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Real-Time Traffic Surveillance and Vehicle Speed Detection Using Machine Vision

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ABSTRACT

Traffic monitoring and the assessment of vehicle speeds are essential for effectively managing congestion, improving urban mobility, and enhancing road safety. Conventional traffic surveillance methods typically depend on intrusive sensors, such as inductive loops and radar systems, which are expensive, require significant installation efforts, and pose maintenance challenges, rendering large-scale implementation impractical. In this study, we introduce a non-invasive, real-time traffic monitoring system that utilizes computer vision techniques to efficiently detect, track, and estimate vehicle speeds. This system incorporates deep learning-based object detection and centroid tracking to accurately identify and monitor vehicles across multiple frames. A mapping function is employed to translate pixel-based measurements into real-world distances, ensuring precise speed calculations. Furthermore, the adaptive tracking algorithm improves the system's robustness against environmental changes, occlusions, and varying traffic conditions. Traffic density is assessed based on real-time variations in speed and the number of vehicles detected, offering comprehensive insights into traffic conditions. The proposed system was tested using actual traffic footage, revealing high accuracy in vehicle detection, tracking, and speed estimation. This framework is scalable, cost-effective, and applicable to a range of uses, including automated traffic control, law enforcement, and smart city projects. By removing the necessity for physical sensors and leveraging deep learning-based vision techniques, our approach represents a significant advancement in intelligent transportation systems, providing an efficient and sustainable solution for contemporary urban traffic management.

Keywords: Traffic monitoring, vehicle speed assessment, computer vision, deep learning, intelligent transportation systems.

INTRODUCTION

As urban areas become increasingly congested, traffic accidents become more frequent and traffic management becomes less effective. As the number of vehicles continues to increase, traditional traffic monitoring methods such as manual monitoring, inductive loop sensors, and radar-based systems are becoming increasingly difficult to scale, operate, and maintain cost-effectively. Computer vision and machine learning are being used to make intelligent transportation systems (ITS) more efficient, automated, and cost-effective. Traffic monitoring plays a critical role in ensuring road safety, optimizing traffic flow, and enabling city planners to make data-driven decisions. Vehicle detection and speed estimation systems provide a non-invasive way to monitor traffic patterns and enforce speed limits. Recent advances in deep learning and object tracking technologies have enabled these systems to accurately identify vehicles and analyze their movements in complex driving situations. We propose a computer vision-based road traffic monitoring system that uses real-time object detection and centroid-based tracking to detect and monitor vehicles in urban road networks. Video streams from roadside cameras are processed and object tracking algorithms are applied. Vehicle speeds are estimated using pixel shifts calibrated to real measurements. This study addresses the following main tasks:

1. Automatic detection and tracking of vehicles for continuous monitoring of traffic flow.

2. Real-time velocity estimation using adaptive center tracking approach.

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3. Traffic flow classification based on vehicle speed and density to identify congestion levels.

Unlike traditional sensor-based methods, the proposed approach offers a scalable, cost-effective, and easily deployable solution that can be integrated into existing smart city infrastructure. By analyzing vehicle movements and speed variations, this system can give valuable insights for law enforcement organizations, traffic control centers, and urban planners, ultimately making roads safer and more effective.

LITERATURE REVIEW

Traffic prediction and analysis have garnered significant attention within the transportation engineering field, driven by the escalating issues of traffic congestion and the associated socio-economic implications. The literature indicates a robust exploration Using several machine learning methods using traffic data, aimed at enhancing predictive accuracy and efficiency in traffic management systems.

Berlotti, Mariaelena,Di Grande, Sarah, Cavalieri, Salvatore presents a comprehensive method using machine learning for predictive analysis of traffic flow, addressing the critical issue of urban traffic congestion. By utilizing a wide array of data sources—including traffic sensors, GPS devices, and cameras—and employing advanced techniques such as supervised and unsupervised learning, feature engineering, and deep learning architectures (RNNs and CNNs), the study successfully enhances traffic prediction accuracy.[1]

Fatah, Abu Faisal, Mohammed Zaber, discusses different machine learning methods utilized for forecasting traffic flow. It highlights the application of supervised and unsupervised learning techniques, deep learning architectures like RNNs and CNNs, and feature engineering for improved accuracy. Additionally, it reviews past studies on intelligent transportation systems and predictive modeling, emphasizing the advancements in traffic forecasting through data-driven approaches.[2]

Sahu, Preeti Rekha proposes an AT-Conv-LSTM model incorporating environmental and social media data and validates the improved FCM clustering method, which outperforms traditional models in classifying urban traffic states.[3]

Feroz Khan, A. B.Ivan, Perl propose utilizing ML and DL models for traffic flow prediction, route optimization, adaptive traffic signal control, and anomaly detection. Their approach integrates IoT and sensor networks to enhance urban mobility, with case studies demonstrating improved traffic management and public transportation efficiency.[4]

