International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 07 Issue: 08 | August - 2023 SJIF Rating: 8.176 ISSN: 2582-3930

Edge-Based Vehicle Tracking and Speed Estimation in Intelligent Transportation

Sumithra S[1], Dr. Ramya R S[2], Dr. Deepak G[3]

[1](PG Scholar, Computer Science Department, Dayananda Sagar College of Engineering, Bengaluru)
[2](Associate Professor, Computer Science Department, Dayananda Sagar College of Engineering, Bengaluru)
[3](Assistant Professor, Computer Science Department, Dayananda Sagar College of Engineering, Bengaluru)

---***---

Abstract - An intelligent transportation system plays an important role in traffic management we have an innovative approach for real-time vehicle tracking and speed estimation in an Intelligent Transportation System (ITS) using YOLOv5 and Deep SORT techniques. The proposed solution is designed to be implemented on an edge device, specifically the Jetson AGX Orin. The combination of YOLOv5, a state-of-the-art object detection algorithm, and Deep SORT, a powerful tracking algorithm, enables efficient and accurate vehicle tracking Subsequently, the Deep SORT algorithm is applied to track the identified vehicles over consecutive frames, allowing for consistent and reliable tracking results. By conducting all computations at the edge using the Jetson AGX Orin, real-time processing is achieved, minimizing latency and enhancing the system's responsiveness. The use of edge computing not only reduces dependence on cloud resources but also ensures data privacy and security, making it an ideal choice for ITS applications

Key Words: traffic management, object detection, vehicle tracking, frames, speed detection, latency

1. INTRODUCTION

In modern society, an efficient and intelligent transportation system is crucial to ensure seamless mobility, safety, and sustainability. However, numerous challenges in vehicle tracking and speed estimation persist, obstructing the realization of an optimized transportation network. These obstacles include occlusion, sensor noise, complex urban environments, real-time data processing, and data privacy concerns. Addressing these issues and achieving accurate and real-time vehicle tracking and speed estimation is essential for enhancing traffic management, enabling autonomous vehicles, and improving overall road safety.

To overcome the challenges in transportation systems, a comprehensive solution that leverages cutting-edge computer vision techniques and edge computing is essential. By combining state-of-the-art algorithms from the research community, we can build a robust vehicle tracking and speed estimation system capable of accurately handling large-scale transportation networks. Such a system will provide valuable insights into traffic patterns, optimize traffic flow, and ensure rapid response to traffic incidents.

Edge computing is a promising approach for achieving low-latency and real-time processing [1]-[3], which is critical for time-sensitive tasks like vehicle tracking and speed estimation. By performing computation closer to the data source, edge-based solutions reduce communication delays and enhance the responsiveness of the system. This allows for timely decision-making, crucial for ensuring the safety of autonomous vehicles and improving traffic management efficiency.

To achieve precise and reliable vehicle tracking, advanced computer vision techniques [8], [9] are employed. For object detection, we leverage the YOLOv5 algorithm, renowned for its real-time performance and ability to handle complex environments effectively. YOLOv5 efficiently identifies vehicles even under challenging conditions, such as adverse weather and occlusions. To enable robust multi-object tracking, we incorporate the Deep SORT algorithm [4], which excels at associating multiple object detections across frames, providing coherent vehicle trajectories.

Tracking the vehicle and speed detection offer numerous advantages, especially when applied in the context of intelligent transportation systems

1. Improved Traffic Management
2. Efficient Resource Allocation
3. Eco-Friendly Initiatives, Smart City Applications

International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 07 Issue: 08 | August - 2023 SJIF Rating: 8.176 ISSN: 2582-3930

