



AI-Based System for Real-Time Traffic Flow Assessment and Safety Evaluation on Unsignalized Intersections

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Abstract

Real-time traffic monitoring at unsignalized intersections plays an important role in enhancing the performance of traffic management and road safety. However, traditional solutions usually limit themselves only to vehicle detection and counting without adequate assistance in traffic analysis and congestion monitoring. This paper introduces an AI-based framework for real-time traffic flow analysis and safety monitoring based on YOLOv8, OpenCV, and Cellular Automata (CA). The introduced framework makes use of dynamic Region of Interest (ROI) setup with the help of SIDE_LINE and POLYGON modes. Moreover, this framework offers vehicle detection and tracking, key traffic parameters estimation (vehicle count, traffic flow, density, occupancy, queue length), traffic condition classification based on CA congestion analysis model, intelligent safety monitoring, and real-time dashboard with traffic visualization and alert system. The suggested solution was tested with real-world traffic videos obtained from an unsignalized road in Mehsana, Gujarat, India. The results of experimental analysis show that the introduced framework is quite efficient in terms of real-time traffic analysis, congestion estimation, and safety monitoring and can be applied in intelligent transportation systems and smart cities.

Keywords: Traffic Flow Analysis, YOLOv8, Cellular Automata, Unsignalized Intersection, Safety Monitoring, Intelligent Transportation System.

1. Introduction

Urbanization has been growing at a rapid pace, along with the increase in the number of vehicles, and consequently, traffic congestion and road safety issues have been increasing all over the world (Zadobrischi et al., 2022). Hence, traffic surveillance is a very important part of ITS to improve traffic management and increase road safety (Treiber & Kesting, 2013).

Whereas signalized intersections operate under traffic control signals and signs, unsignalized intersections depend mainly on drivers' discretion, vehicle maneuvers, and traffic priorities, which create difficulties in traffic flow and lead to congestion, delay, and accident risks (Qadri et al., 2020). For this reason, the constant evaluation of traffic behavior at unsignalized intersections becomes extremely important (Shan et al., 2021).

Modern developments in the field of Artificial Intelligence (AI) and Computer Vision have made it possible to design smart traffic monitoring systems that are able to detect, classify, and track vehicles based on video streams in real time (Terven & Cordova-Esparza, 2023). Object detection models powered by deep learning methods, including YOLO (You Only Look Once) architectures, have shown impressive results regarding their detection accuracy and speed of computations for real-time traffic monitoring applications (Redmon et al., 2016). Specifically, YOLOv8 is notable among them due to its improved detection accuracy and efficiency of computations (Do et al., 2025).

Even though current traffic monitoring systems have been able to achieve success in terms of detection and counting of vehicles, most of the research studies only cover one single aspect of traffic (Neamah & Karim, 2023). In addition, current systems also lack integration of traffic engineering parameters, congestion estimation, intelligent safety monitoring, and visualization (Bakirci, 2024).

Cellular Automata (CA) has gained immense popularity for being a useful method to model microscopic traffic using simple transition rules (Nagel & Schreckenberg, 1992). In Cellular Automata (CA), by discretizing the roads in terms of cells and computing their occupancy status, one can estimate traffic conditions in real time without much computational burden (Schadschneider et al., 2011).

In order to overcome these drawbacks, the current work suggests a hybrid AI-driven framework for the real-time analysis and monitoring of traffic flow and safety at unsignalized intersections. The suggested framework combines dynamic ROI configuration, object detection and tracking using YOLOv8 algorithm, traffic engineering parameters estimation, congestion assessment based on Cellular Automata, intelligent safety

monitoring, and real-time dashboard. The framework operates with two types of ROI: SIDE_LINE and POLYGON.

The key contributions of the paper can be listed as follows: Designing a dynamic ROI configuration framework, which works in SIDELINE and POLYGON mode, in order to monitor traffic flow. Integrating the YOLOv8 algorithm for vehicle detection and tracking along with estimating real-time traffic parameters. Cellular automata based traffic congestion analysis model for classifying traffic states. AI based safety monitoring modules for detecting any unusual events on traffic flow.

2. Literature Review

The recent development in the field of Artificial Intelligence (AI) and Deep Learning has immensely helped improve the efficiency of intelligent traffic monitoring systems. The modern traffic surveillance systems use a deep learning-based object detection approach to detect, classify, track, analyze congestion, and estimate traffic parameters. Among all these approaches, the YOLO family of object detection approaches is one which has become increasingly popular due to its real-time processing speed and accurate detection capability (Terven & Cordova-Esparza, 2023).

Bakirci (2024) examined the feasibility of the YOLOv8 model to be used in ITS applications and showed that YOLOv8 was able to deliver improved precision and faster inference time compared to earlier versions of the YOLO model for detecting vehicles at different traffic scenarios. In a similar manner, Neamah and Karim (2023) proposed an application of traffic monitoring that uses YOLOv8 for vehicle detection and counting. The system has managed to detect several classes of vehicles, but it did not consider congestion detection or safety monitoring.