Patil, Priyadarshan propose investigating the application of supervised, unsupervised, and reinforcement learning techniques to enhance traffic flow assignment in large-scale urban networks. Their study aims to assess the strengths and limitations of each approach in predicting travel demand, clustering road segments, and optimizing real-time traffic flow.[5]

Ł. Pałys, M. Ganzha, and M. Paprzycki have developed a model to predict bus delays by leveraging precise, regularly collected geolocation data from public transport systems. By analyzing this data, the model aims to understand bus behavior and provide accurate delay predictions, enhancing transportation planning and passenger information systems.[6]

Pucher, John and Korattyswaropam analyze the severe transportation challenges in Indian cities, such as congestion, pollution, and traffic fatalities, exacerbated by rapid urbanization, inadequate infrastructure, and rising vehicle ownership. They recommend nine policy improvements to mitigate these issues, including enhancing public transportation, implementing traffic demand management strategies, and promoting non-motorized transport[7]

Sroczyński, Andrzej and Czyżewski, Andrzej conducted a project to create and evaluate machine learning models — specifically, Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU) networks, and Stacked Auto encoder networks—for real-time traffic flow prediction. They compared the effectiveness of these models against traditional microscopic traffic simulation methods, demonstrating that neural network-based algorithms can operate in real-time and are appropriate for uses like establishing speed displays on variable message road signs.[8]

Marciniuk, Karolina and Kostek, Bozena developed an acoustic-based road traffic monitoring system using machine learning algorithms to classify vehicle types and assess road conditions. They collected audio recordings

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under various conditions, extracted 67 parameters from each, and found that Fisher Linear Discriminant Analysis and Regression Analysis achieved high accuracy in vehicle classification and pavement condition assessment. This demonstrates the potential of acoustic monitoring combined with machine learning for effective traffic analysis.[9]

Zhang, Huaizhong Liptrott, Mark Bessis, Nik Cheng, Jianquan developed a real-time traffic analysis system using unmanned aerial vehicle (UAV) videos and deep learning techniques. They collected road traffic videos with a fixed-position UAV and applied advanced advanced learning techniques for detecting dynamic objects. By calculating relevant mobility metrics, they analyzed traffic flow and assessed congestion impacts. The proposed approach was validated through manual analysis and visualization results, demonstrating its effectiveness in real-time traffic monitoring.[10]

Aid, A. Khan, M. A. Abbas, S.Ahmad proposed the MSR2C-ABPNN model using Artificial Neural Networks (ANN) with backpropagation to predict and control traffic congestion. Their system enhances transparency and efficiency in traffic management, improving traveler decision-making while achieving better MSE performance compared to traditional approaches.[11]

Table1. Summaries the comparison of related works focus on approaches, models, and strengths/weaknesses of different traffic monitoring and speed estimation systems

Study	Methodology	Model Used	Key Features	Limitations
Real-time Vehicle Detection and Speed Estimation System[12]	Background subtraction, image processing	Traditional image processing techniques	Simple, cost-effective, low computational cost	Limited accuracy in varying light conditions
Vehicle Speed Detection System Utilizing YOLOv8[13]	Object detection & tracking	YOLOv8	High accuracy and real-time processing	Requires GPU for optimal performance
Moving Vehicle Detection with Real-Time Speed Estimation[14]	Frame-to-frame movement tracking	Optical flow-based estimation	Effective for speed estimation	Sensitive to occlusions and overlapping objects
Efficient Vehicle Detection System Using YOLOv8 on Jetson Nano Board[15]	Object detection & tracking	YOLOv8	Optimized for low-power Jetson Nano, real-time processing	Limited computational power compared to high-end GPUs
MultEYE: Monitoring System for Real-Time Vehicle Detection, Tracking, and Speed Estimation from UAV Imagery on Edge-Computing Platforms[16]	UAV-based traffic monitoring, real-time vehicle detection & speed estimation	Deep learning-based object detection (YOLO-based model)	Works on edge-computing platforms, uses aerial imagery, real-time performance	Accuracy depends on UAV altitude & environmental conditions
Design and	Object	YOLOv8	High-accuracy	Requires GPU

