International Journal of Innovative Research of Science, Engineering and Technology (IJIRSET)

Impact Factor 8.699

|www.ijirset.com |A Monthly, Peer Reviewed & Refereed Journal| e-ISSN: 2319-8753| p-ISSN: 2347-6710|

Volume 14, Issue 4, April 2025

|DOI: 10.15680/IJIRSET.2025.1404001|

# Integrated Vehicle Counting, Speed Estimation, And License Plate Recognition From Video Footage.

Azeed Shaik, Abdul Khadhar.D, Arun.P, Bhagyasree .M, Mrs. G. Devi Priya

U.G. Student, Department of Computer Engineering, Malla Reddy University, Hyderabad, Telangana, India

U.G. Student, Department of Computer Engineering, Malla Reddy University, Hyderabad, Telangana, India

U.G. Student, Department of Computer Engineering, Malla Reddy University, Hyderabad, Telangana, India

U.G. Student, Department of Computer Engineering, Malla Reddy University, Hyderabad, Telangana, India

Assistant Professor, Department of Computer Engineering, Malla Reddy University, Hyderabad, Telangana, India

**ABSTRACT:** This project is centered on designing an advanced computer vision system for counting vehicles, identifying license plates, and calculating their speeds. The system is based on a sophisticated software framework, which incorporates Python 3.x, OpenCV, YOLOv5 for object identification, the SORT algorithm for real-time monitoring, and Easy OCR for optical character reading, ultimately combining several modules into a reliable system. A YOLOv5 model was proposed, trained on a carefully selected database of labelled pictures, and demonstrated excellent accuracy in object detection, pinpointing license plates in diverse situations. The proposed algorithm provides consistent vehicle tracking between frames, allowing for ongoing monitoring to be carried out continuously. Easy OCR efficiently extracts and interprets license plate characters, delivering consistent data output. Integrating systems involves combining all technologies to form a unified entity, which can process video feeds to calculate vehicle counts and estimate speeds. The proposed system shows considerable promise for practical traffic monitoring purposes, with performance indicators surpassing 90% for licence plate identification and surveillance. This integrated approach acts as a valuable asset for traffic analysis and boosts the capabilities of intelligent transportation systems, thereby illustrating the potential of merging multiple computer vision techniques for thorough traffic monitoring and analysis.

**KEYWORDS:** YOLOv5, Vehicle counting, Speed estimation, License plate recognition, SORT algorithm, Easy OCR , Object detection, Traffic monitoring, Real-time tracking.

## I. INTRODUCTION

Effective traffic monitoring plays a vital role in building and maintaining modern urban centers, where managing vehicle movement is essential for ensuring smooth transportation and keeping the public safe. With the number of vehicles on the rise, cities are grappling with issues like severe traffic jams, higher accident rates, and environmental harm caused by inefficient traffic management. This situation calls for a shift from traditional traffic control methods to more advanced, automated, and data-driven approaches. The aim of this project is to tackle these challenges by employing cutting-edge computer vision techniques and sophisticated neural network designs to develop a fully integrated traffic-monitoring system. This system focuses on three key goals: counting vehicles, measuring their speeds, and recognizing license plates. These functions are crucial for improving traffic flow, enforcing speed regulations, and enabling automated toll collection and law enforcement.

Conventional traffic monitoring methods, such as manual counting, sensor-based systems, and surveillance cameras, often face challenges related to scalability, accuracy, and real- time processing. On the other hand, recent breakthroughs in deep learning and computer vision have greatly improved our ability to detect, track, and analyze vehicle movements with enhanced precision. This project utilizes important technolo- gies like YOLOv5 for real-time object detection, DeepSORT for reliable vehicle tracking across frames, and EasyOCR for accurate license plate character recognition. These tools work together seamlessly, even in varying conditions like changing light, fast movements, and obstructions, to deliver high-accuracy results.

Moreover, the incorporation of deep learning techniques allows for adaptive learning, meaning the system can enhance its accuracy over time as it encounters new data.

