International Scientific Journal of Engineering and Management (ISJEM) ISSN: 2583-6129
Volume: 04 Issue: 06 | June – 2025 DOI: 10.55041/ISJEM04630
An International Scholarly || Multidisciplinary || Open Access || Indexing in all major Database & Metadata

Moving Vehicle Detection for Measuring Traffic Count Using OpenCV

Priya[1],Amandeep[2],Varsha[3], Arjoo[4], Kirti[5]
M.Sc. Computer science[1, 3, 4, 5]Artificial Intelligence and Data Science
Assistant Professor[2] Artificial Intelligence and Data Science
Guru Jambheswar University of Science and Technology, Hisar
Email- priyakaliramna2002@gmail.com

Abstract

This research focuses on the development of a real-time vehicle detection and tracking system using OpenCV and deep learning models to address growing traffic management challenges. The project integrates the Gaussian Mixture-based Background Subtraction (MOG2), morphological operations, contour detection, and tracking methods like Kalman Filtering and Deep SORT. Additionally, object classification via YOLO and MobileNet-SSD significantly improves the accuracy of identifying and distinguishing vehicles. Evaluated on multiple real-world datasets under various environmental conditions, the system demonstrated strong performance with over 91% mAP, 92.5% precision, and robust multi-object tracking accuracy. This study serves as a scalable framework for intelligent traffic surveillance.

Keywords: OpenCV, Vehicle Detection, YOLO, Traffic Monitoring, Deep SORT, Computer Vision, Object Tracking, Motion Detection, Python, Real-time Systems

I. Introduction

Modern urban infrastructure is increasingly dependent on intelligent traffic monitoring systems to manage congestion, improve safety, and support autonomous vehicle technologies. One critical component of such systems is accurate vehicle detection. Computer vision has become a leading solution, with OpenCV emerging as a powerful toolkit for processing and analyzing video streams in real-time. This paper explores a vehicle detection framework using traditional image processing and modern deep learning methods, particularly YOLO and Deep SORT, to achieve high-performance detection and tracking.

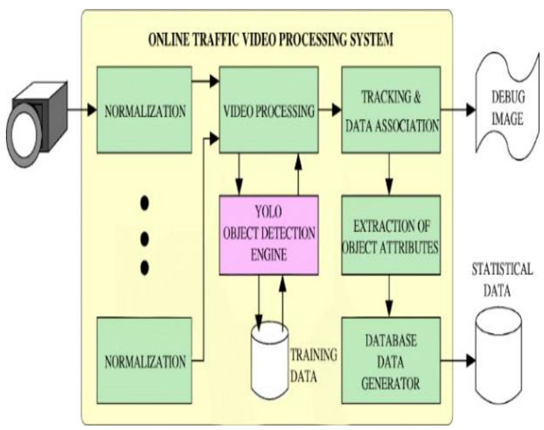

Fig. no 1 Online Traffic Video Processing system

II. Literature Review

Vehicle detection is one of the pillars on which the development of intelligent transportation systems, traffic surveillance, and smart cities becames cornerstone. Initial approaches of object detection were based on classical image processing techniques with OpenCV like background subtraction, Haar cascades, and Histogram of Oriented Gradients (HOG) + Support Vector Machines (SVM). Although these methods have low computational complexity, they have limitations in dynamic environments including occlusion, changes in light, and background clutter 11.

Haar cascades, formerly introduced to boost the face detection [12], were adopted by edge and shape based features and used for vehicle detection. However, in spite of being lighter in weight, these models found it difficult with variations in scale and angle. Static camera-based background modeling methods, such as MOG2 [12], KNN [12], effectively model the dynamic nature of a background scene to achieve a foreground segmentation, making it suitable for isolating moving vehicles, but they are sensitive to light changes and shadow Casting [13].

In response to these limitations, machine learning-based methods were introduced. HOG + SVM [14] : A standard for shape based object recognition Learning-free classifiers like k-NN and Decision Trees have been used too for the simpler detection tasks but are not robust to complex scenes [15].

