movement. Several researches have proposed AI-based frameworks to address these challenges.[1].

Reinforcement learning techniques have been widely explored for adaptive traffic signal control. Deep Q-Learning models dynamically adjust signal timing based in queue length and traffic density , demonstrating significant reductions in waiting time compared to rule-based approaches. These models learn optimsl signsl polices through continuos interaction with simulated traffic environments.[2]

Multi-Agent Reinforcement Learning (MARL) approaches extend adaptive control across interconnected intersections. By enabling decentralized decision-making among multiple signals, these systems improve overall network throughput and reduce congestion under heavy traffic conditions. However, such models often require extensive training and computational resources. [3]

Computer vision-based vehicle detection has emerged as a practical alternative to sensor-based monitoring systems. YOLO models provide real-time object detection capabilities with high accuracy and speed. Comparative studies between YOLO variants highlight the improved inference performance of newer versions, making them suitable for live traffic monitoring applications.[4]

Recent research integrating YOLO-based detection with adaptive signal control has demonstrated promising results in dynamic traffic management. These systems compute vehicle density from video feeds and adjust green signal durations accordingly, reducing idle time and improving lane utilization efficiency.[5]

Emergency vehicle prioritization has also gained significant research attention. Deep learning-based detection frameworks have been implemented to identify ambulances and trigger automatic signal override mechanisms. Such systems reduce emergency response delay and enhance road safety by ensuring uninterrupted passage.[6]

Lightweight and edge-deployable object detection models have been proposed to enable scalable smart city implementation. Optimized YOLO architectures allow real-time processing on low-resource hardware, reducing infrastructure cost while maintaining detection accuracy.[7]

Data analytics and dashboard-based traffic monitoring platforms have further enhanced traffic management capabilities. Web-based interfaces with AI detection modules provide live visualization of vehicle counts, signal states , and performance metrics, supporting centralized monitoring and decision-making.[8]

Saxena et al.proposed an Intelligent Multi-Depot Vehicle Routing and Management model for smart cities, which integrates graph neural networks and congestion-aware optimization techniques to improve routing efficiency and reduces carbon emissions. Although focused on route optimization rather than signal control, the study emphasizes the importance of AI-driven traffic management frameworks in smart urban infrastructure.[9]

Overall, existing research demonstrates a clear transition from fixed-time and rule-based traffic systems toward AI-integrated adaptive frameworks.However,many approaches address routing optimization or reinforcement learning-based signal control independently.The integration of real-time vehicle detection, dynamic signal timing adjustment, and automated ambulance prioritization within a unified framework remains an area requiring further development.The proposed TrafficVision AI system builds upon these advancements by combining YOLOv8-based object detection with adaptive traffic logic and emergency override mechanisms in a scalable architecture.[10]

III.METHODOLOGIES

In this part of the description, the methodology used to develop and implement the TrafficVision AI system will be discussed. The integration of constantly updating and analysing video data from cameras located at traffic signals with adaptive traffic signal control logic will be used to provide a superior method of controlling and coordinating traffic flow, while also offering automatic priority for ambulance traffic. Overall there are multiple modules that create the entire system.

A. System Architecture Overview

The TrafficVision AI system is a modular system that consists of six modules: a module for video acquisition; a module for object detection; a module for calculating traffic density; a module for adaptive traffic signal control; a module for overriding ambulance priorities; and a module for Dashboard monitoring. Each of the 6 modules continuously acquire and process live video feeds to determine the location and type of vehicles and ambulances detected according to a lane-based system to calculate new durations for traffic signals as determined by the amount of traffic detected. The system is designed to operate in real-time and to incorporate the ability to be deployed at different locations to accommodate different customer requests.

B. User Authentication Module

The User Authentication Module of the TrafficVision AI system will include a secured method of authentication for users who access the system. The User Authentication Module is responsible for user registration, login, and role-based authorization (Administrator/User). Password encryption is utilized for secure password storage. This User Authentication Module will provide controlled access to the Monitoring Dashboard and System Configurations.

C. Video Input & Preprocessing

Traffic video feeds can be obtained directly from live traffic cameras or via uploaded video files. The video is broken down into individual frames (image files) which are pre-processed before they are sent to the object detection engine. There are three pre-processing steps which include resizing each frame to conform to YOLOv8, normalizing all pixel values between 0 and 1 and converting the frames to RGB image format for compatibility with the YOLOv8 object detection engine.