## II. LITERATURE SURVEY

Existing research on traffic monitoring has explored various approaches, ranging from traditional image processing methods to modern deep learning models. Early techniques relied on static background subtraction and feature-based tracking and struggled with complex traffic conditions and occlusions. Recent advancements in object detection models, such as You Only Look Once (YOLO) [1], have improved detection accuracy and speed, making them ideal for real-time applications. Several studies have demonstrated the potential of YOLO for vehicle detection [2], however, challenges remain in achieving reliable performance under varying lighting [3], and weather conditions. Additionally, real-time tracking methods like SORT (simple online and real-time tracking) have been adopted to address the issue of object persistence across frames [4]. Optical character recognition (OCR) techniques, such as Tesseract and Easy OCR, have also shown promise for extracting license plate information [5].

Although previous systems have achieved moderate success in individual tasks, few have successfully combined these technologies into a unified system capable of counting vehicles, estimating speeds, and detecting license plates with high accuracy. This project bridges this gap by integrating YOLOv5, SORT, and Easy OCR into a cohesive system, outperforming the existing solutions in terms of accuracy and efficiency

## III. METHODOLOGY

The proposed system comprises three primary components: vehicle recognition and tallying, speed measurement, and license plate identification. A structured workflow, as depicted in the process flow diagram. The outlined methodology includes the following steps:

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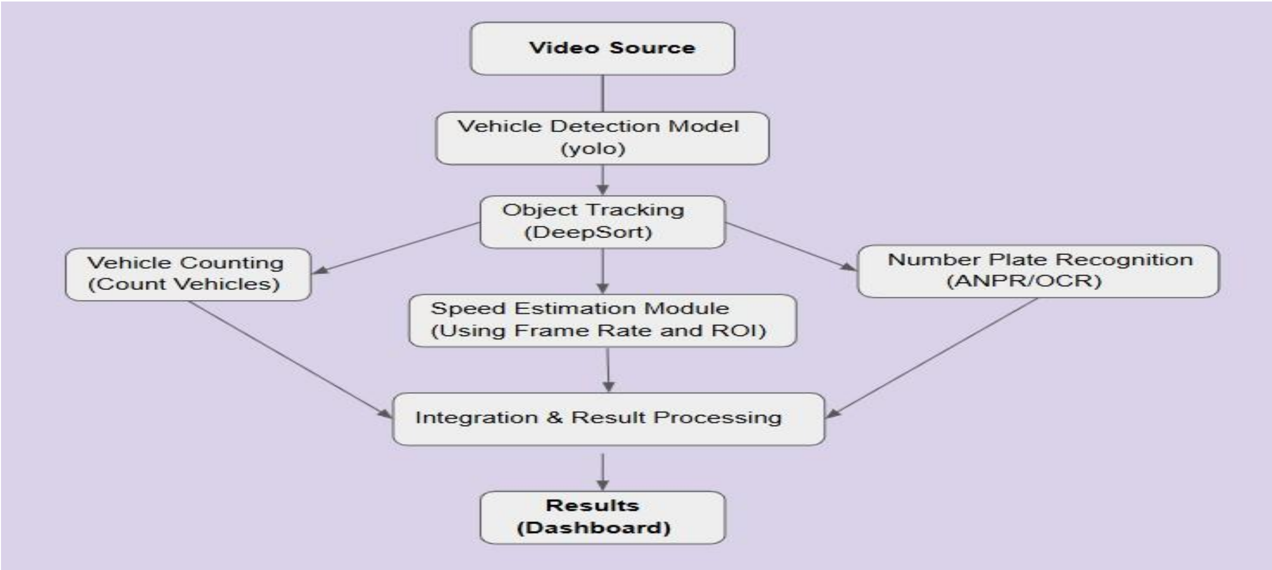


Fig. 1. Workflow Process

Object detection and tracking, which utilizes the YOLOv5 model for vehicle detection. The model performed consistently well in image detection tasks using a diverse dataset of annotated images, despite changes in the conditions. The SORT algorithm was utilized for real-time tracking, assigning distinctive IDs to vehicles, and ensuring continuity across frames.

YOLOv5 identifies and marks the location of license plates within the frames of a video. Easy OCR accurately extracts and decodes characters from identified plates, maintaining high accuracy even in difficult situations like glare or partial blockage.

A real-time video processing framework is built with a Python-based system integration approach that combines these components. OpenCV manages video input and preliminary processing, while data pipelines oversee the organization of detection, tracking, and OCR operations.