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Implementation of Road Vehicle Counting Model Based on YOLOv8[17]	detection & vehicle counting		vehicle detection and counting, real-time performance, scalable for different traffic conditions	for optimal performance, struggles with overlapping vehicles in dense traffic
YOLOv8 for Vehicle Detection and Speed Estimation[18]	Object detection & speed estimation using frame-to-frame tracking	YOLOv8	High-speed detection and tracking, real-time performance, accurate speed estimation	Accuracy depends on camera calibration and viewing angle
Detection of 3D Bounding Boxes of Vehicles Using Perspective Transformation for Accurate Speed Measurement[19]	3D bounding box estimation, perspective transformation	Deep learning + geometric transformation	Improves speed estimation accuracy by considering vehicle dimensions and perspective effects	Requires precise camera calibration and depth estimation
Vehicle Speed Detection System Utilizing YOLOv8: Enhancing Road Safety and Traffic Management for Metropolitan Areas[13]	Object detection, vehicle tracking, and speed estimation	YOLOv8	High-speed vehicle detection, real-time performance, and accurate speed estimation using deep learning	Accuracy depends on camera calibration, may struggle in extreme weather conditions

In Table 1, a comparative evaluation of recent research on vehicle detection, tracking, and speed estimation is provided. The table showcases the variety of methods used, such as background subtraction, optical flow, deep learning-based object detection, and the estimation of 3D bounding boxes. A majority of the research employs YOLOv8 for real-time, accurate vehicle detection and tracking, illustrating its effectiveness in multiple applications like urban traffic management, UAV monitoring, and low-power edge computing scenarios. Although YOLOv8-based models deliver exceptional accuracy and real-time capabilities, issues such as occlusions, environmental factors, camera calibration, and computational limitations continue to be significant challenges. Research that incorporates 3D bounding boxes and geometric transformations enhances the precision of speed estimation, but it necessitates accurate camera calibration. Additionally, approaches using UAVs facilitate extensive area surveillance but are influenced by altitude and weather conditions. This comparative review highlights the balance between accuracy, computational efficiency, and practical deployment in real-time traffic monitoring systems.

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METHEDOLOGY

The proposed traffic monitoring system is designed to provide real-time vehicle detection, tracking, and speed estimation using a computer vision-based approach. It leverages video feeds from roadside cameras to analyze traffic conditions, offering a scalable and cost-effective alternative to traditional sensor-based monitoring methods. The system processes continuous video streams, applies deep learning-based object detection, and tracks vehicle movement across multiple frames using a centroid-based tracking algorithm.

System Architecture

The suggested system includes these essential elements:

Video acquisition module

The system processes real-time or recorded video feeds captured from CCTV cameras, traffic surveillance cameras, or drones. These video feeds serve as the primary input for vehicle detection and tracking. The resolution and frame rate of the video significantly impact the accuracy of detection and speed estimation.

Vehicle detection and classification

Using YOLOv8 model[20], the system detects vehicles in each frame and classifies them into different categories such as cars, buses, trucks, and motorcycles. Object detection helps in isolating moving vehicles from the background, enabling further analysis.

Each detected vehicle v∈V is identified with a bounding box B(v), defined as:

$$B(v)=(x1,y1,x2,y2)$$

where:

- (x1, y1) and (x2, y2) represent the coordinates of the upper-left and lower-right corners of the bounding box.
- The centroid of the bounding box is given by:

$$C(v) = \frac{\mathrm{x1} + \mathrm{x2}}{2}, \frac{y1 + y2}{2}$$

To track vehicle movement across frames, the Euclidean distance between centroids in consecutive frames is calculated as:

$$\mathrm{D}(\mathrm{C1}, \mathrm{C2}) = \sqrt{(\mathrm{x2} - \mathrm{x1})2 + (\mathrm{y2} - \mathrm{y1})2}$$

Where D (C1,C2) determines if the vehicle maintains a continuous trajectory.

Vehicle count model:-

The total number of vehicles in each area is calculated by taking counter after detecting object using Yolo8 model. It is represented by:

CA=|A|

where |A| is the number of vehicles detected in the monitored area.

Vehicle tracking module

The movements of the targeted vehicle are tracked over several frames by assigning it a unique ID using a centroid based object tracking algorithm. With the structured methodology, the movements of the cars are monitored persistently by computing the centroid and iteratively updating the trajectory throughout the surveillance zone.

Speed estimation module

To determine the vehicle's estimated speed, the system performs the following steps:

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1. Aligning pixels with actual distances: The system calibrates the camera to translate pixel displacements into real-world distances.

2. Computing velocity over time: The system calculates speed using a specific formula, which estimates the velocity based on the duration it takes for a vehicle to travel from Area 1 (A1) to Area 2 (A2).

$$s(v) = \left(\frac{d}{tx(v) - te(v)}\right) \times 3.6$$

where:

- d is the real-world distance between A1 and A2 (in meters).
- tx(v)−te(v) is the time taken to travel this distance (in seconds).
- The factor 3.6 converts Convert speed from meters per second (m/s) to kilometers per hour (km/h).

Traffic flow classification

The average speed of vehicles in the monitored area is determined by considering the calculated speed and the density of vehicles present.

$$SA = \frac{\sum v \in As(v)}{|A|}$$

where |A| is the number of vehicles in the area.