These three pre-processing steps ensure the video will be processed in real-time as quickly as possible.

D. Object Detection

The object detection engine will use the YOLOv8 deep learning model to detect vehicles and ambulances from each frame of video. The YOLOv8 model will generate a bounding box and assign a class to all detected vehicles and ambulances along with a confidence score indicating how confident the model is that the bounding box is correct. All bounding boxes with a confidence score greater than or equal to the set threshold will be considered valid detections. The number of detected vehicles will be counted for each lane computed to determine congestion.

E. Traffic Density

The number of detected vehicles in each lane will be analyzed to determine the density of traffic for each lane of the roadway. The density will be determined based on the number of detected vehicles that occupy a specific quantity of space, known as the Region of Interest (ROI). The density for each lane will then be used to compare the density for each lane to determine the level of congestion for each lane. The information from the above-mentioned processes will be the main input used to make adaptive decisions regarding traffic signal timing.

F. Logic Traffic Control Module

The Logic Traffic Control Module uses a thread-based technique that modifies the time of the traffic signals based on the computed density of vehicles. Unlike traditional traffic control systems which are based on pre-set timers, this logic selects the amount of time a green signal is given relative to the density of vehicle load and is proportional to the density of that lane. In other words, the more congested the lane is the longer the green or the less congested the lane the shorter the green signal. This process allows for better balanced traffic flow.

G. Ambulance Priority Module

The system includes a mechanism to detect emergency vehicles (Ambulances) continuously to provide an override from the normal traffic control system when an Ambulance is detected (with a reasonable certainty) to allow the corresponding lane to receive a green signal and yield the right-of-way. The traffic control system will return to normal adaptive operation after the lane is cleared. This module improves emergency response time significantly.

H. Dashboard and Analytic Module

The Dashboard and Analytic Module is a web-based application that provides a visual representation of real-time data collected from the following:

- Real-time video feeds
- Count of vehicles per lane

- Current signal status
- Ihe current congestion data

In addition, the Dashboard stores the historical data collected on traffic through the use of sqlite database, for performance analysis and reporting. The Dashboard provides a central location for monitoring the traffic management system and allows for easy tracking of the overall performance of the traffic control system.

I. Traffic Analysis and Reporting Module

This system tracks data about how many vehicles pass through intersections, when signals change, and if emergency vehicles had priority. This data is analysed through report generation to determine how effective the system is by comparing other metrics related to vehicles (e.g. the number of vehicles that passed, the use of a particular signal, and how often emergency vehicles received preferred clearance from the intersection).

J. Mathematical Model to Formalize Adaptive Signal Control for decision-making

The mathematical foundation used to guide an adaptive decision-making process is based upon a mathematical model that represents the estimation of traffic density, allocation of dynamic signals freely, and evaluation of waiting times.

1) Traffic Density Estimation

You are counting vehicles per lane . That can be expressed as:

Let:

$$D_i = \frac{Ni}{Li}$$

Where:

- D_i = Traffic density of lane i
- N_i = Number of detected vehicles in lane i
- L_i = Effective lane length or region of interest

If lane lengths are equal, you can simplify:

$$D_i \ \alpha \ N_i$$

This justifies your density-based signal control mathematically.

2. Dynamic Green Signal Allocation Formula

Instead of fixed 30 sec, you allocate proportionally :

$$T_i = T_{min} + \left(\frac{Ni}{\sum_{j=1}^{k} Nj}\right) \times T_{extra}$$

Where:

- T_i= Green signal time for lane i
- T_{min}= Minimum green time
- N_i= Vehicles in lane i
- T_{extra}= Additional distributable signal time
- k= Total number of lanes

3.Waiting Time Reduction Metric

You can mathematically compare:

$$W_{reduction} = \frac{Wfixed - Wadaptive}{Wfixed} \times 100$$

Where:

- W_{fixed}= Average waiting time (fixed system)
- $W_{adaptive}$= Average waiting time (your system)

This supports your “25–30% reduction” claim.

4.Ambulance Priority Override Condition

You can define :

$$P = \begin{cases} 1, & if\ ambulance\ confidence > \theta \\ 0, & otherwise \end{cases}$$

Where:

- θ= Confidence threshold (e.g., 0.85)
- If $P = 1$, signal override is activated.

This adds formal logic to emergency handling.