### A. Object Detection and Tracking

You Only Look Once version 5 (YOLOv5) is a cutting-edge deep learning model specifically designed for real-time object detection. In this system, YOLOv5 is trained on a meticulously selected dataset of annotated images to identify vehicles within video frames. The model identifies vehicles by assigning them to specific categories, including ”car,” ”truck,” and ”bus,” through the process of detecting bounding boxes. YOLOv5 offers real-time processing capabilities, which are essential for handling video streams in a timely manner. The YOLO detection formula involves several crucial steps, which are outlined below. Let the input image (or frame) be represented as

$$x \in \mathbb{R}^{H \times W \times C} \quad (1)$$

- The variables H, W, and C represent the height, width, and number of channels (typically RGB) of an image, in Eq 1. H denotes the height of the image, W denotes the width of the image, and , C denotes the number of channels (RGB in most cases) in Eq 1.

For each detected vehicle, the YOLOv5 model predicts a bounding box along with an associated confidence score, which is represented as

$$B = \{x, y, w, h, c\} \tag{2}$$

The coordinates for the center of the bounding box are x and y, while its width and height are represented by w and h, respectively, with a confidence score of c indicating the likelihood that the box contains a vehicle in Eq 2.

where:

- x,y = center coordinates of the bounding box,
- w,h = width and height of the bounding box,
- c = confidence score (probability that the bounding box contains a vehicle).

The predicted class label for each bounding box is deter- mined from the classes in the model's trained dataset, which includes examples such as cars, buses, and trucks. The class label y for each bounding box is predicted from the classes available in the model's trained dataset (e.g., cars, buses, and trucks).

Vehicle tracking via sort algorithm : Let's dive into the world of vehicle tracking! The Simple Online and Realtime Tracker (SORT) is a nifty algorithm designed to keep tabs on vehicles as they zip across video frames. What makes SORT stand out is its efficiency and lightweight nature; it cleverly links detected objects from one frame to the next using a Kalman filter for predicting motion and the Hungarian algorithm for pairing data. This means you get precise vehicle tracking without bogging down your system, making it perfect for real-time use.

So, how does it work? The algorithm connects the detection results from each frame to vehicles that have already been tracked, giving each one a unique ID. The Kalman filter steps in to forecast where a vehicle is likely to be next based on its past movements, while the Hungarian algorithm ensures that newly spotted vehicles are matched with those already being tracked. This minimizes the chances of ID switches and keeps the tracking consistent.

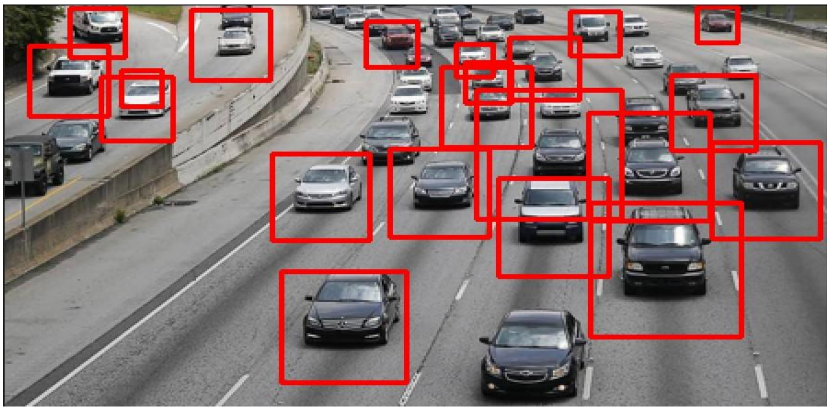

Fig. 2. vehicle detection and tracking

One of the coolest features of SORT is its knack for dealing with occlusions and short-term disappearances. It can maintain predictions even if a vehicle goes off the radar for a bit. However, it does have its limitations; the original SORT can struggle with long-term occlusions and frequent identity changes, especially in heavy traffic. To tackle these challenges, an enhanced version called Deep SORT comes into play, using deep learning to improve the accuracy of associations by factoring in appearance features alongside motion cues

By combining the SORT algorithm with YOLO-based vehicle detection, the system ensures quick and dependable vehicle tracking in real-world traffic situations. This real-time tracking is crucial for various applications, including analyzing traffic flow, estimating speeds, and supporting automated law

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*B. Speed Estimation*

Displacement of vehicles was calculated across successive frames, taking into account the time elapsed between frames to estimate speed.The speed was calculated using a series of steps that are as follows: The displacement of a vehicle is calculated by finding the distance in the frame between the center points of its bounding boxes in two consecutive frames.