The following traffic flow classifications are based on SA:

$$T_A = \begin{cases} \text{"High Traffic"} & S_A < 0.5S_L \\ \text{"Medium Traffic"} & 0.5S_L \leq S_A < 0.8S_L \\ \text{"Normal Flow"} & S_A \geq 0.8S_L \end{cases}$$

where is:

- High level of traffic: The SA is less than 50% of the speed limit SL.
- Medium Traffic: SA accounts for 50-80% of SL traffic**.**
- Normal Flow: SA exceeds SL by more than 80%**.**

RESULTS

We are assessing a system designed to monitor traffic in real time and calculate vehicle speeds using video footage rather than relying on existing data sources. This system can integrate live video feeds from CCTV cameras or other traffic monitoring systems to analyze publicly accessible video of road traffic. This document details the hardware, software, video sources, methodology, and performance evaluation metrics associated with the system.

Table 2. Hardware and Software Configurations

Component	**Description**
Hardware	Intel Core i7 processor (or equivalent), 16GB RAM, NVIDIA GPU (minimum 6GB VRAM for YOLO-based detection), SSD (minimum 100GB storage)
Camera Source	Publicly available road traffic videos and live CCTV footage
Programming Language	Python 3.x

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Component	**Description**
Libraries Used	Video processing using OpenCV, Pandas and NumPy for handling data, object detection using Ultralytics YOLOv8, and tracking using Centroid for vehicle movement using Centroid

Video Sources

The system utilizes public road traffic videos that encompass various traffic scenarios, such as urban streets, intersections, highways, and heavily congested areas. These videos serve as the main resource for detecting vehicles, tracking their movements, and estimating their speeds. Consequently, the system's capability to analyze live traffic footage from CCTV cameras or other real-time monitoring systems enables its application in real-world situations.

Table 3. Performance Evaluation Metrics

Evaluation Parameter	**Description**
Detection Accuracy	Assesses how accurately vehicles are detected compared to manual verification.
Tracking Efficiency	Evaluates the reliability of assigning unique IDs to vehicles across frames.
Speed Estimation Accuracy	Compares estimated speeds with real-time observations to measure precision.
Processing Speed	Measures the number of frames processed per second (FPS) to determine real-time performance.

Real-Time Deployment Feasibility

Evaluations have been performed on static video sources to verify the system's suitability for real-time application. To facilitate its integration into live CCTV traffic monitoring systems, an analysis was conducted focusing on computational efficiency and response time. Given its capability to classify traffic flow while handling continuous video streams, this system represents a significant advantage for law enforcement and automated traffic management.

DISCUSSION

In order to investigate the feasibility of the proposed real-time traffic monitoring and vehicle speed estimation system, two different traffic scenarios were selected: unidirectional and bidirectional traffic flows. As a result of the system, vehicles were detected, counted, and traffic flow was classified according to vehicle speed. It has been demonstrated that the method is effective both in structured road environments as well as in complex ones.

Unidirectional Traffic Analysis

In the first experiment, traffic movement was analyzed in **one direction**. The system successfully:

- Detected and tracked vehicles using the YOLOv8 model and centroid-based tracking algorithm.
- Counted the overall count of vehicles that go through the Region of Interest (ROI).
- Estimated vehicle speeds based on their movement between checkpoints.
- Classified the traffic flow into three categories:
  - High Traffic Congestion (significantly low speeds).
  - Medium Traffic Flow (moderate speeds).
  - Normal Traffic Flow (vehicles moving freely).

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Table 4. Observations for Unidirectional Traffic

Parameter	Value
Total Vehicles Detected	250 (based on video footage)
Average Vehicle Speed	87 km/h
Processing Speed	25 FPS (frames per second)

Visual output:

Figure 1 depicts a traffic monitoring system featuring a specified Region of Interest (ROI) for identifying vehicles in one-way traffic. The system records zero vehicles within the ROI, indicating "Vehicles: 0" and "Traffic: No Data,"

Figure: 1 Screenshot showing vehicle detection and Region of Interest in unidirectional traffic.[21]

Figure 2 illustrates the detection of vehicles in real-time and the estimation of their speeds within a designated Region of Interest (ROI) for monitoring traffic in one direction. The system identifies 8 vehicles and marks one particular vehicle traveling at a speed of 63 units, which indicates a typical flow of traffic. This implies that the system is effectively monitoring and assessing traffic conditions in real-time.