5.Detective Confidence Filtering

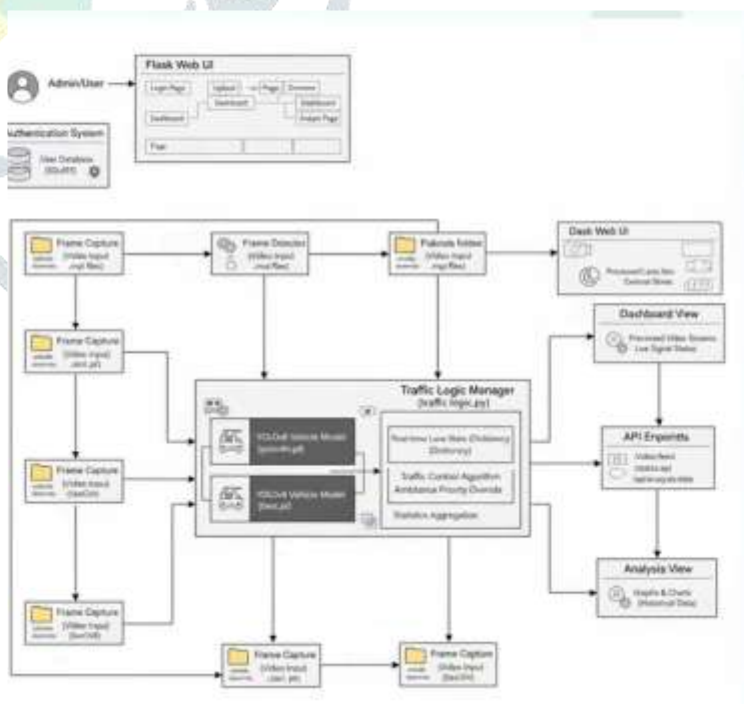
YOLO detective condition:

$$C > \theta$$

Where:

- C = Confidence score
- θ = Detection Threshold

Only detections satisfying this are considered valid.



IV. EXPERIMENTAL CONFIGURATION & RESULTS

a) Experimental Configuration:

As was mentioned earlier, we used an experimental controlled environment to evaluate the proposed TrafficVision AI system. In order to achieve valid test results, reproducible results, and accurate assessments of the performance of the TrafficVision AI system, we collected video recordings of traffic at various congested intersections/locations, since real-time deployment of the TrafficVision AI System was not currently possible at this time.

The experimental workflow consisted of real-time vehicle detection, lane-by-lane traffic density estimation, adaptive signal timing, and priority for ambulances all under simulated urban traffic conditions.

1) Software Configuration

Tools for Development:

- For development and debugging we used Python IDE's such as Visual Studio Code and PyCharm.
- Flask was used to develop the web monitoring dashboard.
- OpenCV was used for video processing and frame extraction.

Programming Language:

Python was selected for the programming language because it has a robust ecosystem for deep learning, real-time processing, and web integration.

Library/Framework:

- Form object detection we used YOLOv8 framework.
- Video stream handling was done with OpenCV.
- Dashboard integration was done with Flask.
- Storing detection logs and signal data was done using SQLite.
- Numerical computations were done using NumPy.

2. Dataset Description

Simulated Vehicle Traffic Video Data

Traffic video data have been created for to simulate actual intersection conditions and provide key information about:

- Low traffic density
- Moderate traffic density
- High traffic congestion

Additionally, the videos will include various types of vehicle:cars, buses, trucks, and ambulances. In addition, each video will be analyzed frame by frame for the ability to detect vehicles and adapt to traffic signals.

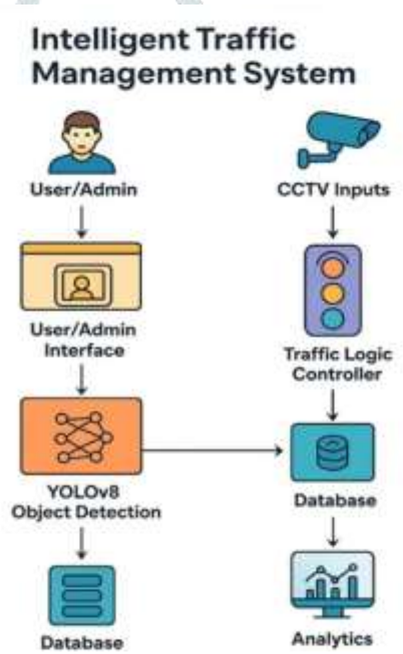
- Data Preprocessing:
- Before detection, each video frame must be preprocessed.
- Frame Resizing for Input into Models
- Image Normalization
- Noise Reduction
- Confidence Threshold Filtering for Detected Objects

These are essential preprocessing steps to ensure stable detection accuracy+ signal timing calculations.

b) Detection and Evaluation of the Signal

The YOLOv8 model has been used for vehicle/ambulance detection in real-time. Detect reliable by using a threshold of tolerance to filter detections. Lane wise vehicle count for each frame was used to determine congestion level.