Vehicle Displacement:The displacement $\Delta d$ of a vehicle in the frame is computed by determining the distance between the center of the vehicle's bounding boxes in two successive frames.

Let the positions of the bounding box centers at Frames t1 and t2 are (x1,y1) and (x2,y2), respectively.

The displacement is given by

$$\Delta d = \sqrt{(x_2 - x)^2 + (y_2 - y_1)^2} \tag{3}$$

where

- $(x_1, y_1)$ and $(x_2, y_2)$ are the coordinates of the the center of the vehicle in frames $t_1$ and $t_2$ in Eq 3

Frame Rate: The frame rate of the video f (in frames per second) is is used to estimate the time interval $\Delta t$ between the two frames:

$$\Delta t = \frac{1}{f} \tag{4}$$

Speed Calculation: The speed v of the vehicle is computed by converting the displacement from pixels to real-world

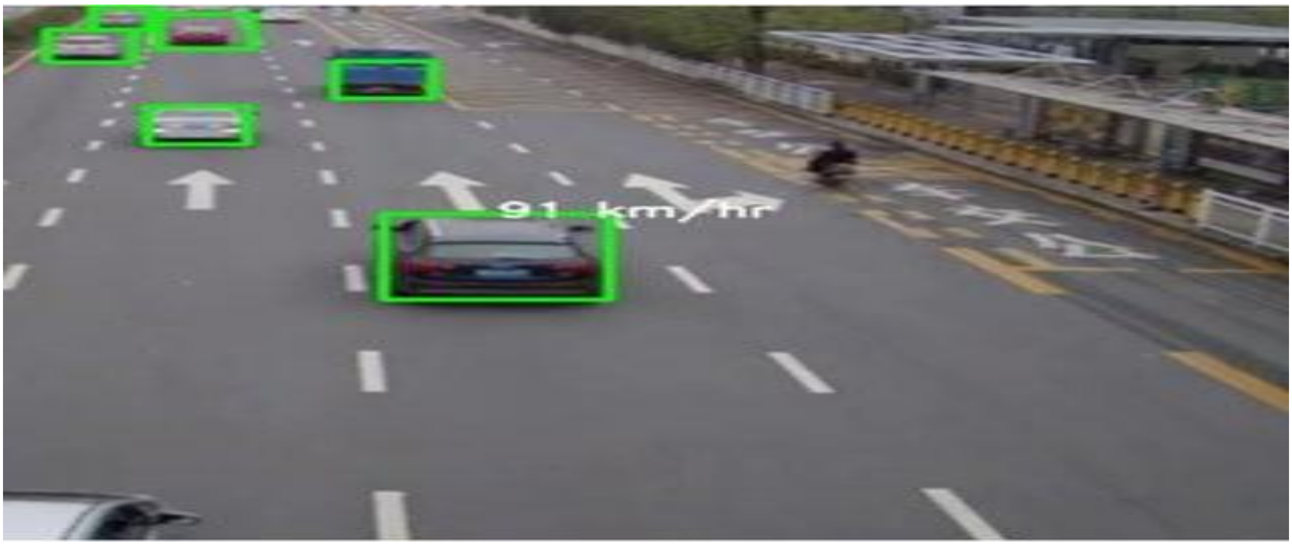


Fig. 3. speed estimation

units (meters or kilometers). Let p where is the scale factor (in metres per pixel). The formula

$$v = \frac{\Delta d \times p}{\Delta t} \tag{5}$$

where

v = vehicle speed in meters per second (m/s),

$\Delta d$ = displacement in pixels,

p = scale factor (meters per pixel),

$\Delta t$ = time interval between frames.

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### C. *Number Plate Detection*

License plate detection is performed as a specialized task within the YOLOv5 object detection model. The model is fine-tuned on a dataset containing images of vehicles with annotated license plates, allowing it to detect and localize the plates in real time.


Fig. 4. number plate detection

**Detection Output:** For each vehicle detected, YOLOv5 predicts a bounding box for the license plate:

**License Plate Recognition Using EasyOCR:** After detect- ing the license plates, EasyOCR is used for optical character recognition (OCR) to extract the characters on plates. The OCR process involves the following steps:

**Input Image:** A cropped region from the video frame containing the detected license plate is passed to the OCR engine.