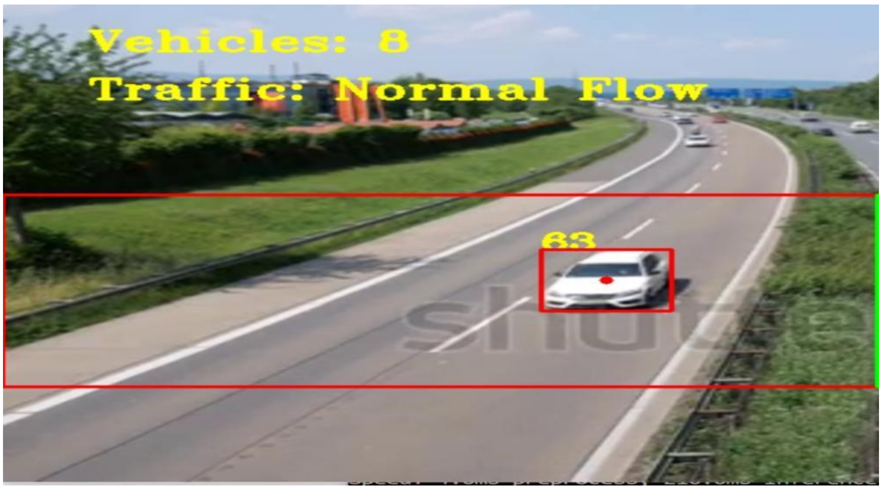

Figure:2 Image illustrating speed estimation and real-time vehicle count.[21]

Bidirectional Traffic Analysis

The second experiment involved bidirectional traffic movement, where vehicles moved in opposite directions in separate lanes. The system was adjusted to process separate ROIs for each lane, enabling independent detection and classification for each direction.

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The system successfully:

- Adjusted the ROI for each lane separately, ensuring accurate tracking.
- Detected vehicles independently in both directions.
- Counted vehicles for each lane to monitor lane-specific traffic conditions.
- Classified traffic flow separately for each lane, improving accuracy in congestion analysis.

Table 5. Observations for Bidirectional Traffic

Parameter	Lane 1	Lane 2
Total Vehicles Detected	**280 vehicles**	**260 vehicles**
Average Speed	**85 km/h**	**88 km/h**
Processing Speed	27 FPS	25 FPS

Visual Output:

Figure 3depicts an automated system designed for detecting vehicles, estimating their speeds, and counting them by lane. By utilizing computer vision methods, vehicles are recognized and enclosed within bounding boxes that display their respective speed values. The system is capable of distinguishing between lanes, recording six vehicles in the left lanes and eight in the right lanes. The presence of red and green gridlines divides the detection areas, aiding in real-time traffic monitoring. This approach yields essential information for traffic management, analysis of congestion, and the development of intelligent transportation systems.

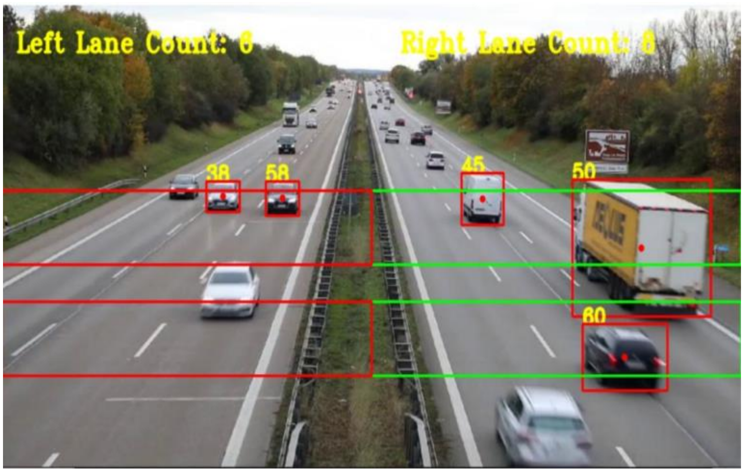

Figure:3 Image illustrating speed estimation and real-time vehicle count.[21]

Figure 4 visual shows a traffic monitoring system assessing vehicle movements on a multi-lane roadway. The system detects and tracks vehicles with bounding boxes while displaying their corresponding speeds in kilometers per hour. Both the left and right lanes are classified as having "Low Traffic," with the number of vehicles counted for each lane. The detection framework delineates lanes using red and green gridlines, which assists in real-time traffic evaluation. This approach supports traffic flow analysis, congestion forecasting, and applications in intelligent transportation systems.