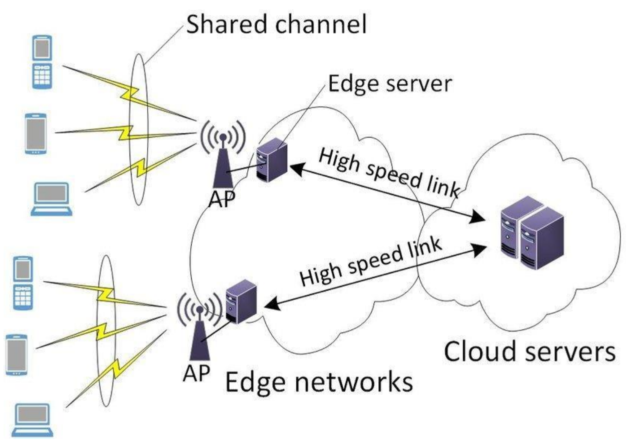


Fig -1: Cloud & Edge Computing Mode

The process of edge computing and cloud computing is shown in Fig 1. In cloud computing mode the data will be sent to a centralized system, such as a traffic management center (TMC) [5], Under the current design, the captured video data need to be sent back to a TMC from cameras. While cameras are located at the edge, the TMC can be viewed as a centralized cloud located somewhere deeper in the network. Therefore, forwarding the video data from cameras to the TMC can raise two major challenges:

(1) Processing and analyzing the video data in real-time is nearly impossible. The delay of forwarding the video data on the backhaul network may become serious when the network condition is bad (i.e. limited data rate).

(2) Continuous capturing and transferring of video data generates a huge and permanent pressure on the network paths to the TMC

Edge computing can be effectively utilized in the Jetson AGX Orin platform to bring computation and data processing closer to the data source, providing several benefits for various applications, Jetson AGX Orin, being a powerful edge device, can process data locally in real-time without the need for constant data transmission to a centralized cloud server

We propose a traffic flow detection scheme at the edge of intelligent transportation system that has the following novel ideas:

1) A vehicle detection network based on improved YOLOv5 object detection algorithm. The system detects the type of vehicle with improved speed so that it can be implemented for real time requirements.
2) A vehicle tracking network using the Deep Sort multiple object tracking algorithm, to track the vehicles based on the trained datasets which helps to improve the accuracy of tracking results
3) A vehicle speed detection technique is one of the most widely used metrics in traffic analysis systems which help to optimize the travel time and optimize the roots based on speeds of the traffic.

Fig -2: Traffic flow detection process

1.1 Motivation

By integrating state-of-the-art computer vision techniques such as YOLOv5 for real-time object detection and Deep SORT for multi-object tracking, the proposed project aims to create a robust and efficient system capable of continuously monitoring vehicles in dynamic traffic scenarios. The seamless integration of these algorithms within the versatile OpenCV framework ensures accessibility and scalability for real-world implementation.

The significance of this research lies in its potential to revolutionize traffic surveillance and management. A reliable and real-time vehicle speed and traffic tracking system can empower traffic authorities to make data-driven decisions, optimize traffic flow, enforce speed limits effectively, and enhance road safety measures. Additionally, such a system can contribute valuable insights to urban planning, transportation infrastructure improvements, and sustainable mobility solutions.

1.2 Contribution

We propose a traffic flow detection scheme at the edge of intelligent transportation system that has the following novel ideas:

1) A vehicle detection network based on improved YOLOv5 object detection algorithm. The system detects the type of vehicle with

improved speed so that it can be implemented for real time requirements.

2) A vehicle tracking network using the Deep Sort multiple object tracking algorithm, to track the vehicles based on the trained datasets which helps to improve the accuracy of tracking results
3) A vehicle speed detection technique is one of the most widely used metrics in traffic analysis systems which help to optimize the travel time and optimize the roots based on speeds of the traffic.

2. RELATED WORK

Several other methods that have been used to detect vehicles and track the vehicles along with their speed detection that are studied here.

Haar Cascades and HOG are classic computer vision techniques used for vehicle detection. Haar Cascades are based on Haar-like features, while HOG computes the gradients of image patches to identify object boundaries. A real-time vehicle detection and tracking system based on Haar Cascades for intelligent transportation applications [6]. These methods can be computationally efficient but may have limitations in handling complex scenarios and real-time tracking.