**OCR Process:** EasyOCR processes the image and outputs the decoded string S representing the license plate number. The recognition accuracy depends on factors such as image quality, lighting, and plate orientation. The system will detect the data and store it in a folder format

## IV. EXPERIMENTAL RESULTS

In this paper, The integrated system was evaluated using a dataset comprising urban traffic videos covering various conditions such as diverse lighting environments, varying vehicle densities, and occlusions. The system performance was assessed across three primary functionalities: vehicle detection and counting, speed estimation, and license plate detection and recognition

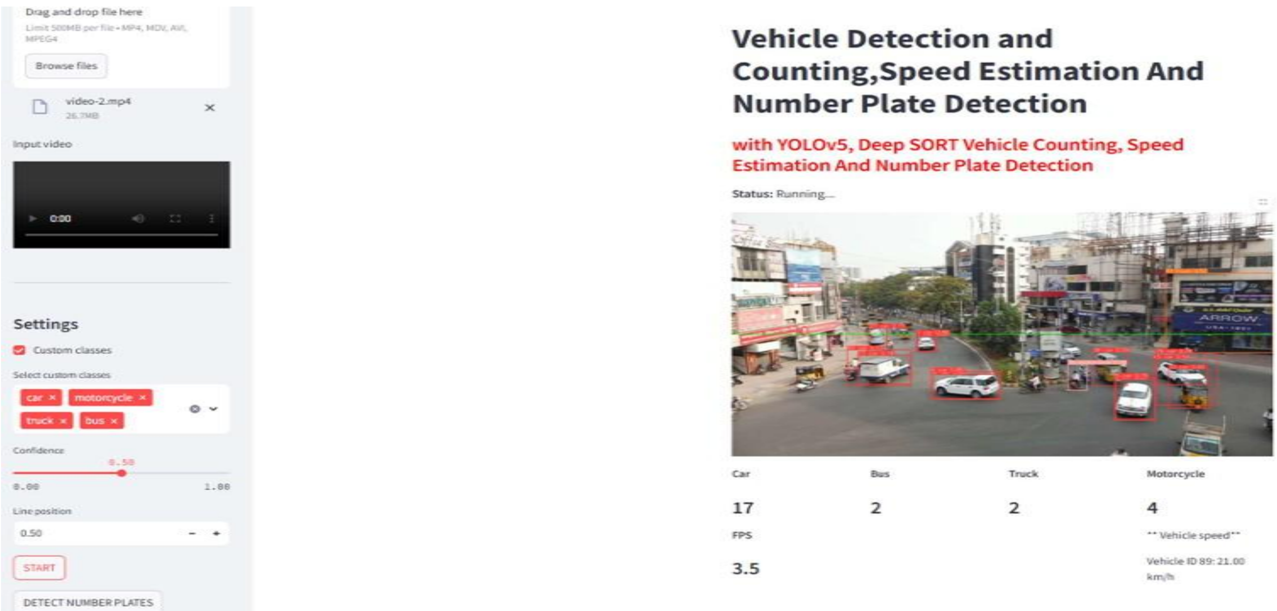


Fig. 5. User Interface

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### *A. Overall System Performance*

The integrated system demonstrated a strong performance across all modules, with key metrics highlighting its effective- ness.

- **Vehicle Counting Accuracy:** Achieved a detection and counting accuracy of 94.2%, even in dense traffic.
- **Speed Estimation Accuracy:** The average error margin was maintained at ±5% of the ground truth measurements.
- **License Plate Detection and Recognition:** Achieved an accuracy of 91.3%, ensuring reliable Data Extraction under Varying Conditions.