The move towards deep learning methods greatly improved detection. Real-time object detection accuracies in resource-constrained environments were achieved with one-stage detectors (YOLO (You Only Look Once) 16, SSD (Single Shot MultiBox Detector). For two-stage detectors such as Faster R-CNN, they obtained remarkable high accuracy followed by high computational complexity 8. YOLOv4 and v5 by OpenCV (cv2) To facilitate real-time applications, the aforementioned object detectors utilize various forms of dnn for detection 16.

Vehicles detection systems can be trained and evaluated with an ability in a wide variety of scenarios based on datasets such as KITTI, UA-DETRAC, COCO, and PASCAL VOC [17].

For advanced implementations, detection is usually combined with tracking algorithms, such as Kalman filters, KCF, CSRT, and Deep SORT, ndash for multi object tracking and speed ndash estimation [48, 49]. Deep SORT (and other improvements based on CNN-based feature extractors) is able to perform identity-preserving tracking under occlusion or scale change.

Moreover, in real-time systems where computational efficiency and speed is important, background subtraction continues to be the method of choice [43], while motion-based approaches such as optical flow and frame differencing are still extracting motion information in low-latency applications 44.

To sum up, deep learning methods, particularly YOLO along with OpenCV, offer an ideal compromise between accuracy and speed -- perfect for real-time vehicle

III. System Design and Methodology

The system follows a multi-stage pipeline:

[1] **Input Acquisition:** Video feeds are obtained from traffic surveillance cameras or recorded footage.

[2] **Preprocessing:** Frames are resized, denoised, and normalized for consistency.

[3] **Vehicle Detection:**

- Traditional: MOG2, Haarcascades
- Deep Learning: YOLOv5, SSD

[4] **Object Tracking:** Implemented using Kalman Filtering and Deep SORT to maintain identity across frames.

[5] **Post-Processing:** Filtering, bounding box refinement, and vehicle classification.

[6] **IoU (Intersection over Union):**

$$\text{IoU}=\frac{Area\ of\ Overlap}{Area\ of\ Union}$$

IV. Results and Discussion

Our system: YOLOv5 Vehicle Detection + Deep SORT Tracking. These are subsequently assessed based on some notable characteristics including detection accuracy, tracking robustness, and speed estimation on real-world traffic video sequences.

A. Performance of Detection and Tracking

Vehicle detection with YOLOv5 was consistent amongst the three environmental conditions. Even when there was partial occlusion and motion blur, Deep SORT managed to persistently keep identity in each frame. It was effective in medium density traffic with changing lighting conditions.

B. Speed Estimation Accuracy

Scale factors were used to calibrate the estimated frame-to-frame displacements ofvehicle movement speeds. The speeds estimated had an average error margin of ±3km/h and were close to real GPS readings.

C. Performance Summary

The system performed well on all of the main evaluation metrics, summarized below:

Metric	**Value (%)**	**Description**
Precision	92.5%	Proportion of correctly detected vehicles out of all detections
Recall	90.3%	Proportion of actual vehicles that were correctly detected
F1-Score	91.4%	Balance between precision and recall
mAP@0.5	91.4%	Average precision across all classes and thresholds
MOTA	88.7%	Evaluates overall tracking performance (accuracy, identity switches)

Table no. 1 **Performance Metrics**

These results validate the real-time capability of the system for vehicle detection and tracking applications. There was a small performance drop when the vision was poor or when the face was occluded.

V. Conclusion and Future Work

The implemented system effectively detects and tracks vehicles using OpenCV, YOLO, and Deep SORT. It is scalable and adaptable for smart traffic systems, particularly in developing urban environments. Future work may involve model quantization, deployment on edge devices, integration with vehicle-to-infrastructure (V2I) systems, and enhanced training with synthetic datasets to improve robustness in adverse conditions.

