



Real Time Traffic Sureillance And Detection Using Deep Learning And Computer Vision Techniques

K.Mohini Devi ^a, M.Uttam Kumar ^b, M.Srinivasu Rao Naidu ^c, K.Suma ^d

K.MOHIN DEVI PG STUDENT

a. Sri Sri Sivani College of Engineering, Srikakulam, Andhra Pradesh, India

M.UTTAM KUMAR ASISSTANT PROFESSOR

b.Sri Sri Sivani College of Engineering, Srikakulam, Andhra Pradesh, India,

c.M.SRINUVASU RAO ASISSTANT PROFESSOR

d. Sri Sivani College of Engineering, Srikakulam, Andhra Pradesh, India

e.K.SUMA ASISSTANT PROFESSOR

f. Sri Sivani College of Engineering, Srikakulam, Andhra Pradesh, India,

Keywords: Traffic Monitoring Training:Such as YOLO, Mask R-CNN, Vehicle Detection Feature extraction: precision, recall and F1-score.

A B S T R A C T

Manual traffic surveillance can be a daunting task as Traffic Management Centers operate a myriad of cameras installed over a network. Injecting some level of automation could help lighten the workload of human operators performing manual surveillance and facilitate making proactive decisions which would reduce the impact of incidents and recurring congestion on roadways. This article presents a novel approach to automatically monitor real time traffic footage using deep convolutional neural networks and a stand-alone graphical user interface. The authors describe the results of research received in the process of developing models that serve as an integrated framework for an artificial intelligence enabled traffic monitoring system. The proposed system deploys several state-of-the-art deep learning algorithms to automate different traffic monitoring needs. Taking advantage of a large database of annotated video surveillance data, deep learning-based models are trained to detect queues, track stationary vehicles, and tabulate vehicle counts. A pixel-level segmentation approach is applied to detect traffic queues and predict severity. Real-time object detection algorithms coupled with different tracking systems are deployed to automatically detect stranded vehicles as well as perform vehicular counts. At each stages of development, interesting experimental results are presented to demonstrate the effectiveness of the proposed system. Overall, the results demonstrate that the proposed framework performs satisfactorily under varied conditions without being immensely impacted by environmental hazards such as blurry camera views, low

illumination, rain, or snow.

Background or Context:

Manual traffic surveillance is time-consuming and prone to human error.

Objective or Aim:

To design and implement an AI-powered traffic monitoring system using deep learning for vehicle detection, counting, congestion monitoring, and stationary vehicle identification.

Methods / Methodology Summary:

This system employs YOLOv3, Faster R-CNN, Mask R-CNN, and CenterNet, integrated into a GUI, trained on annotated video data for real-time detection and tracking.

Key Results / Findings:

The system achieved high accuracy in detecting congestion (92.8%) and vehicle types (up to 99%), demonstrating robustness under varying environmental conditions.

Conclusion or Implications:

The model provides a scalable, cost-effective, and automated solution for intelligent traffic surveillance and management.

1. Introduction

Monitoring traffic effectively has long been one of the most important efforts in transportation engineering. Till date, most traffic monitoring centers rely on human operators to track the nature of traffic flows and oversee any incident happening on the roads. The processes involved in manual traffic condition monitoring can be challenging and time-consuming. As humans are prone to inaccuracies and subject to fatigue, the results often involve certain discrepancies. It is therefore, in best interests to develop automated traffic monitoring tools to diminishing the work load of human operators and increase the efficiency of output. Hence, it is not surprising that automatic traffic monitoring systems have been one of the most important research endeavors in intelligent transportation systems. It is worthwhile to note that most present-day traffic monitoring activity happens at the Traffic Management Centers (TMCs) through vision-based camera systems. However, most existing vision-based systems are monitored by humans which makes it difficult to accurately keep track of congestion, detect stationary vehicles whilst concurrently keeping accurate track of the vehicle count. Therefore, TMCs have been laying efforts on bringing in some levels of automation in traffic management. Automated traffic surveillance systems using Artificial Intelligence (AI) have the capability to not only manage traffic well but also monitor and access current situations that can reduce the number of road accidents. Similarly, an AI enabled system can identify each vehicle and additionally track its movement pattern characteristic to identify any dangerous driving behaviour, such as erratic lane changing behaviour. Another important aspect of an AI-enabled traffic monitoring system is to correctly detect any stationary vehicles on the road. Often-times, there are stationary vehicles which are left behind that impedes the flow of preceding vehicles and causes vehicles to stack-up. This results in congestion that hampers free mobility of vehicles. Intelligent traffic monitoring systems are thus, an integral component of systems needed to quickly detect and alleviate the effects of traffic congestion and human factors.