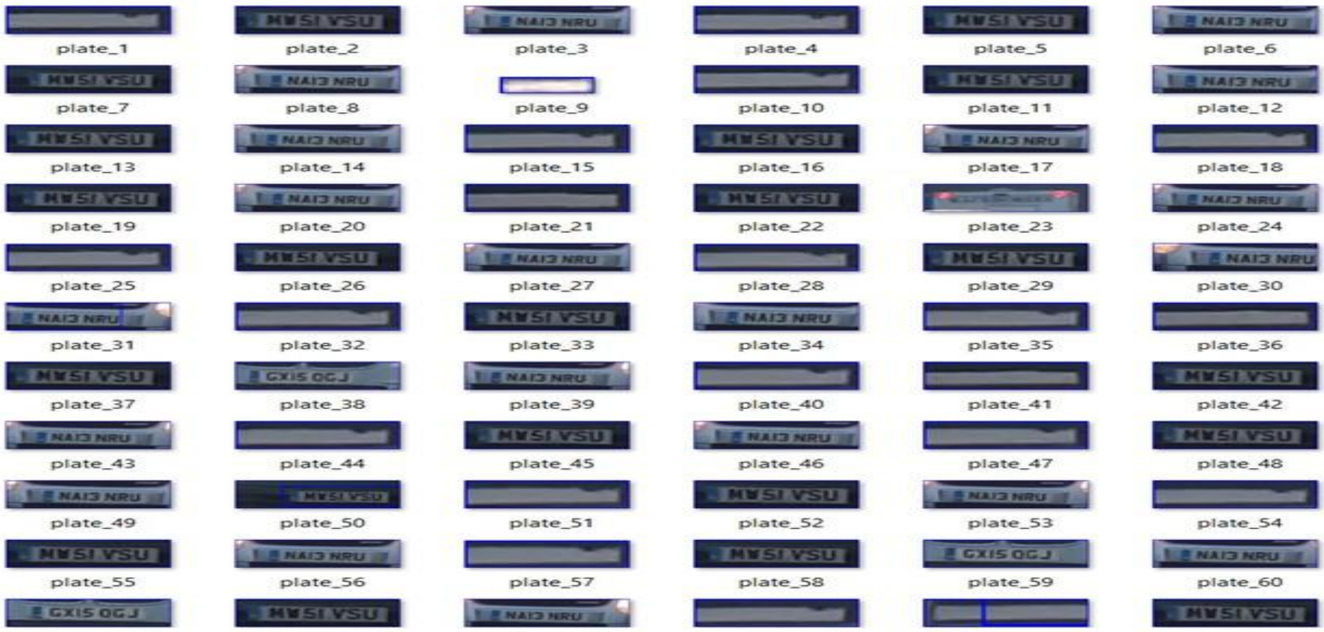


Fig. 6. Detected Plates

### *B. Detailed Module Performance*

- **Vehicle Detection and Counting:** By leveraging YOLOv5, the system achieved a high detection accuracy under various lighting conditions (day and night) and dense traffic scenarios. The SORT algorithm ensures the seamless tracking of vehicles across frames, enabling ac- curate counting and continuous monitoring. Performance Metric: Detection accuracy of 94.2%.
- **Speed Estimation:** The system employs frame-to-frame displacement analysis combined with calibrated scaling factors to estimate the speeds in real-world units. This method proved effective across multiple vehicle categories, maintaining a consistent error margin of ±5%.
- **License Plate Detection and Recognition:** Using YOLOv5 for plate localization and Easy OCR for optical character recognition (OCR), the system accurately identified and decoded license plates, even in cases involving glare, motion blur, or occlusions. Performance Metric: Recognition accuracy of 91.3%.

## V. CONCLUSION

The proposed system represents a significant advancement in traffic monitoring by integrating cutting-edge computer- vision techniques for real-time vehicle counting, speed estimation, and license plate detection. By leveraging well- established algorithms and state-of-the-art deep learning models, the system achieves high performance and reliability in challenging scenarios such as varying lighting conditions, high vehicle densities, and occlusions.

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The combination of YOLOv5 for precise object detection, SORT for real-time and consistent vehicle tracking, and Easy OCR for accurate optical recognition, ensures a comprehensive and scalable solution. These modules work cohesively to address the key challenges in traffic management, including data accuracy, system scalability, and real-time performance.

This system is not only robust but also versatile, making it applicable to various use cases, such as traffic flow optimization, law enforcement, and intelligent transportation systems. The high accuracy rates achieved across all metrics, including license plate detection (91.3%) and vehicle tracking (93.8%), underscored the potential of the system for real-world deployment. Additionally, the ±5% error margin in speed estimation further highlights its precision and practical utility. Future work could explore the integration of additional functionalities such as vehicle classification by type, detection of traffic violations, and predictive traffic flow analytics. Enhancing the system with cloud-based deployment and edge- computing capabilities could further improve scalability and performance in large-scale implementations.

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