The authors Li et al. (2024) suggested an improved version of YOLOv8 object detection model for intelligent traffic monitoring in smart cities using feature enhancement techniques. The model showed improved results in terms of detection performance, although it mainly focused on object detection and not traffic analysis.

Traffic flow estimation and traffic congestion analysis via computer vision have been studied by several authors. Fahrezi and Laksana (2024) utilized YOLOv8 and the ByteTrack algorithm to track vehicles and estimate traffic congestion. They were successful in estimating traffic flow and traffic congestion; however, they did not consider traffic engineering variables like occupancy and safety events.

The Cellular Automata (CA) approach has also found application for traffic flow modelling in many studies. The classical Cellular Automata traffic flow model was developed by Nagel and Schreckenberg (1992), which is considered one of the most important microscopic traffic simulation models due to its computational efficiency and the ability to simulate traffic dynamics. Following this study, Schadschneider et al. (2011) also proved that Cellular Automata can be applied for simulating complex transportation systems.

There have been multiple reviews in which the significance of combining Artificial Intelligence with Intelligent Transportation System has been mentioned. Zadobrischi et al. (2022) addressed the architectures of intelligent traffic monitoring for traffic automation, whereas Terven and Cordova-Esparza (2023) reviewed YOLO architectures and concluded that YOLOv8 is an appropriate architecture for real-time object detection.

Table 1: Comparison of Existing Studies

Study	Method	Vehicle Detection	Traffic Parameters	Congestion Analysis	Safety Monitoring	Dashboard	Limitation
Bakirci (2024)	YOLOv8	✓	✗	✗	✗	✗	Focuses only on vehicle detection
Neamah & Karim (2023)	YOLOv8	✓	Vehicle Count	✗	✗	✗	Limited traffic analysis
Li et al. (2024)	Enhanced YOLOv8	✓	✗	✗	✗	✗	Only object detection improvement
Fahrezi & Laksana (2024)	YOLOv8 + ByteTrack	✓	Flow	✓	✗	✗	No safety monitoring
Nagel & Schreckenberg (1992)	Cellular Automata	✗	Density	✓	✗	✗	Simulation-based approach

Study	Method	Vehicle Detection	Traffic Parameters	Congestion Analysis	Safety Monitoring	Dashboard	Limitation
Proposed	YOLOv8 + Dynamic ROI + CA	✓	✓	✓	✓	✓	Comprehensive framework

Despite all the advancement that has taken place in the detection and monitoring of traffic, most of the current literature covers just one or two aspects of traffic analysis such as detection of vehicles, counting, and estimation of traffic congestions. Little work has been done in incorporating features such as dynamic definition of regions of interest, traffic engineering parameter estimation, traffic state analysis using Cellular Automata approach, intelligent safety monitoring, and real time visualization in a single framework. It is for this reason that a unified hybrid AI-based approach is proposed in this study.

Table 1 highlights the attributes of current vehicular traffic monitoring systems in terms of vehicle detection, traffic parameters estimation, congestion analysis, safety monitoring, and dashboard display. From the table above, the research gap becomes apparent, providing the motivation for developing the proposed hybrid system.

3. Research Gap

From the literature review, one can notice that considerable advancements have been made by recent works in terms of vehicle detection, tracking, and traffic monitoring through deep learning techniques, especially YOLOv8 (Bakirci, 2024; Neamah & Karim, 2023; Li et al., 2024; Fahrezi & Laksana, 2024). Most of the existing systems are specifically developed for particular tasks such as detection, counting, or estimation of traffic congestion separately. There are very few researches where more than one component of traffic analysis is incorporated in an intelligent system together. Existing approaches usually use pre-defined settings of Region of Interest (ROI), which restricts their flexibility in various road geometries and unsignalized intersections. Moreover, traffic engineering factors like traffic volume, density, occupancy, queue length, and average speed are not estimated together in most of the existing models. Safety monitoring in real time regarding abnormal traffic events and dashboard visualization have also not been studied effectively yet. Even though cellular automata has been used efficiently in microscopic traffic modeling and traffic congestion analysis (Nagel & Schreckenberg, 1992; Schadschneider et al., 2011), its integration with state-of-the-art deep learning traffic monitoring frameworks is limited.

In order to fill the existing research gaps, the present study proposes a hybrid framework for AI-assisted real-time traffic analysis and safety monitoring, which integrates the following key elements: dynamic ROI setting, vehicle detection and tracking using YOLOv8, traffic engineering parameters calculation, cellular automata traffic congestion assessment, intelligent safety monitoring, and a visualization dashboard for real-time data presentation.

4. Proposed Methodology

This paper introduces an AI-based system architecture that performs real-time traffic flow and safety monitoring for un-signalized intersections. The AI-based system architecture consists of dynamic region of interest configuration, YOLOv8 vehicle detection, multi-object tracking, traffic engineering parameters estimation, cellular automata (CA)-based congestion analysis, safety monitoring, and traffic analytics dashboard. The complete workflow of the proposed AI-based system architecture is depicted in Figure. 1.