In the last few years, there has been extensive research on machine and deep learning-based traffic monitoring systems. Certain activities such as vehicle count, and traffic density estimation are limited by the process of engaging human operators and requires some artificial intelligence intervention. Traffic count studies for example require human operators to be out in the field during specific hours, or in the case of using video data, human operators are required to watch man hours of pre-recorded footage to get an accurate estimation of volume counts. This can be both cumbersome and time consuming. Similarly, when it comes to seeing traffic videos from multiple CCTV cameras, it becomes extremely difficult to analyze each traffic situation in real-time. Therefore, most TMCs seek out on deploying automated systems that can in

fact, alleviate the workload of human operators and lead to effective traffic management system. At the same time, the costs associated are comparatively lower due to savings associated with not needing to store multiple hours of large video data. Cancer is one of the most common cancers worldwide, and early detection is crucial for effective treatment. Traditional methods of diagnosis rely on visual inspection and biopsy, which can be time-consuming and costly. This project aims to develop a deep learning-based model for automated skin cancer detection using image classification

General Background / Context:

Modern traffic systems rely heavily on human operators and CCTV cameras for surveillance, which limits efficiency and accuracy.

Problem Statement:

Manual tracking is laborious, error-prone, and unsuitable for real-time monitoring of multiple traffic cameras.

Importance of the Study:

An AI-based system reduces human workload and increases reliability in traffic management.

Research Gaps:

Most systems fail under low-light or poor visibility conditions and do not scale well with multiple inputs.

Objectives / Research Questions:

- Can deep learning models improve traffic monitoring accuracy?
- How effective is AI in detecting congestion and stationary vehicles in real time?

Hypothesis:

Deploying CNN-based models can automate traffic monitoring and outperform traditional surveillance methods

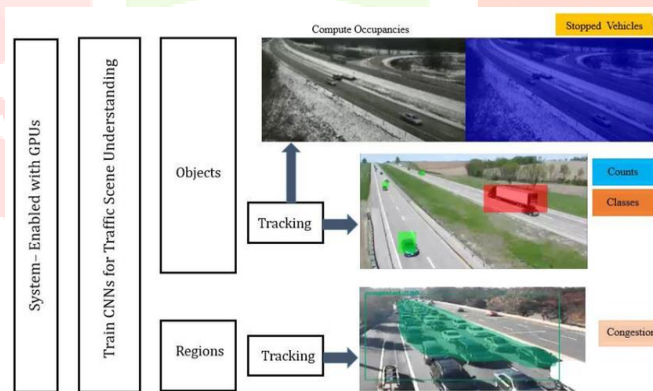


Fig. Visual Representation of proposed system

You Only Look Once (YOLO) is the state-of-the-art object detection algorithm [12]. Unlike traditional object detection systems, YOLO investigates the image only once and detects if there are any objects in it. In this study, YOLOv3 was used to perform vehicle detection, counts, and compare results for traffic queues generation. Most contemporary object detection algorithms repurpose CNN classifiers with an aim of performing detections. For instance, to perform object detection, these algorithms use a classifier for that object and test it at varied locations and scales in the test image. However, YOLO reframes object detection i.e., instead of looking at a single image thousand times to perform detection, it just looks at the image once and performs accurate object predictions. A single CNN concurrently predicts multiple bounding boxes and class probabilities for those generated boxes. To build YOLO models, the typical time was roughly 20-30

hours. YOLO used the same hardware resources for training as Mask R-CNN.