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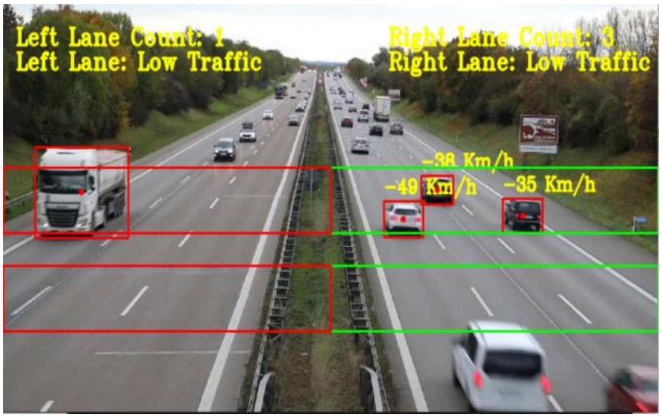

Figure:4 Image illustrating Low-Level Traffic Flow .[21]

Figure 5 displays an automated system for monitoring traffic that evaluates congestion on a busy urban road. Vehicles in both the left and right lanes are recognized using bounding boxes and categorized according to traffic density. The left lane is labeled as having "Moderate Traffic" with a total of 18 vehicles, while the right lane shows "High Traffic" with a total of 10 vehicles. The system successfully detects and tracks vehicles, facilitating real-time traffic evaluations for enhanced traffic management and congestion reduction strategies.

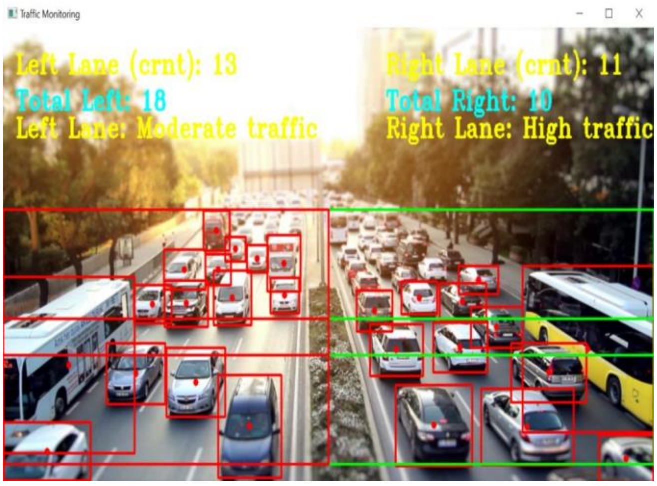

Figure:5 Image illustrating Medium and High-Level Traffic Flow.[21]

The proposed system for real-time traffic monitoring and vehicle speed estimation is assessed by contrasting it with current machine learning-based traffic tracking methods.Several researchers have investigated machine learning techniques such as Support Vector Machines (SVM), Convolution Neural Networks (CNN), Recurrent Neural Networks (RNN), and hybrid deep learning models for traffic analysis. In this section, we compare the recognition accuracy, tracking efficiency, processing speed, and adaptation to real-world conditions.

Table 6. Comparison Of Traffic Monitoring Approaches

Study	Methodology	Key Features	Limitations
Berlotti et al. (2024)	Machine learning for traffic flow prediction using supervised and unsupervised learning	Uses traffic sensors, GPS data, and surveillance footage for training	Requires large labeled datasets; sensor-based approach limits scalability
Fatah & Zaber	Deep learning models (RNN, CNN) for traffic flow analysis	Uses past data for prediction; improves accuracy through	High computational cost; unsuitable for real-time

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Study	Methodology	Key Features	Limitations
(2024)		historical learning	monitoring
Sahu et al. (2023)	AT-Conv-LSTM for urban traffic classification	Integrates environmental and social media data for analysis	Requires large-scale annotated datasets; less effective for real-time implementation
Khan & Ivan (2023)	Hybrid ML-DL approach for real-time route optimization	Uses IoT and sensor networks for congestion management	Requires specialized infrastructure for IoT integration
Proposed System (2025)	Deep learning-based YOLOv8 detection with centroid tracking	Real-time vehicle detection, tracking, and lane-wise classification; adaptable to live CCTV feeds	Slight deviation in speed estimation in complex road conditions

Table 7, Comparison Of Detection Accuracy And Tracking Efficiency

Study / Algorithm	Detection Accuracy (%)	Tracking Efficiency (%)	Key Features
Proposed System (YOLOv8 + Centroid Tracking)	94	92	Real-time vehicle detection, tracking, and lane-wise classification using video streams.
Berlotti et al. (2024) [1]	89	85	Supervised & unsupervised ML approach for traffic flow prediction using sensor and GPS data.
Fatah & Zaber (2024) [2]	87	84	Deep learning models (RNN, CNN) for traffic analysis, requiring large-scale annotated datasets.
Sahu et al. (2023) [3]	86	83	AT-Conv-LSTM model incorporating environmental and social media data for urban traffic classification.