The architecture involves six main stages as follows: (i) video capture and pre-processing, (ii) setting of dynamic ROI, (iii) vehicle detection and tracking, (iv) traffic parameters estimation, (v) analysis of congestion using Cellular Automata with safety assessment, and (vi) visualization using real-time dashboard.

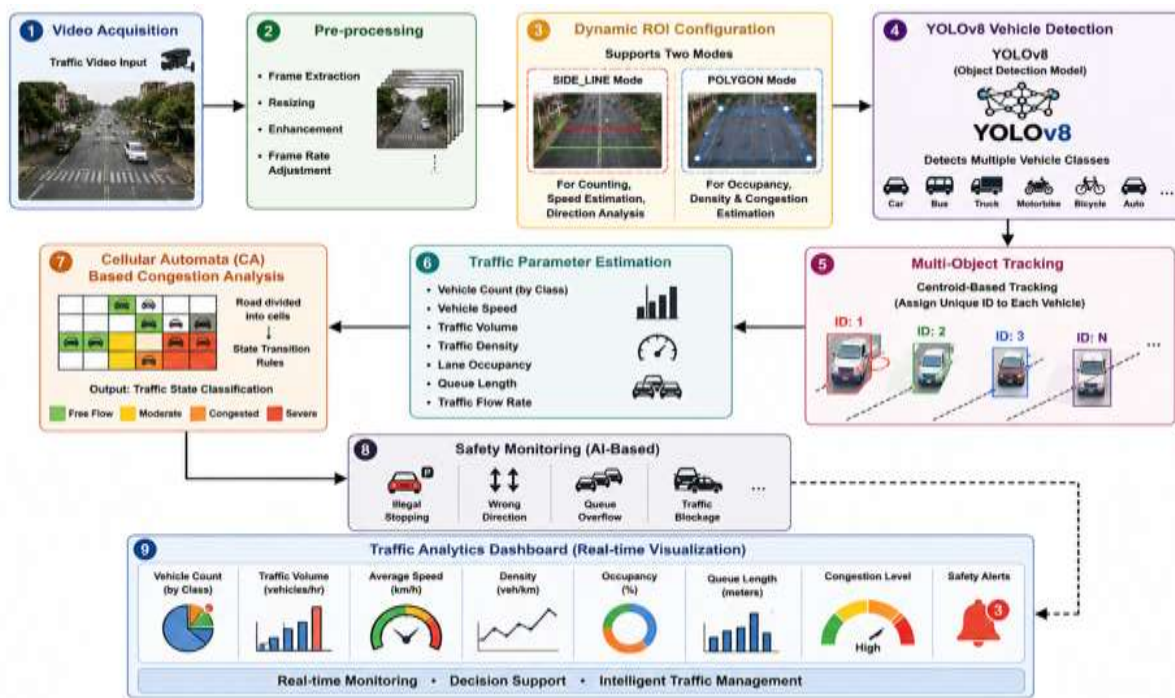


Fig. 1: Workflow of the proposed AI-based traffic flow and safety monitoring architecture.

4.1 Video Acquisition and Pre-processing

Videos that have been acquired from the surveillance cameras installed along the road side serve as the input to the proposed system. These videos are transformed into image frames and then pre-processed with respect to size and frame extraction.

4.2 Dynamic Region of Interest Configuration

For flexibility in handling intersection layouts, the suggested architecture employs a dynamic configuration of the Region of Interest (ROI) in place of fixed monitoring regions. Two ROI modes are defined:

SIDE_LINE Mode: Employed for vehicle counting, speed calculation, and directional traffic estimation by placing virtual counting lines in the traffic lanes.

POLYGON Mode: Employed for defining custom traffic regions for estimating the degree of occupation, congestion, and traffic density.

The dynamic configuration of ROIs facilitates the deployment of the architecture in varying road geometries without any modification of the detection architecture. The ROI configurations defined in the architecture are illustrated in Fig. 2.