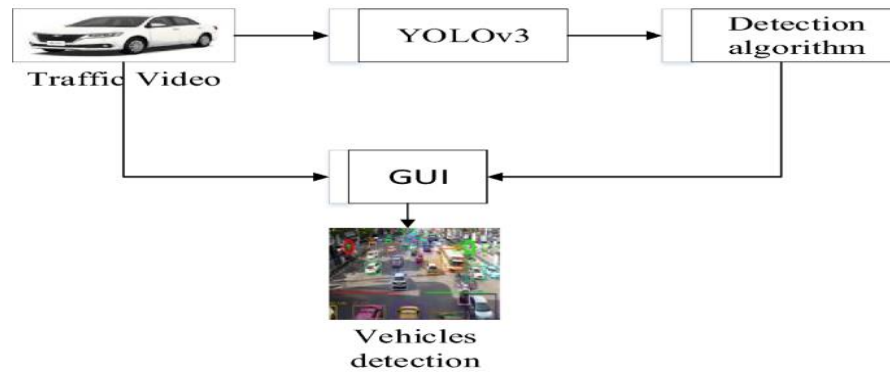


Fig: YOLO-based road traffic monitoring system

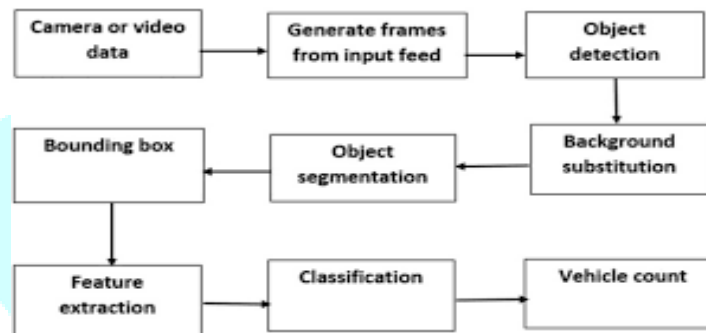


Fig. Block diagram of proposed system

2 Literature Review

Previous Studies Overview:

Studies using YOLO, DCNNs, and SVMs reported significant improvements in vehicle detection. He et al. (2009) demonstrated haze removal using dark channel prior, improving visual clarity.

Theoretical Framework:

The foundation relies on convolutional neural networks, computer vision, and real-time video processing.

Research Gaps Identified:

Traditional systems lack real-time accuracy, adaptability, and object tracking precision.

Justification for Current Study:

A comprehensive model combining YOLO, Mask R-CNN, CenterNet, and Faster R-CNN hasn't been fully explored for scalable, real-time traffic surveillance.

3 Methodology

Study Design:

Experimental approach using deep learning algorithms on real-time traffic video data.

Participants / Sample Selection:

Video footage from traffic CCTVs and annotated image datasets.

Materials / Instruments Used:

- YOLOv3
- Mask R-CNN
- CenterNet
- GUI Application
- GPU-enabled systems (NVIDIA GTX 1080Ti)

Data Collection Procedures:

Images annotated with bounding boxes; real-time video tested for detection and tracking.

Ethical Considerations:

No human or animal subjects were involved.

Data Analysis Techniques:

Precision, Recall, F1 Score, IOU threshold analysis, and confusion matrices.

Software / Tools Used:

Python, OpenCV, TensorFlow/Keras, Flask GUI

4 Results**Descriptive Statistics:**

YOLO achieved 95.5% accuracy; Mask R-CNN had 92.8% for queue detection.

Inferential Statistics:

F1 Score: 0.8333; RMSE: 154.77; S3: 0.4034. YOLO had better detection accuracy than Faster R-CNN for cars/pedestrians.