An improved speed estimation using deep homography transformation regression network [16] by Ervin Yohannes solves an important issue in vehicle speed estimation where a pretrained DeepSort and YOLOv4 models to detect and track vehicles, and apply homography transformation to transform monocular videos into bird's eye view videos, but there are other ideas to get more higher accuracy and reliable vehicle speed result.

Jiaxing Zhang implemented roadside lidar to track vehicles and speed estimation. Vehicle clusters were detected from the raw point clouds using a three-step schema in the first instance. Lidar sensors [14] can be employed for accurate speed monitoring, instruments with higher laser beams longer scanning ranges will improve vehicle detection and tracking, but with limitations relating to short working range and occlusions.

R-CNN and its variants, such as Fast R-CNN [7], Faster R-CNN, and Mask R-CNN, are widely used deep learning approaches for object detection and instance segmentation. These models can be adapted for vehicle detection, and the use of tracking algorithms can enable vehicle tracking over time.

Kalman Filters and Particle Filters are popular tracking algorithms used to estimate the state of an object over time, including vehicle position and speed. These filters can be combined with object detection methods to track vehicles and estimate their speeds.

Monocular camera-based methods [10] estimate vehicle speed by analyzing the change in size of the vehicle in the image as it approaches the camera. These methods require calibration of the camera and knowledge of the vehicle's dimensions.

A novel method for vehicle speed measurement using a stereo camera pair [17]. By estimating the standard deviation which should be less than 1 km/h that is required to meet the 3km/h tolerance with 99.9% probability but the total execution time of all steps exceeds 50ms which makes this implementation unsuitable for real time processing of 20 frames per second.

A vehicle detection algorithm based on YOLOv3 (you only look once) model [11] by Chen Chen trained with great volume of traffic data, which also detects and tracks the vehicle using Deep Sort algorithm by retraining the feature extractor for multiple object vehicle tracking algorithms to realize the detection of traffic flow. Which was also implemented on the edge device Jetson TX2 platform which can efficiently detect the traffic flow with an average processing speed of 37.9 FPS (frames per second), but there are updated versions of YOLO and edge device Jetson.

A hierarchical GLOSA system [15] is designed by Zhaolong Zhang, Yuan Zou to assist eco-driving. By estimating the queue length and calculating the effective green light duration and estimating the optimal speed curve, but the real-vehicle field test is also insufficient due to limited experimental resources.

In this paper we suggest a better edge device Jetson AGX Orin which is a new model/platform in Edge Computing and AI which is six times the processing power of Jetson AGX Xavier [12], [13], in the same form factor it is by far the most powerful GPU powered device Designed for AI at the Edge and in embedded devices.

International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 07 Issue: 08 | August - 2023 SJIF Rating: 8.176 ISSN: 2582-3930

3. PROBLEM DEFINITION

The project aims to develop an efficient and accurate system that utilizes edge computing to track vehicles and estimate their speeds in real-time within an intelligent transportation environment.

1) Vehicle Detection using YOLOv5:

Let D represent the set of detected vehicles in a given frame.

YOLOv5 algorithm provides bounding box coordinates and confidence scores for each detected vehicle $d \in D$.

Mathematical equation for YOLOv5 object detection: $d = (x, y, w, h, c)$, where (x, y) is the center, w is the width, h is the height, and c is the confidence score.

2) Vehicle Tracking using Deep SORT:

Let T represent the set of tracked vehicles across consecutive frames.

Deep SORT algorithm associates detected vehicles with existing tracks based on a matching criterion.

Mathematical equation for Deep SORT tracking:

Associate $(d, t) \rightarrow t$, where Associate is the matching function that associates detected vehicle d with an existing track t.

3) Speed Estimation using Optical Flow:

Let V represent the set of estimated vehicle speeds.

Optical flow analysis calculates the motion vectors of tracked vehicles between frames.

Mathematical equation for speed estimation using optical flow:

$V = \Delta D / \Delta t$,

where ΔD represents the displacement of a vehicle over time Δt.