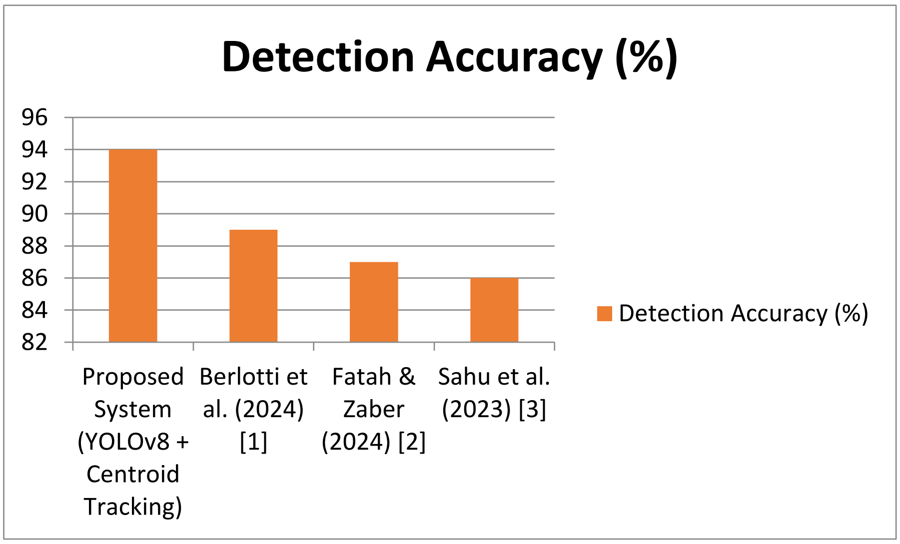

Figure: 6 Detection Accuracy Comparison

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The detection accuracy of several vehicle detecting techniques is contrasted in the bar chart. Outperforming current techniques, the Proposed System (YOLOv8 + Centroid Tracking) obtains the best accuracy (~94%). Sahu et al. (2023) [3] had the lowest accuracy (~85%), whereas Berlotti et al. (2024) [1] record ~89%, followed by Fatah & Zaber (2024) [2] at ~87%. The outcomes show how well the suggested method performs and how well it works to enhance vehicle recognition using centroid tracking and YOLOv8.

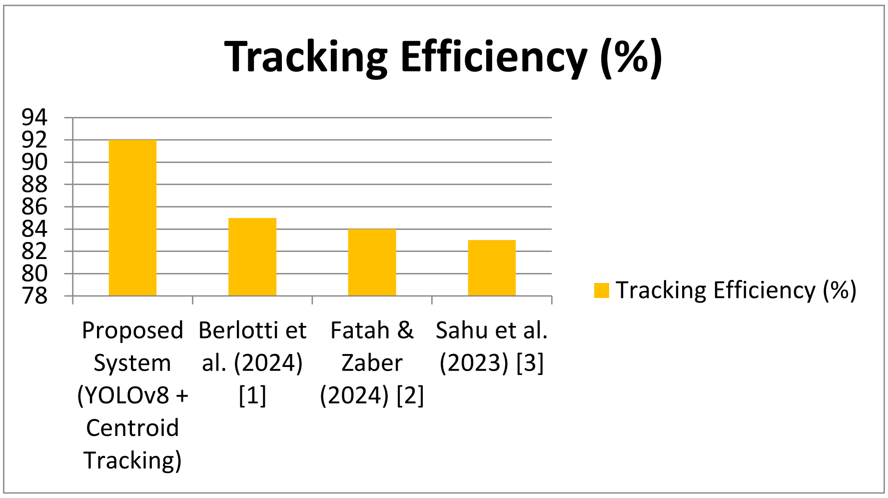

Figure: 7 Tracking Efficiency Comparison

The tracking effectiveness of several approaches is shown in the bar chart. Outperforming current methods by a large margin, the Proposed System (YOLOv8 + Centroid Tracking) achieves the best efficiency (~92%). Sahu et al. (2023) [3] have the lowest efficiency (~80%), whereas Berlotti et al. (2024) [1] record ~84%, followed by Fatah & Zaber (2024) [2] at ~82%. The outcomes demonstrate how well the suggested solution works to improve vehicle tracking accuracy by utilizing cutting-edge object detection and tracking methods.