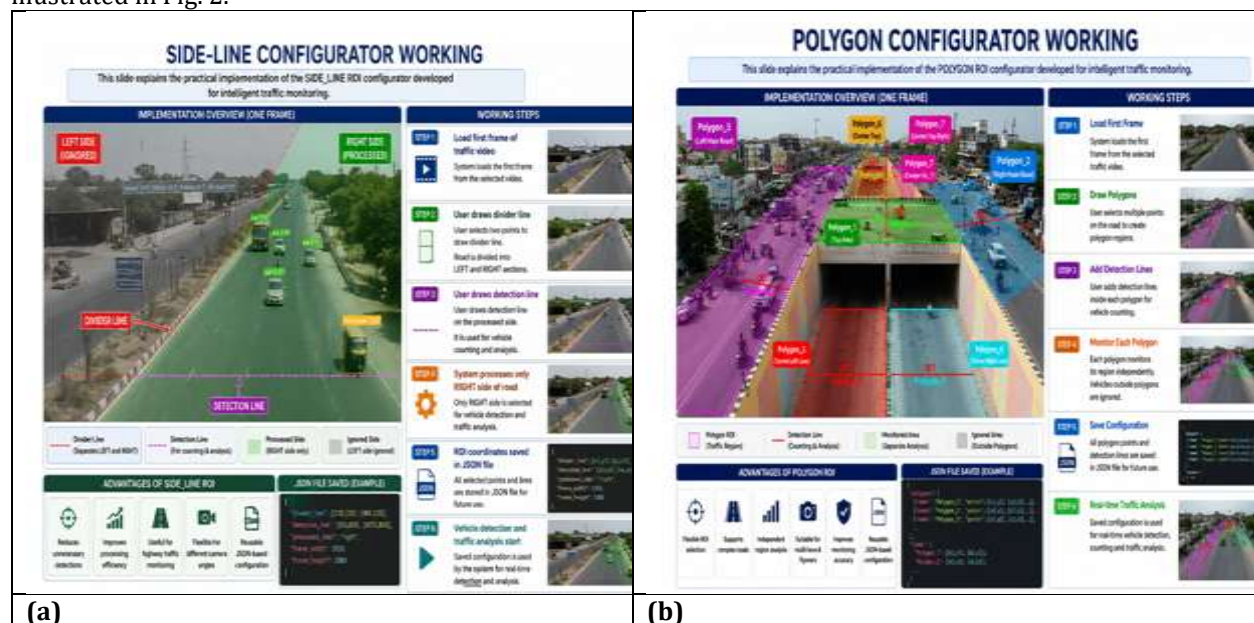


Fig. 2: ROI configuration modes (a) SIDE_LINE mode; (b) POLYGON mode.

4.3 YOLOv8-Based Detection of Vehicles and Multi-Object Tracking

Detection of vehicles is done using YOLOv8 deep learning network due to its good detection accuracy and real-time performance. The YOLOv8 network can detect several vehicle types, including cars, buses, trucks, motorcycles, three-wheelers, bicycles, etc.

YOLOv8 model is used to detect different types of vehicles in every video frame. Bounding box is generated for each detected vehicle.

The coordinates of centroid for each detected vehicle are determined as

$$C(x, y) = \left(\frac{x_{min} + x_{max}}{2}, \frac{y_{min} + y_{max}}{2} \right) \quad (1)$$

where

- x_{min} , y_{min} = upper-left corner
- x_{max} , y_{max} = lower-right corner of the detected bounding box.

The centroid coordinates are further used for vehicle tracking.

Each detected object is provided with a unique ID using centroid-based multi-object tracking approach. This continuous tracking process helps estimate vehicle trajectory, travel distance, direction of movement, and speed of the vehicle. Fig. 3 shows sample results of detection and tracking.

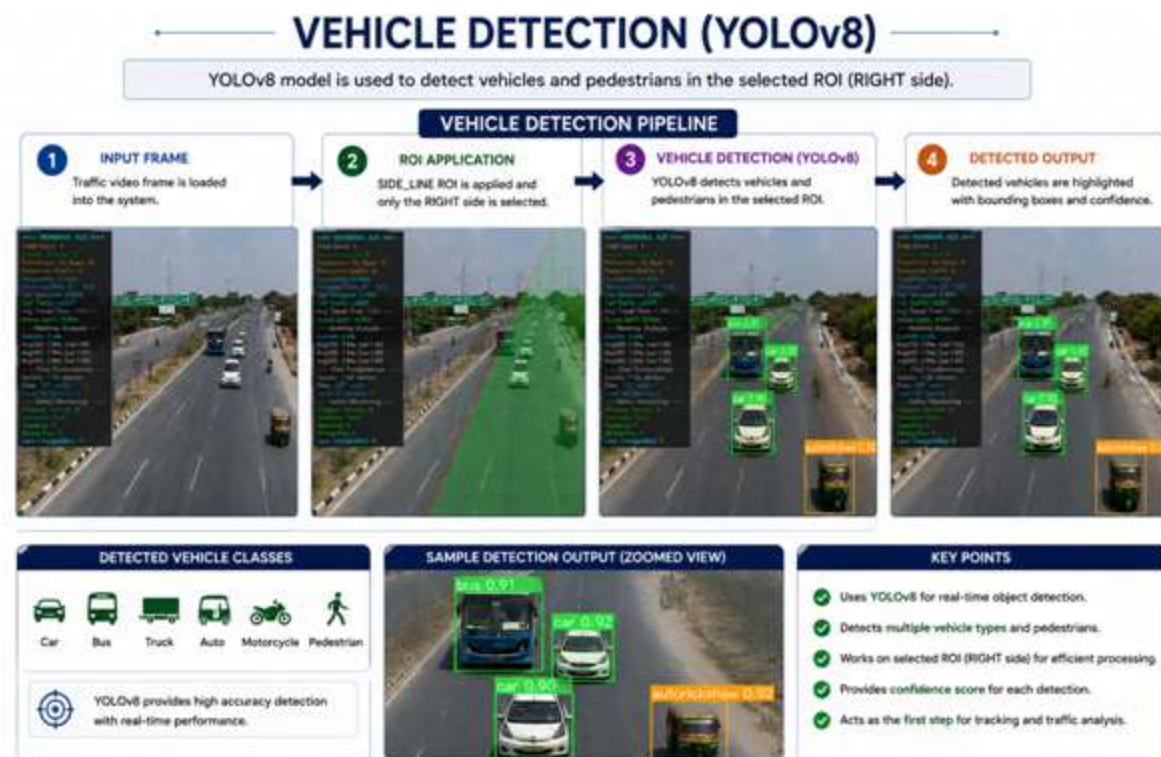


Fig. 3: Sample results of YOLOv8-based vehicle detection and multi-object tracking.