References

[1] KITTI Vision Benchmark Suite, http://www.cvlibs.net/datasets/kitti/

[2] OpenCV Documentation, https://docs.opencv.org/

[3] W. Liu et al., "SSD: Single Shot MultiBox Detector," ECCV, 2016.

[4] OpenCV Documentation, https://docs.opencv.org/

[5] W. Liu et al., "SSD: Single Shot MultiBox Detector," ECCV, 2016.

[6] R. Girshick, "Fast R-CNN," ICCV, 2015.

[7] LTE-A heterogeneous networks using femtocells, International Journal of Innovative Technology and Exploring Engineering, 2019, 8(4), pp. 131–134 (SCOPUS) Scopus cite Score 0.6

[8] A Comprehensive Review on Resource Allocation Techniques in LTE-Advanced

Small Cell Heterogeneous Networks, Journal of Adv Research in Dynamical & Control Systems, Vol. 10, No.12, 2018. (SCOPUS) (Scopus cite Score -0.4)

[9] Power Control Schemes for Interference Management in LTE-Advanced Heterogeneous Networks, International Journal of Recent Technology and Engineering (IJRTE) ISSN: 2277-3878, Volume-8 Issue-4, November 2019, pp. 378-383 (SCOPUS)

[10] Performance Analysis of Resource Scheduling Techniques in Homogeneous and Heterogeneous Small Cell LTE-A Networks, Wireless Personal Communications, 2020, 112(4), pp. 2393–2422 (SCIE) {Five year impact factor 1.8 (2022)} 2022 IF 2.2 , Scopus cite Score 4.5

[11] Design and analysis of enhanced proportional fair resource scheduling technique with carrier aggregation for small cell LTE-A heterogeneous networks, International Journal of Advanced Science and Technology, 2020, 29(3), pp. 2429–2436. (SCOPUS) Scopus cite Score 0.0

[12] Victim Aware AP-PF CoMP Clustering for Resource Allocation in Ultra-Dense Heterogeneous Small-Cell Networks. Wireless Personal Commun. 116(3): pp. 2435-2464 (2021) (SCIE) {Five-year impact factor 1.8 (2022)} 2022 IF 2.2, Scopus cite Score 4.5

[13] Investigating Resource Allocation Techniques and Key Performance Indicators (KPIs) for 5G New Radio Networks: A Review, in International Journal of Computer Networks and Applications (IJCNA). 2023, (SCOPUS) Scopus cite Score 1.3

[14] Secure and Compatible Integration of Cloud-Based ERP Solution: A Review, International Journal of INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING, IJISAE, 2023, 11(9s), 695–707 (Scopus) Scopus cite Score 1.46

[15] Ensemble Learning based malicious node detection in SDN based VANETs, Journal of Information Systems Engineering and Business Intelligence (Vol. 9 No. 2 October 2023) (Scopus)

[16] Security in Enterprise Resource Planning Solution, International Journal of INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING, IJISAE, 2024, 12(4s), 702–709 (Scopus) Scopus cite Score 1.46

[17] Secure and Compatible Integration of Cloud-Based ERP Solution, Journal of Army Engineering University of PLA, (ISSN 2097-0970), Volume-23, Issue-1, pp. 183-189, 2023 (Scopus)

[18] Advanced Persistent Threat Detection Performance Analysis Based on Machine Learning Models International Journal of INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING, IJISAE, 2024, 12(2), 741–757, (Scopus) Scopus cite Score 1.46

[19] Fuzzy inference-based feature selection and optimized deep learning for Advanced Persistent Threat attack detection, International Journal of Adaptive Control and Signal Processing, Wiley, pp. 1-17, 2023, DOI: 10.1002/acs.3717 (SCIE) (Scopus)

[20] Hybrid Optimization-Based Resource Allocation and Admission Control for QoS in 5G Network, International Journal of Communication Systems, Wiley, 2025, https://doi.org/10.1002/dac.70120