4. DATASET

Kaggle, a popular platform for data science and machine learning enthusiasts, hosts several datasets that provide car images. One notable Kaggle dataset that researchers can use for pre-training or fine-tuning machine learning models related to cars is the "Cars Dataset" on Kaggle contains a diverse collection of car images, covering a wide range of car makes and models. It includes thousands of images, each annotated with relevant metadata such as make, model, and year. This dataset is valuable for training computer vision models for car recognition, classification, and other automotive-related tasks.

Fig -3: Car dataset with different angles

5. Why Use the Edge Device Jetson AGX Orin

Edge AI- Jetson AGX Orin. With six times the processing power of Jetson AGX Xavier, in the same form-factor, it is by far the most powerful GPU-powered device designed for AI at the edge and in embedded devices. NVIDIA designed Orin to be an “energy-efficient AI supercomputer” meant for use in robotics, autonomous and medical devices, as well as edge AI applications that may seem impossible at the moment

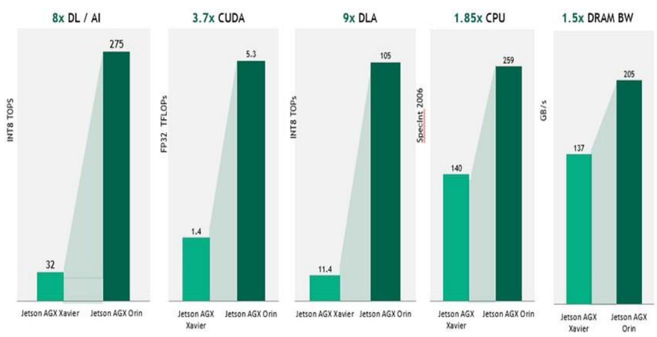


Fig -3: Jetson AGX Orin delivers 8X the AI performance of Jetson AGX Xavier

Equipped with an Ampere-class Nvidia GPU, a Cortex-A78AE CPU, and up to 32 GB of RAM, Jetson AGX Orin is capable of delivering 275 trillion operations per second (TOPS) on INT8 workloads, which is more than an 8x boost compared to the previous top-end device, the Jetson AGX Xavier [12], [13].

6. PROPOSED SOLUTION

In this section, the proposed system is explained in details with three subsections, which are:

International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 07 Issue: 08 | August - 2023 SJIF Rating: 8.176 ISSN: 2582-3930

1. Vehicle Detection
2. Vehicle Tracking
3. Vehicle Speed Detection

Figure 1 shows the workflow/pipeline of the proposed system.

6.1. Vehicle Detection Results

During inference, YOLOv5 predicts bounding boxes around detected vehicles and assigns a confidence score to each detection, representing the model's confidence in its predictions. The model can detect multiple vehicles in a single pass, making it highly efficient for real-time applications.

YOLOv5 can be fine-tuned on custom datasets for specific vehicle detection tasks, such as detecting different vehicle types, detecting vehicles in varying lighting conditions, or detecting vehicles from specific camera angles.

Overall, YOLOv5's speed and accuracy make it a popular choice for vehicle detection in various computer vision applications, including traffic surveillance, autonomous vehicles, and intelligent transportation systems

Fig -4: Type of vehicle detected with confidence interval

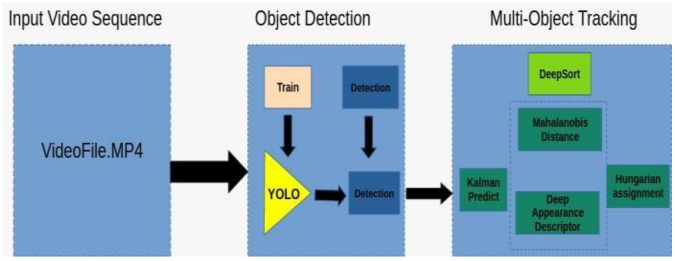
6.2. Vehicle Tracking Results

Vehicle tracking using YOLOv5 and Deep SORT combines the strengths of both algorithms to achieve accurate and real-time tracking of vehicles in video streams. YOLOv5 (You Only Look Once version 5) is used for initial object detection, while Deep SORT (Simple Online and Realtime Tracking) is employed for multi-object tracking over time.