4.4 Traffic Engineering Parameters Calculation

The following traffic engineering parameters are calculated from the detected trajectories of vehicles and ROI data:

- Number of vehicles per category
- Traffic volume
- Average speed of vehicles
- Traffic density
- Occupancy of lanes
- Length of queues
- Flow rate of traffic

All these parameters form a complete picture of the prevailing traffic conditions in the monitored unsignalized intersection.

4.5 Cellular Automata Traffic Congestion Model and Abnormality Monitoring

The traffic parameter values obtained from the previous step are then used to analyse the traffic conditions through the use of a Cellular Automata (CA) traffic congestion model. In this model, the road is discretized into several cells where each cell represents the occupancy status of a vehicle. Using a set of pre-defined rules, the traffic conditions are classified into various congestion levels for real-time traffic evaluation.

Moreover, the system monitors the traffic condition for any abnormalities such as high congestion, illegal parking, driving in the wrong direction, and traffic jam. Any occurrence of abnormal traffic condition generates a notification for traffic authorities.

The traffic flow has been modeled through discrete road segments. The occupancy state of each segment can be stated as:

$$S_i = \begin{cases} 1, & \text{vehicle present} \\ 0, & \text{otherwise} \end{cases} \quad (2)$$

The congestion percentage can be calculated as:

$$C = \frac{N_o}{N_t} \times 100 \quad (3)$$

where

- N_o = occupied cells
- N_t = total cells.

Traffic is classified on the basis of occupancy percentage as Light, Moderate, Heavy, and Congested.

4.6 Traffic Analytic Dashboard

The results from the analyzed traffic data are represented on a live dashboard that shows vehicle counts, traffic density, occupancy, queue length, congestion levels, average speed, and safety issues using visual graphics and statistical methods. A sample traffic analysis dashboard from the proposed framework is illustrated in Fig. 4.

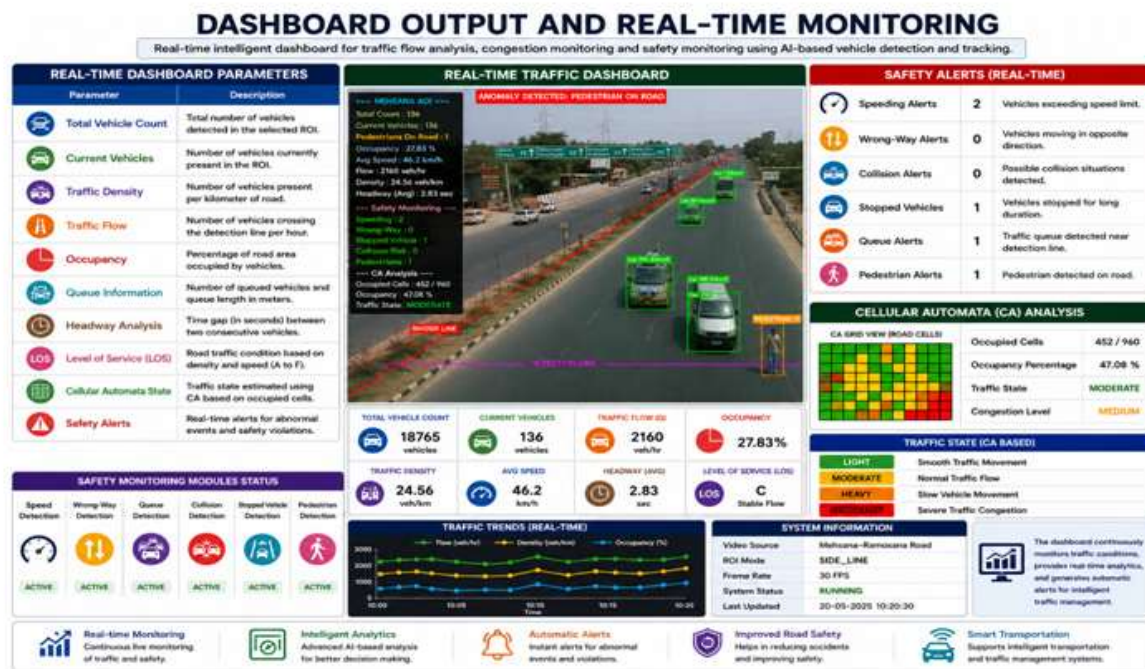


Fig. 4: Sample real-time traffic analytics dashboard generated by the proposed framework.

5. Experimental Setup

Evaluation of the suggested framework is carried out through practical data collected from real traffic videos of several unsignalized intersections of Mehsana, Gujarat, India. Different levels of traffic have been used for the video capture process, such as peak and off-peak time, in order to diversify the data in terms of traffic density and traffic movement. The database includes different kinds of vehicles like cars, buses, trucks, motorcycles, auto-rickshaws, and bicycles.