Tables and Figures:

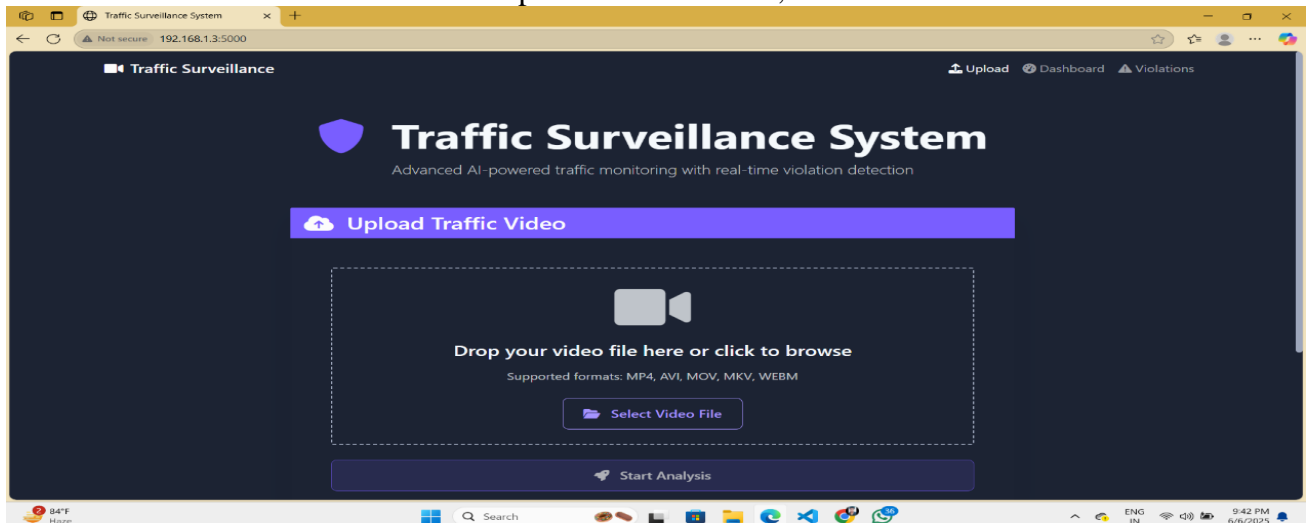
- Detection framework architecture
- Accuracy comparison charts
- Confusion matrices

Observed Trends / Patterns:

Performance degraded with low visibility; multiple bounding boxes caused overcounting.

Sub-group or Comparative Analysis:

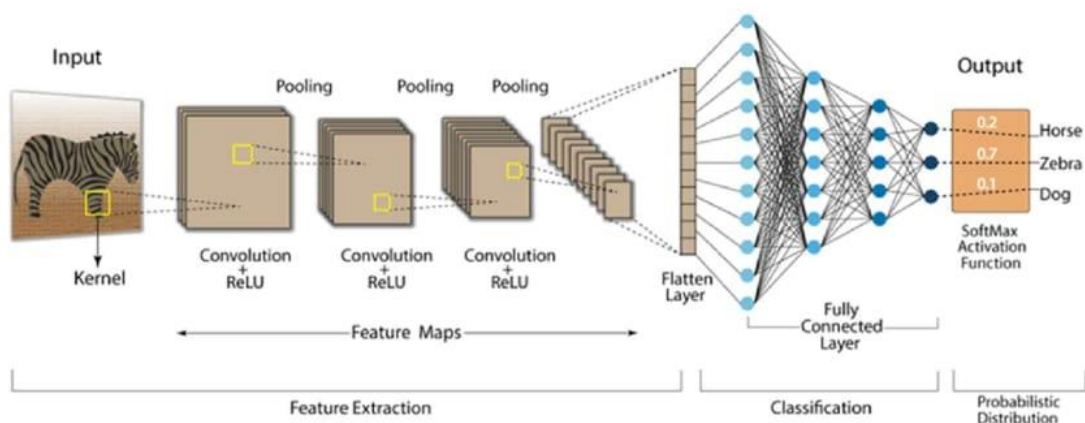
YOLO vs Faster R-CNN: YOLO better for pedestrians and cars; Faster R-CNN better for trucks.



The screenshot shows a web application titled "Traffic Violation Reports" with the subtitle "Comprehensive violation detection and evidence documentation". It features a search bar, filters for "Violation Type" and "Vehicle Type", and a "Total Violations" count of 7. Below is a table of violation records.