In the first stage, YOLOv5 processes each frame of the video to detect and localize vehicles with high accuracy and efficiency. YOLOv5 predicts bounding boxes around the detected vehicles and assigns confidence scores to each detection.

In the second stage, the detected vehicle bounding boxes are fed into the Deep SORT algorithm. Deep SORT uses the Kalman filter for prediction and data association based on the Hungarian algorithm to establish correspondences between detections in consecutive frames. This data association process allows Deep SORT to maintain track identities, handle occlusions, and track vehicles continuously even in complex traffic scenarios.

By combining YOLOv5's real-time object detection capabilities with Deep SORT's robust multi-object tracking abilities, the integrated system can accurately track multiple vehicles in real-time video streams. This approach is valuable in traffic surveillance, autonomous driving, and various applications that require precise and continuous vehicle tracking.



(a)

(b)

Fig -5: a) Deep sort multiple objects tracking flow chart. b) Deep sort multiple objects tracking visuals.

6.3. Vehicle Speed Detection Results

An efficient method to detect the speed of a vehicle using solely software technologies involves leveraging computer vision techniques. The process begins by setting up a high-resolution camera pointed towards the road, where the vehicles pass by. Images or frames from the camera feed are continuously captured. To identify and locate the vehicles in each frame, a vehicle detection algorithm is implemented, potentially utilizing deep learning-based object detection models like YOLO or SSD. To calculate the speed, the identified vehicles are tracked across multiple frames using algorithms like

Kalman filters or Hungarian methods. By measuring the distance between the vehicle's position in the current and previous frames and recording the time interval between frames, the vehicle's speed can be calculated (Speed = Distance / Time). Some additional steps might involve camera calibration for real-world measurements, filtering or smoothing techniques for accurate speed estimates, and appropriate visualization or data storage. The implementation faces challenges such as varying lighting conditions and occlusions, and optimization is necessary for real-time processing. The pipeline can be enhanced with advanced techniques based on specific project requirements and constraints.

7. CONCLUSIONS

The experimental results demonstrate that the proposed algorithm is feasible and promising for traffic monitoring systems which has to be implemented on the edge for better analysis, reducing the need for cloud-based processing and ensuring low latency. The edge-based approach allows the system to handle video streams from multiple cameras in real-time, making it suitable for deployment in intelligent transportation systems. The Jetson AGX Orin edge device plays a crucial role in this application by providing high-performance computing capabilities in a compact and energy-efficient form factor. Its integration into the system enables rapid inference of computer vision models, allowing real-time decision-making at the edge without the need for constant data transmission to a centralized server. Its potential for traffic management, congestion alleviation, and the ability to enhance safety on roadways make it a valuable asset for future smart city deployments and traffic infrastructure improvements.

REFERENCES

[1] Liu D, Liang H, Zeng X, Zhang Q, Zhang Z and Li M (2022) Edge Computing Application, Architecture, and Challenges in Ubiquitous Power Internet of Things. Front. Energy Res. 10:850252. doi:10.3389/fenrg.2022.850252

[2] S. Nastic et al., "A Serverless Real-Time Data Analytics Platform for Edge Computing," in IEEE Internet Computing, vol. 21, no. 4, pp. 64-71, 2017, doi: 10.1109/MIC.2017.2911430.

[3] W. Yu et al., "A Survey on the Edge Computing for the Internet of Things," in IEEE Access, vol. 6, pp. 6900-6919, 2018, doi: 10.1109/ACCESS.2017.2778504.

[4] J. Yang, Y. Li, Q. Zhang and Y. Ren, "Surface Vehicle Detection and Tracking with Deep Learning and Appearance Feature," 2019 5th International Conference on Control, Automation and Robotics (ICCAR), Beijing, China, 2019, pp. 276-280, doi: 10.1109/ICCAR.2019.8813345.