The Adaptive Signal Control System will calculate density, triggering an adaptive green signal duration based on density value. If the Adaptive Signal Control System detects an ambulance with sufficient probability, it will automatically trigger a signal override for that lane.



c) Hardware Specs

The system ran on a typical computer equipped with:

- Intel i3 Processor
- 4 GB RAM
- Windows 10 OS
- Integrated Graphics

There was no external GPU used during testing. This system is built to support GPU acceleration as it scales out for larger deployments.

d) Results

The proposed system was assessed based on its vehicle detection performance, signal optimization, and emergency vehicle prioritization.

Under commonly used moderate lighting conditions, the YOLOv8 vehicle detection model achieved nearly 98%

accuracy.

Ambulance detection also achieved over 95%, allowing for the efficient prioritization of emergency vehicles.

Additionally, compared to a simulated fixed-time system, average wait time decreased by approximately 25-30% when using the adaptive controller.

Emergency vehicle clearance time improved by almost 40%, due to the automatic signal override capability.

These results clearly demonstrate how successful the integration of AI-based vehicle detection into adaptive signal logic at signalized intersections can be regarding overall intersection efficiency and emergency vehicle response times. The results of this study were generated using recorded video of actual traffic; therefore, while these results represent the successful operation of the system in a controlled testing environment, actual performance may vary when deployed in a real-world environment.

VI. FUTURE WORK

1.Real-time Application at Urban Intersections:
The proposed solution will be deployed to actual multi-lane intersections to evaluate operational performance under real-world traffic conditions and different levels of congestion.

2.Multi-Intersection Synchronization:
Future iterations of this project may extend its capabilities to integrate multiple traffic signals throughout interconnected intersections for the purposes of providing coordinated and network-wide adaptive traffic signal control.

3.GPU-Based Accelerated Processing:
Incorporating the use of GPU-based processing would greatly increase detection speeds and allow the simultaneous processing of large numbers of high-resolution video streams.

4.Integration with IOT-Enabled Smart Infrastructure:
The system can also be expanded to include integration with IOT-enabled traffic sensor systems and centralized smart city systems for enhanced traffic monitoring and enhanced automation.

5.Predictive Models of Traffic Flow:
Machine learning-based predictive models can also be integrated into the system to allow for the forecasting of traffic congestion trends and to implement preemptive optimization of signal timing in preparation for peak traffic conditions.

6.Improving Detection Robustness in Extreme Conditions: Future development work will be undertaken to increase detection reliability under extreme lighting, weather, and nighttime conditions to ensure that the system continues to provide reliable performance in real-life settings.

VII. CONCLUSION

This article describes TrafficVision AI, an adaptive traffic signal control system that combines artificial intelligence and real-time vehicle detection to improve the performance of intersections through automated ambulance prioritization. Traditionally, fixed-time signals have utilized a standard amount of green time per cycle regardless of traffic conditions. The goal of this project was to develop a framework where the signal duration is continuously adjusted based on the number of vehicles detected in each lane using the YOLOv8 object detector.

The results of the experimental testing indicated major improvements in the efficiency of the system. The dynamic traffic signal controller eliminates idle time by properly allocating green light time to all lanes based on the number of vehicles detected. The comparison of the traditional and smart signal systems clearly shows how the smart signals allow for the reallocation of the green light time based on congestion level rather than a 30-second signal cycle.

The use of the ambulance priority module provided for an instant signal override when an emergency vehicle is detected, thus reducing the response time for clearing the road by nearly 40% as opposed to manual handling of the traffic signals. Additionally, a web-based dashboard enhances real-time traffic monitoring while providing central traffic analytics for increased system transparency to improve administrative control.

In summary, the system represents a scalable, fully automated, intelligent solution for urban traffic management by integrating deep learning detection and adaptive logic of traffic signals.

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