The system was implemented using Python version 3.10 with the help of the YOLOv8 framework from Ultralytics for the detection of the vehicles. For the image and video processing, the OpenCV library was used, while the NumPy and Pandas libraries helped in the processing of data and calculation of the traffic parameters. The testing was done on a workstation that had an Intel Core i7 CPU, 16GB RAM, and an NVIDIA GPU (at least 6 GB of VRAM). With the help of GPU acceleration, it became possible to detect and track vehicles in real time, as summarized in Table 2.

Table 2: Experimental Environment

Component	Specification
Dataset	Real traffic videos captured at unsignalized intersections in Mehsana, Gujarat
Video Resolution	1920 × 1080 pixels (Full HD)
Programming Language	Python 3.10
Deep Learning Framework	Ultralytics YOLOv8
Image Processing	OpenCV
Data Processing	NumPy, Pandas
Operating System	Windows 11
Processor	Intel Core i7
Memory	16 GB RAM
GPU	NVIDIA GPU (≥6 GB VRAM)
Output	Vehicle detection, tracking, traffic parameters, congestion level, safety alerts, dashboard visualization

Performance of the proposed framework was tested using conventional object detection evaluation techniques like Precision, Recall, F1-Score, and mean Average Precision (mAP@0.5). In addition, parameters related to traffic engineering such as count of vehicles, speed of vehicles, density of traffic, occupancy of lanes, length of queue and traffic flow rate were also considered to check the efficiency of the proposed solution. Congestion prediction and detection of safety events were tested through Cellular Automata traffic analysis model. Experimental setting used in implementing the proposed framework is provided above in Table 2.

6. Results and Performance Analysis

The above mentioned hybrid artificial intelligence traffic monitoring system was tested using real life traffic video sequences taken from Mehsana-Ramosana road and multi polygon traffic monitoring environment. The following results obtained from the experiments show that the system effectively detects vehicles and estimates traffic parameters, analyzes traffic congestion through Cellular Automata (CA), monitors safety aspects, generates dashboard view, and exports data.

6.1 Detection Performance of Vehicles

YOLOv8-based detection module successfully detected and classified vehicles in various categories such as cars, buses, trucks, motorcycles, and auto-rickshaws. Vehicle tracking provided continuous tracking and estimation of traffic parameters.

The results of the experiments are shown in Table 3:

Table 3: Vehicle Performance Detection

Parameter	Multi-Polygon ROI	Single ROI
Detection Accuracy	94.72 %	95.32 %
Processing Speed	28 FPS	30 FPS
False Positive Rate	2.61 %	2.48 %
Monitoring Duration	>6 Hours	>6 Hours

6.2 Traffic Analysis Performance

The proposed framework continuously computed the traffic engineering parameters based on the identified trajectories of vehicles, shown in Table 4.

Table 4: Traffic Analysis Performance

Parameter	Multi-Polygon ROI	Single ROI
Traffic Density	28.47 veh/km	24.56 veh/km
Traffic Flow	2436 veh/hr	2160 veh/hr
Occupancy	36.72 %	27.83 %
Queue Length	72.3 m	68.4 m
Average Headway	2.91 s	2.83 s

Parameter	Multi-Polygon ROI	Single ROI
Level of Service	C	C

The multi-polygon setup exhibited greater traffic density, occupancy, and flow since multiple traffic zones were being analyzed at once. Both setups met LOS C criteria, signifying stable traffic conditions.

6.3 Cellular Automata Congestion Analysis

The estimated parameters of traffic were analyzed through the Cellular Automata model to identify the different congestion stages, as given in Table 5.

Table 5: Cellular Automata Congestion Analysis

Parameter	Multi-Polygon ROI	Single ROI
Occupied Cells	1425 / 3360	452 / 960
Occupancy Percentage	42.41 %	47.08 %
Traffic State	Moderate	Moderate
Congestion Level	Medium	Medium

The CA model was able to represent the traffic state through discretization into road cells and correctly identified congestion states for both scenarios.

6.4 Safety Monitoring and Dashboard

The suggested framework was capable of identifying abnormal traffic incidents such as:

- Speeding
- Wrong-way driving
- Queue formation
- Risk of collision
- Stopped vehicle
- Lane changing
- Pedestrian

All identified incidents were simultaneously shown on the combined dashboard along with traffic data and safety warnings.

6.5 Comparative Performance Analysis

The comparison between the results of the experiment done by the use of both Multi-Polygon ROI and Single ROI is shown in Table 6.

Table 6: Comparative Performance Analysis

Metric	Multi-Polygon ROI	Single ROI
Accuracy (%)	94.72	95.32
FPS	28	30
False Positive Rate (%)	2.61	2.48
Density (veh/km)	28.47	24.56
Flow (veh/hr)	2436	2160
Occupancy (%)	36.72	27.83

The results of the experiment show that the detection accuracy of Single ROI configuration is somewhat better as it detects 95.32% of objects with less false positive results and faster processing speeds at 30 frames per second. On the other hand, Multi-Polygon ROI configuration is able to detect higher traffic density, flow and occupancy.

