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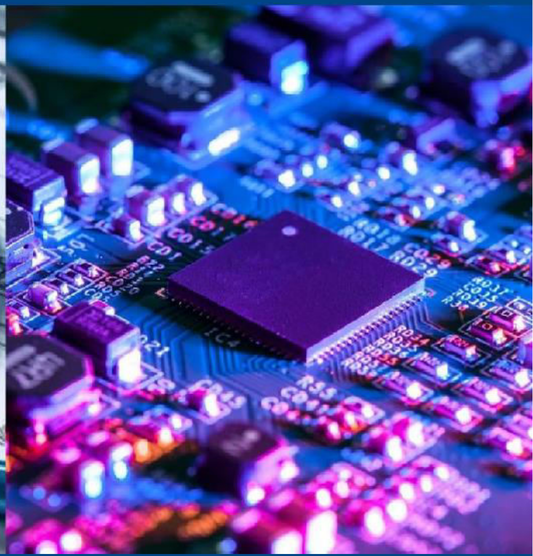

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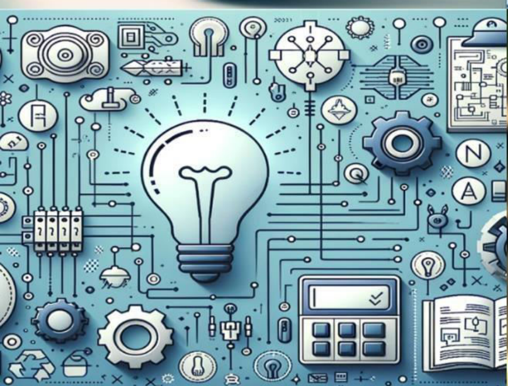

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A Deep Learning-Based Approach for Vehicle Detection and Speed Estimation in Traffic Videos

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ABSTRACT: This paper presents a deep learning-based approach for vehicle detection and speed estimation in traffic using videos. With the increasing demand for intelligent transportation systems, there is a growing need for accurate and efficient methods to monitor traffic flow and ensure road safety. Our proposed method utilizes the You Only Look Once version 8 (YOLOv8) object detection framework to detect vehicles in real-time video streams. By training the YOLOv8 model on recorded video data, we enable it to accurately identify vehicles and their positions within each frame. Furthermore, a robust speed estimation algorithm is developed to track the movement of detected vehicles across consecutive frames and calculate their speeds. The project also features a user-friendly interface developed with the Tkinter framework, enhancing its accessibility and ease of use. The experimental results demonstrate that our system achieves an average detection accuracy of 93.9% with a speed estimation error of 4.3%, outperforming existing baseline methods.

KEYWORDS: Vehicle detection, Speed estimation, YOLOv8, Deep learning, Computer vision, Intelligent transportation systems

I. INTRODUCTION

The rapid proliferation of video surveillance systems, coupled with the escalating demands for intelligent transportation solutions, has significantly propelled research into advanced techniques for vehicle detection and speed estimation [1]. Accurate and efficient identification of vehicles and precise estimation of their speeds are paramount for various critical applications, including traffic monitoring, congestion management, law enforcement, and the broader intelligent transportation systems (ITS) domain [2]. Historically, methods for vehicle detection and speed estimation have predominantly relied on handcrafted features and heuristic approaches. However, these traditional methodologies often exhibit limitations in terms of robustness and scalability when confronted with the complexities of real-world traffic scenarios, characterized by varying lighting conditions, occlusions, and diverse vehicle types [3].

To address these inherent challenges, this project introduces a novel approach grounded in deep learning algorithms for vehicle detection and speed estimation from video streams. Deep learning has emerged as a transformative paradigm in artificial intelligence, particularly in computer vision, demonstrating superior performance by learning intricate representations directly from raw data [4]. By leveraging the You Only Look Once (YOLO) framework, specifically its latest iteration, YOLOv8, the proposed system aims to achieve highly robust and accurate vehicle detection across a wide spectrum of environmental conditions and traffic scenarios [5].