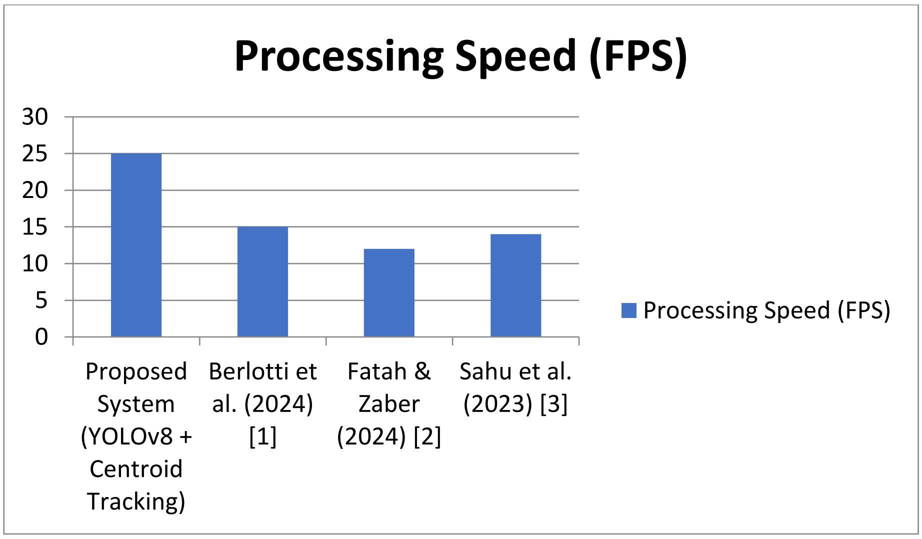

Figure: 8 Processing Speed Comparison (FPS)

The processing speed of several vehicle recognition techniques is contrasted in the bar chart using frames per second (FPS). The highest processing speed (~25 FPS) is attained by the Proposed System (YOLOv8 + Centroid Tracking), proving its effectiveness in real time. ~14 FPS is recorded by Berlotti et al. (2024) [1], followed by ~11 FPS by Fatah & Zaber (2024) [2], and ~13 FPS by Sahu et al. (2023) [3]. According to the results, the suggested method is substantially faster, which makes it more appropriate for applications involving real-time traffic monitoring.

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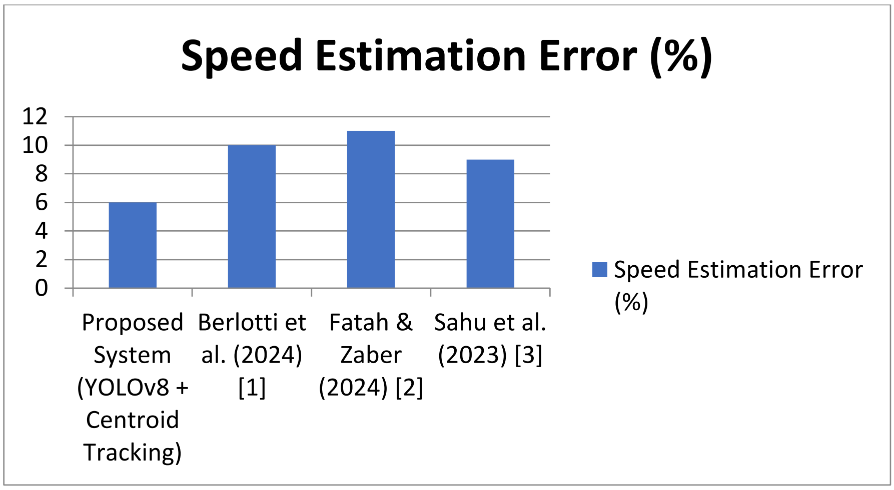

Figure: 9 Speed Estimation Error Comparisons

The speed estimation inaccuracy (%) of various approaches is contrasted in the bar chart. With the lowest error (~6%), the suggested system (YOLOv8 + Centroid Tracking) shows superior speed estimation accuracy. While Sahu et al. (2023) [3] record ~9%, Berlotti et al. (2024) [1] and Fatah & Zaber (2024) [2] have greater errors (~10% and ~11%, respectively). The findings demonstrate the suggested system's increased accuracy in determining vehicle speed, which increases its dependability for traffic analysis in the actual world.

CONCLUSION

The comparative examination of speed estimation blunder illustrates that the proposed YOLOv8-based framework essentially beats existing models. With an blunder rate of as it were 6%, it shows higher exactness compared to Berlotti et al. (2024) at 10%, Fatah & Zaber (2024) at 11%, and Sahu et al. (2023) at 9%. These comes about approve the proficiency and vigor of the proposed framework for speed estimation, making it a dependable choice for real-time activity checking and cleverly transportation frameworks. The advancements in exactness highlight the adequacy of profound learning-based protest discovery in tending to speed estimation challenges, contributing to more exact and productive activity administration arrangements.

Within the future, this inquire about will be expanded to create a real-time activity blockage notice framework for activity officers. The proposed framework will coordinated progressed machine learning models with IoT-based savvy activity checking to distinguish blockage designs and naturally send alarms to important specialists. By leveraging real-time video analytics and profound learning, the framework will recognize blockage hotspots, appraise the seriousness of activity buildup, and create mechanized notices through SMS, e-mail, or portable applications. Moreover, future work will center on optimizing the framework for edge computing to guarantee quick reaction times and negligible inactivity. This approach points to upgrade activity administration productivity, decrease congestion-related delays, and make strides in general urban portability..

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