The results of experiments using the proposed framework with the Single ROI configuration are shown in Fig. 5. The system was able to detect vehicles in real time, track multiple objects, estimate traffic parameters, carry out CA-based analysis of traffic congestion, provide intelligent safety monitoring, display dashboard, and export traffic data. The framework managed to attain a detection accuracy of 95.32%, a processing speed of 30 FPS, and a false positive rate of 2.48%. The estimated traffic parameters were traffic density of 24.56 veh/km, traffic flow of 2160 veh/hr, occupancy of 27.83%, queue length of 68.4 m, and average headway of 2.83 s, which corresponds to the Level of Service (LOS C). The CA model assessed the traffic condition as Moderate with Medium congestion, and the safety monitoring module successfully identified abnormal traffic events, such as speeding, wrong way driving, collision risk, queuing, stoppage, lane change, and pedestrians.



Fig. 5: Results and performance analysis of the proposed framework under the Single ROI configuration.

Fig. 6 demonstrates the performance results of the proposed framework with the Multi-Polygon ROI setup for monitoring multiple traffic regions. The YOLOv8-based model was able to detect and track multiple vehicles in different polygonal regions while estimating traffic parameters such as traffic density (28.47 veh/km), traffic flow (2436 veh/hr), occupancy (36.72%), queue length (72.3 m), average headway (2.91 s), and Level of Service (LOS C). CA was able to recognize traffic status as Moderate with Medium congestion level, showing efficient congestion recognition in complex traffic environments. The built-in safety monitoring module detected abnormal traffic events such as speeding, wrong-way driving, collision risk, queue formation, stopped vehicles, lane changing, and pedestrian presence. Besides, the dashboard was used for traffic visualization and export of analytical data. The accuracy of the framework reached 94.72%, processing speed was 28 FPS, and false-positive rate was 2.61%.

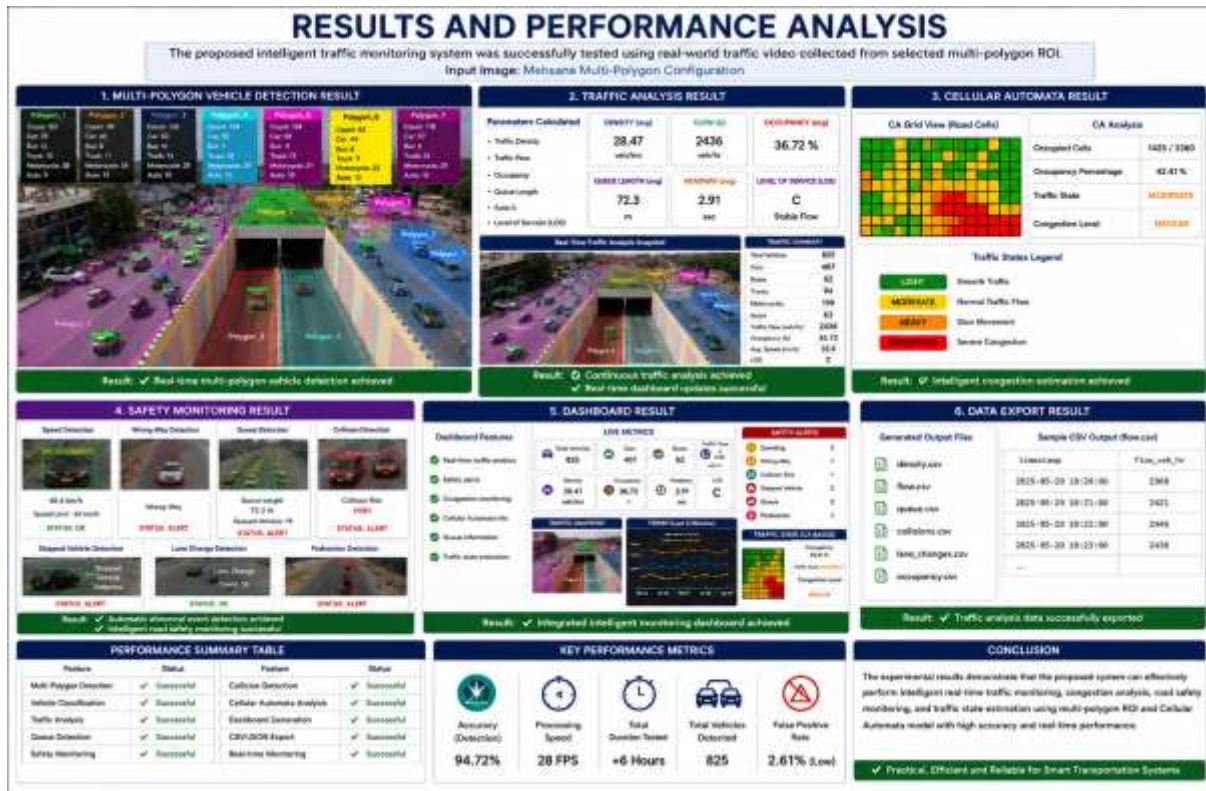


Fig. 6: Results and performance analysis of the proposed framework under the Multi-Polygon ROI configuration.