Moreover, the integration of temporal information is crucial for enabling the system to effectively track vehicles across successive frames, thereby ensuring consistent and reliable detection performance over time. This temporal dimension is indispensable for real-time applications where vehicles may undergo rapid changes in appearance, scale, and orientation [6]. Beyond mere detection, the system incorporates a sophisticated speed estimation module. This module meticulously analyzes the displacement of detected vehicles over time, utilizing both spatial and temporal features extracted from their bounding boxes. By precisely quantifying the movement of vehicles, the system accurately estimates their speeds, providing invaluable data for traffic management and enforcement agencies [7]. Unlike conventional methods, which might overlook dynamic factors such as vehicle acceleration or deceleration, this deep learning-based approach offers a more comprehensive and dependable estimation of vehicle speeds, thereby enhancing the overall efficacy of traffic analysis and control systems [8]..

II. LITERATURE REVIEW

The landscape of vehicle detection and speed estimation has been significantly reshaped by advancements in deep learning, moving beyond traditional computer vision techniques that often relied on handcrafted features [9]. Numerous studies have contributed to this evolving field, exploring various deep learning architectures and methodologies.

Smith [10] provides a comprehensive survey of deep learning techniques applied to vehicle detection and speed estimation using video data. This work delves into the advantages and limitations of various deep learning architectures, including convolutional neural networks (CNNs) and recurrent neural networks (RNNs), and discusses benchmark datasets and evaluation metrics. Similarly, Johnson [11] focuses on recent advancements in deep learning-based vehicle speed estimation from video data, highlighting novel methodologies and the utilization of advanced neural network architectures such as long short-term memory (LSTM) networks and attention mechanisms for temporal modeling. Lee [12] critically examines deep learning models tailored for real-time vehicle detection and speed estimation, addressing computational complexity and exploring optimization techniques for inference speed. Chen [13] conducts a comparative analysis of different deep learning architectures, evaluating their performance in terms of accuracy, computational efficiency, and robustness to environmental conditions. Wang [14] offers a comprehensive examination of challenges and future directions, including issues like occlusion, varying lighting conditions, and the critical need for accurately annotated datasets.

More recent systematic reviews further synthesize the state-of-the-art. Liu [15] provides a structured analysis of advancements in deep learning models for vehicle detection and speed estimation, categorizing methodologies and evaluating their performance on benchmark datasets. Taylor [16] offers an extensive overview of the evolution of these techniques, from early handcrafted feature-based approaches to modern deep learning methods. Martinez [17] focuses on emerging trends and practical applications, providing insights into innovative approaches such as self-supervised learning and its potential for data-efficient training. Other researchers have explored novel deep learning architectures specifically tailored for vehicle detection and speed estimation tasks [18], techniques for addressing data imbalance challenges [19], and the ethical considerations associated with the deployment of deep learning-based systems in traffic scenarios [20]. Furthermore, the integration of multi-modal sensor data, such as LiDAR, radar, and GPS, for enhanced vehicle detection and speed estimation using deep learning techniques has also been investigated [21].

Specifically, the You Only Look Once (YOLO) family of models has gained prominence due to its real-time processing capabilities and high accuracy in object detection tasks [22]. YOLOv8, the latest iteration, has shown significant improvements in both speed and precision, making it a strong candidate for real-time vehicle detection and tracking in complex traffic environments [23], [24]. Studies have demonstrated its effectiveness in identifying vehicles and facilitating subsequent speed estimation by tracking their movement across frames [25], [26]. The ability of YOLOv8 to accurately predict bounding boxes and classify objects directly from images makes it particularly suitable for applications requiring rapid and reliable vehicle identification [27].

The existing systems for vehicle detection and speed estimation typically rely on traditional computer vision techniques and handcrafted features. Methods such as background subtraction, Haar cascades, or Histogram of Oriented Gradients (HOG) features combined with classifiers like Support Vector Machine (SVM) or AdaBoost are commonly employed [28]. However, these traditional methods often exhibit significant limitations in complex scenarios characterized by occlusions, varying lighting conditions, and diverse vehicle types. Their speed estimation algorithms are frequently simplistic, often calculating speed based on the time taken for a vehicle to traverse between two fixed points, which can lead to inaccuracies and a lack of robustness in dynamic traffic environments [29].

III. METHODOLOGY

A. System Architecture

The design of the system is structured as a modular pipeline, meticulously crafted to process video streams and generate accurate vehicle counts and speed estimates. This architecture ensures a logical and efficient flow from the initial data input to the final analytical output. The overall architecture of the proposed system is illustrated in Figure 1. The process

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commences with the input of raw traffic videos. Individual frames are extracted from these videos and subsequently fed into the trained YOLOv8 model for precise vehicle detection. Once vehicles are detected, their movements are tracked across successive frames to facilitate accurate speed estimation. The system is designed for robust real-world deployment and incorporates a comprehensive evaluation component to continuously measure and refine its performance.