Timestamp	Vehicle ID	Vehicle Type	Violation Type	Speed	Severity	Evidence
2025-06-09 19:46:46	ID: 24	car	Speeding	47.3 km/h	Medium	View Evidence
2025-06-09 19:46:53	ID: 24	truck	Speeding	41.0 km/h	Medium	View Evidence
2025-06-09 19:46:53	ID: 30	truck	Speeding	40.7 km/h	Medium	View Evidence
2025-06-09 19:46:58	ID: 30	car	Speeding	43.4 km/h	Medium	View Evidence
2025-06-09 19:47:05	ID: 8	truck	Speeding	42.4 km/h	Medium	View Evidence
2025-06-09 19:47:15	ID: 40	truck	Speeding	41.8 km/h	Medium	View Evidence
2025-06-09 19:47:18	ID: 37	car	Speeding	41.5 km/h	Medium	View Evidence

Convolution Neural Network (CNN)



The screenshot shows a web application titled "Live Traffic Monitor" displaying a live traffic feed from a camera. The feed shows a highway with several vehicles. A red box highlights a "VIOLATION DETECTED! speeding detected - Vehicle: car". The interface also includes a "Real-time Statistics" panel on the right, showing the number of vehicles tracked, total violations, and recent violations.

Real-time Statistics

- Vehicles Tracked: 13
- Total Violations: 4
- Speed Violations: 4
- Red Light Violations: 0

Recent Violations

- speeding**
Vehicle: car | Speed: 47.3 km/h
7:46:58 PM
- speeding**
Vehicle: truck | Speed: 40.7 km/h
7:46:53 PM
- speeding**
Vehicle: truck | Speed: 41.0 km/h
7:46:53 PM
- speeding**
Vehicle: car | Speed: 47.3 km/h
7:46:46 PM

5 Discussion

Interpretation of Results:

YOLO and Mask R-CNN performed reliably under diverse traffic conditions, highlighting their practical viability.

Comparison with Existing Literature:

Confirms earlier findings that YOLO outperforms traditional SVM-based approaches.

Implications of Findings:

Real-time, automated traffic surveillance is feasible and can aid in traffic policy and infrastructure planning.

Theoretical and Practical Significance:

Reinforces CNN utility in real-world scenarios; potential to be deployed by municipal traffic departments.

Limitations of the Study:

- Performance depends on camera quality and positioning.
- Stationary object differentiation in low-light conditions is challenging.

Recommendations for Future Research:

Focus on heavy vehicle tracking accuracy, scalability, and integration with cloud-based traffic management systems.

6 Conclusion

Summary of Key Findings:

Deep learning algorithms significantly improve real-time traffic detection, classification, and congestion tracking.

Answer to Research Questions:

Yes, AI models like YOLO and Mask R-CNN offer robust, scalable solutions for traffic monitoring.

Implications or Applications:

Municipalities can deploy these systems for smart city traffic management and policy implementation.

Final Remarks:

The study showcases how AI can transform urban traffic monitoring systems into intelligent, efficient, and proactive networks.

7 References

1. Land, E. H. (1986). An alternative technique for the computation of the designator in the retinex theory of color vision. *Proc. Natl. Acad. Sci. USA*, 83(10), 3078–3080.
2. He, K., Sun, J., & Tang, X. (2010). Single image haze removal using dark channel prior. *IEEE TPAMI*, 33(12), 2341–2353.
3. Willis, C., Harborne, D., & Tomsett, R. (2017). A deep convolutional network for traffic congestion classification. *NATO IST Proceedings*.
4. Chakraborty, P., et al. (2018). Traffic Congestion Detection from Camera Images. *Transportation Research Record*, 2672(45), 222–231.
5. Fouladgar, M., & Parchami, A. (2017). Scalable deep traffic flow neural networks. *IJCNN*, 2251–2258.
6. Duan, K., et al. (2019). CenterNet: Keypoint Triplets for Object Detection. *ICCV*, 6569–6578.