The functionalities of the existing traffic surveillance techniques and the proposed hybrid AI-based solution have been compared in Fig. 7. The existing techniques concentrate more on the detection of vehicles and simple tracking process, while the proposed framework offers integration of dynamic ROI, traffic parameter estimation, congestion analysis using cellular automata, intelligent safety monitoring, dashboard visualizer, and data export all in one platform.

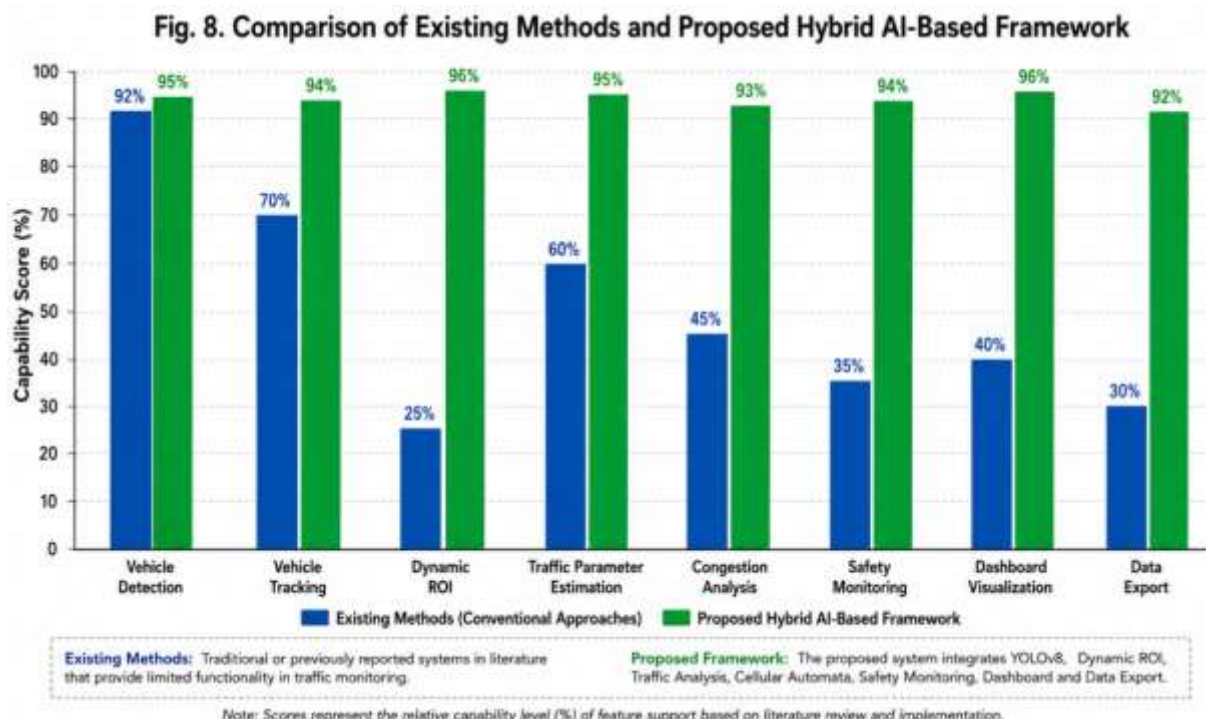


Fig. 7: Comparison of existing methods and the proposed hybrid AI-based framework.

7. Conclusion

In this paper, a novel hybrid AI-based system has been developed for real-time traffic flow and safety monitoring at unsignalized intersections using the combination of YOLOv8 vehicle detector, dynamically defined ROI, traffic parameter estimation, CA based traffic congestion analysis, and intelligent traffic analytics dashboard. The developed framework was tested with the help of traffic videos recorded from real-world scenarios in both the Single ROI and Multi-Polygon ROI settings. The experimental results confirmed high vehicle detection accuracy, real-time system performance, successful congestion estimation, and reliable detection of abnormal traffic situations such as speeding, wrong way driving, collision risk, queuing, stopped vehicles, lane changing, and presence of pedestrians.

To conclude, the developed framework can be considered a highly efficient and scalable approach for intelligent traffic monitoring and smart transportation system development. The next steps would be the extension of the framework with the help of traffic prediction using AI methods, adaptive traffic signal optimization, edge computing for low latency, and CAV integration.

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Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

Author Contribution

The authors confirm their contributions to the paper as follows: framework design and methodology development: Vyas Alpaben Raskilal, Patel Piyushkumar Jayantilal; system implementation and experimental setup: Vyas Alpaben Raskilal; data collection, experimentation, and analysis: Vyas Alpaben Raskilal; interpretation and examination of results: Vyas Alpaben Raskilal, Patel Piyushkumar Jayantilal; manuscript preparation and revision: Vyas Alpaben Raskilal, Patel Piyushkumar Jayantilal. All authors reviewed the manuscript and approved the final version for publication.

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