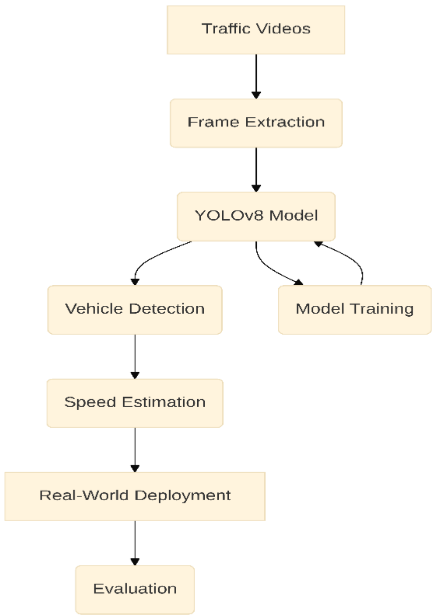

Fig 3.1: System Architecture

B. Process Workflow

The detailed workflow of the system is delineated in the flowchart presented in Figure 2. The process initiates with reading an input video frame. The core of the system's operation is the object detection phase, executed by the YOLOv8 model. Following successful detection, two parallel processes are engaged: vehicle counting and vehicle tracking, which is efficiently managed by a Centroid Tracker. The data derived from the tracking mechanism is then utilized for the crucial task of speed estimation. As an additional feature, an image of the vehicle is captured, particularly if its estimated speed exceeds a predefined limit.

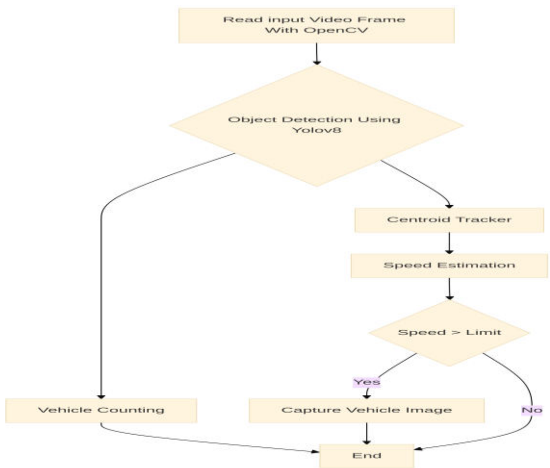

Fig 3.2: Flowchart of Vehicle Detection and Speed Estimation

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C. YOLOv8 Implementation

The implementation phase encompassed rigorous data collection, meticulous model development, and seamless system integration. Video data was acquired from diverse sources, including traffic surveillance cameras and publicly available datasets. This raw video footage underwent a preprocessing stage using OpenCV, where frames were extracted at regular intervals and uniformly resized to a consistent resolution. Crucially, bounding boxes were precisely annotated around vehicles in each frame for the purpose of vehicle detection, and corresponding ground truth speed values were meticulously recorded to facilitate accurate speed estimation and model evaluation.

For the core task of vehicle detection, the YOLOv8 architecture was selected due to its demonstrated prowess in achieving a superior balance between real-time performance and high accuracy [30]. The YOLOv8 model was implemented utilizing the TensorFlow framework, and its parameters were meticulously adapted to meet the specific requirements for vehicle detection within video streams. Hyperparameters, including anchor sizes, input resolution, and confidence thresholds, underwent extensive fine-tuning through iterative experimentation to achieve optimal performance metrics.