[5] G. Liu et al., "Smart Traffic Monitoring System Using Computer Vision and Edge Computing," in IEEE Transactions on Intelligent Transportation Systems, vol. 23, no. 8, pp. 12027-12038, Aug. 2022, doi: 10.1109/TITS.2021.3109481.

[6] S. Choudhury, S. P. Chattopadhyay and T. K. Hazra, "Vehicle detection and counting using haar feature-based classifier," 2017 8th Annual Industrial Automation and Electromechanical Engineering Conference (IEMECON), Bangkok, Thailand, 2017, pp. 106-109, doi: 10.1109/IEMECON.2017.8079571.

[7] Z. Cai and N. Vasconcelos, "Cascade R-CNN: Delving into High Quality Object Detection," in 2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), Salt Lake City, UT, USA, 2018 pp. 6154-6162, doi: 10.1109/CVPR.2018.00644

[8] "Deep Learning-based Vehicle Detection and Tracking for Autonomous Driving" Bojarski, M.; Yeres, P.; Choromanska, A.; Choromanski, K.; Firner, B.; Jackel, L. D. 2016 IEEE 19th International Conference on Intelligent Transportation Systems (ITSC)

[9] Z. Luo, M. Attari, S. Habibi and M. V. Mohrenschildt, "Online Multiple Maneuvering Vehicle Tracking System Based on Multi-Model Smooth Variable Structure Filter," in IEEE Transactions on Intelligent Transportation Systems, vol. 21, no. 2, pp. 603-616, Feb. 2020, doi: 10.1109/TITS.2019.2899051.

[10] Gharib, M., Ranjbar, A., & Karray, F. (2019). Vision-based vehicle speed estimation: A comprehensive review and evaluation. In Proceedings of the IEEE International Conference on Robotics and Automation (ICRA) (pp. 3655-3661).

[11] C. Chen, B. Liu, S. Wan, P. Qiao and Q. Pei, "An Edge Traffic Flow Detection Scheme Based on Deep Learning in an Intelligent Transportation System," in IEEE Transactions on Intelligent Transportation Systems, vol. 22, no. 3, pp. 1840-1852, March 2021, doi: 10.1109/TITS.2020.3025687.

[12] Wang, C., Wang, S., Xu, S., & Chen, Y. "Real-time pedestrian detection on Jetson AGX Xavier." In Proceedings of the International Conference on Control and Robots (ICCR). vol.4 pp. 1-6. 2020

[13] Zhang, X., Li, Y., Shen, C., & Liu, H. "Deep learning for traffic sign recognition using Jetson AGX Xavier." In Proceedings of the IEEE Intelligent Vehicles Symposium (IV) vol. 8, pp. 797-802. 2019

[14] J. Zhang, W. Xiao, B. Coifman and J. P. Mills, "Vehicle Tracking and Speed Estimation From Roadside Lidar," in IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 13, pp. 5597-5608, 2020

[15] Z. Zhang, Y. Zou, X. Zhang and T. Zhang, "Green Light Optimal Speed Advisory System Designed for Electric Vehicles Considering Queuing Effect and Driver's Speed Tracking Error," in IEEE Access, vol. 8, pp. 208796-208808, 2020, doi: 10.1109/ACCESS.2020.3037105.

[16] E. Yohannes, C. -Y. Lin, T. K. Shih, T. Thaipisutikul, A. Enkhbat and F. Utaminingrum, "An Improved Speed Estimation Using Deep Homography Transformation Regression Network on Monocular Videos," in IEEE Access, vol. 11, pp. 5955-5965, 2023, doi: 10.1109/ACCESS.2023.3236512.

[17] P. Najman and P. Zemčík, "Vehicle Speed Measurement Using Stereo Camera Pair," in IEEE Transactions on Intelligent Transportation Systems, vol. 23, no. 3, pp. 2202-2210, March 2022, doi: 10.1109/TITS.2020.3035262.