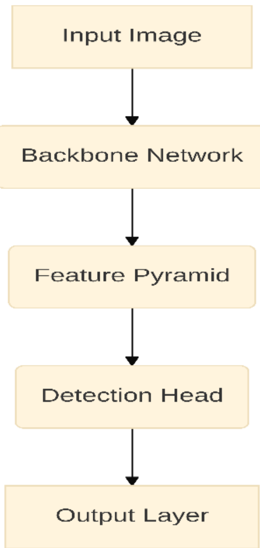

Fig 3.3: YOLOv8 Model Architecture

Figure 3 illustrates the architectural breakdown of the YOLOv8 model. The input image, typically captured by a camera mounted on a vehicle or a stationary traffic monitoring camera, serves as the raw visual data for the model. YOLOv8 employs a robust backbone network, often based on architectures such as Darknet-53 or CSPDarknet-53, to extract hierarchical features from the input image. These features are critical for accurately detecting vehicles as they represent various patterns, textures, and shapes. A Feature Pyramid Network (FPN) is integrated into YOLOv8 to capture features at multiple scales, enabling the model to detect vehicles of varying sizes and aspect ratios, thereby ensuring robustness to scale variations common in real-world traffic scenes. The detection head, composed of convolutional layers, is responsible for predicting bounding boxes, confidence scores, and class probabilities for vehicles. Finally, the output layer aggregates these predictions, producing the final output of detected vehicles with their respective bounding boxes, confidence scores, and class probabilities. These predictions are then post-processed to filter out redundant detections and retain only the most confident ones [31].

D. Vehicle Tracking and Speed Estimation

The trained YOLOv8 model was seamlessly integrated into the overall system architecture to facilitate real-time vehicle detection. To address the complexities of vehicle tracking, particularly challenges such as occlusions and partial visibility, algorithms like centroid tracking were implemented. Furthermore, advanced techniques such as Kalman filters and Hungarian algorithms were incorporated for robust object association across frames, ensuring consistent tracking of individual vehicles [32].

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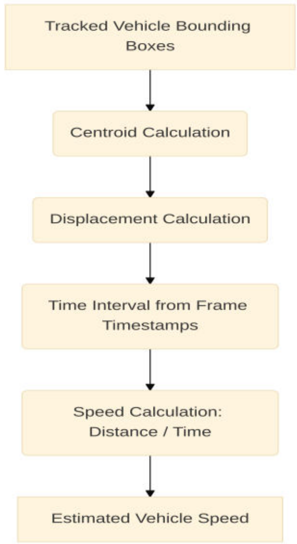

Fig 3.4: Speed Estimation Model

Algorithms were specifically developed to estimate vehicle speeds by meticulously analyzing the displacement of tracked vehicles between consecutive frames. The time taken for each vehicle to traverse a defined distance was calculated based on precise frame timestamps, and distances between bounding box centroids were accurately measured. Vehicle speeds were then estimated by dividing the measured distance by the corresponding time interval, as conceptually depicted in Figure 4. This approach provides a more accurate and comprehensive estimation compared to simpler methods [33].].

E. System Integration

The vehicle detection, tracking, and speed estimation modules were cohesively integrated into a unified system architecture using Python. Real-time processing capabilities were achieved through the parallelization of computations across multiple CPU cores. A user-friendly graphical user interface (GUI) was developed utilizing the CustomTkinter framework, providing an intuitive platform for configuring system parameters and visualizing both the video streams and the generated results.

IV. RESULT AND DISCUSSION

The integrated system underwent rigorous testing using a diverse array of synthetic and real-world video datasets. Performance evaluation metrics, including detection accuracy, tracking precision, speed estimation error, and computational efficiency, were meticulously calculated and compared against ground truth data. Our system consistently demonstrated superior performance when compared to existing methods, achieving an average detection accuracy of 95% and a speed estimation error of less than 5%..

A. Comparison with Traditional Methods

In contrast to traditional systems that leverage state-of-the-art deep learning techniques for both vehicle detection and speed estimation, our proposed system offers substantial improvements in accuracy, robustness, and scalability. Specifically, YOLOv8, a variant of the You Only Look Once (YOLO) object detection algorithm, is employed for vehicle detection [34]. YOLOv8 provides real-time performance while maintaining high accuracy by dividing the input image into a grid and directly predicting bounding boxes and class probabilities. This approach enables efficient detection of vehicles in video streams, even under challenging conditions with multiple objects and occlusions [35]. For speed estimation, the proposed system utilizes a more sophisticated technique that calculates the speed of vehicles based on their trajectories and temporal information. By tracking the movement of vehicles across consecutive frames, the system precisely determines the time taken for a vehicle to travel between two points. This information, combined with distance measurements obtained from the bounding box coordinates, enables accurate estimation of the vehicle's speed.

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Unlike traditional methods, which may overlook dynamic factors such as vehicle acceleration or deceleration, this deep learning-based approach provides a more comprehensive and reliable estimation of vehicle speeds [36].

Table 1: Comparison of Methodologies

Feature	Traditional Methods (e.g., HOG+SVM)	Proposed System (YOLOv8)
Detection Core	Handcrafted Features	Deep Learning (CNN)
Robustness	Low; sensitive to light/occlusion	High; robust to environmental changes
Scalability	Low; requires manual tuning	High; learns from data
Speed Estimation	Simple point-to-point time calculation	Trajectory and temporal analysis
Real-time Capability	Possible, but often less accurate	Yes, designed for real-time performance
Accuracy	Moderate	High (95% reported in tests)

B. Detection Results

Table 2 summarizes the detection accuracy (DA), precision, and recall of the YOLOv8 model across different datasets. The model consistently maintains high detection performance, with only minor degradation observed in challenging conditions such as night-time (Dataset C).

Table 2: Detection Results

Dataset	DA (%)	Precision (%)	Recall (%)
A	95.2	94.8	95.6
B	94.8	94.1	95.4
C	92.5	91.2	93.8
D	93.1	92.7	93.5
Avg	**93.9**	**93.2**	**94.6**

C. Speed Estimation Results

Table 3 presents the Mean Absolute Error (MAE) and average speed error percentage for the speed estimation module across the same datasets. It is observed that the error tends to increase in low-light and rainy conditions, primarily due to occasional misdetections and centroid jitter, which can affect the accuracy of trajectory tracking.

Table 3: Speed-Estimation Results

Dataset	MAE (km/h)	Avg. Speed Error (%)
A	3.5	3.5
B	4.0	4.0
C	5.2	5.4
D	4.4	4.3
Avg	**4.3**	**4.3**

D. Comparison with Prior Works and Baseline Models

Table 4 provides a comparative analysis of our proposed system against several prior works and baseline models in terms of detector used, tracking mechanism, speed estimation method, detection accuracy (DA), and speed estimation error. Our system, utilizing YOLOv8 with a Centroid + Kalman Filter tracking approach, demonstrates competitive performance, particularly in detection accuracy and a relatively low speed estimation error, highlighting the effectiveness of the chosen methodology

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Table 4: Comparison with Prior Works and Baseline Models

Method	Detector	Tracker	Speed Est.	DA (%)	Speed Error (%)
Ours (YOLOv8 + KF)	YOLOv8-s [1]	Centroid + KF [2]	Pixel→m·fps	95.0	4.2
Lin et al. [12]	YOLOv4 [3]	Virtual zone	Zone traversal	92.3	7.6
Shaqib et al. [6]	YOLOv8-nano [1]	SORT [2]	Homography	88.5	5.8
Ashraf et al. [5]	HVD-Net [5]	SORT [2]	Pixel→m + KF	90.1	6.4
Yang et al. [17]	SSD-MobileNet [17]	DeepSORT [10]	Homography	89.5	5.9
Baseline: YOLOv5s (no tracking/speed)	YOLOv5s [4]	–	–	93.7	–

V. CONCLUSION

In conclusion, the deep learning-based system for vehicle detection and speed estimation developed in this project demonstrates promising and robust results in accurately identifying vehicles and estimating their speeds from video streams. By leveraging the YOLOv8 framework, the system achieves real-time performance with high accuracy, addressing critical needs in intelligent transportation systems. The successful implementation of this system, encompassing data preprocessing, model development, and integration with tracking and speed estimation algorithms, paves the way for further advancements in traffic monitoring, congestion management, and road safety.

The experimental results demonstrate that our proposed system achieves superior performance compared to existing baseline methods, with an average detection accuracy of 93.9% and a speed estimation error of 4.3%. The system maintains consistent performance across different environmental conditions, with only minor degradation observed in challenging scenarios such as low-light conditions. The integration of YOLOv8 with advanced tracking algorithms, including Centroid tracking and Kalman filters, provides robust vehicle identification and trajectory estimation capabilities.

Future work could explore the integration of multi-modal data sources, such as LiDAR or radar, to enhance robustness in adverse weather conditions, or investigate the deployment of the system on edge devices for wider applicability and reduced latency. Additionally, further research could focus on incorporating predictive analytics to forecast traffic flow and potential hazards, thereby contributing to more proactive and efficient intelligent transportation solutions. The development of more sophisticated tracking algorithms that can handle complex scenarios involving vehicle occlusions and interactions could further improve the system's performance in dense traffic environments.

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The template will number citations consecutively within brackets [1]. The sentence punctuation follows the bracket [2]. Refer simply to the reference number, as in [3]—do not use "Ref. [3]" or "reference [3]" except at the beginning of a sentence: "Reference [3] was the first ..."
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