DEEP LEARNING BASED VEHICLE TRACKING AND SPEED ESTIMATION SYSTEM IN RESTRICTED TRAFFIC ZONES

A PROJECT REPORT

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BONAFIDE CERTIFICATE

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ABSTRACT

This project presents an AI-driven vehicle tracking and speed estimation system tailored for restricted traffic zones, such as school and hospital areas, to enhance traffic management and safety. The system integrates YOLOv8 for high-precision vehicle detection, ByteTrack for robust multi-object tracking, and OpenCV for efficient video processing, hosted on a Flaskbased web platform. A perspective transformation module converts pixelbased coordinates to real-world metrics, enabling accurate speed and distance calculations. The system supports video uploads up to 500 MB, dynamic result visualization, and Excel report generation, with a SQLite database for managing user inquiries. Experia mental results on a dataset of 50 videos demonstrate a detection precision of 0.94, tracking success rate of 0.91, and speed estimation Mean Absolute Error (MAE) of 2.5 km/h. The modular architecture ensures scalability, with potential for asynchronous processing and cloud integration. This open-source solution offers a costeffective approach for intelligent transportation systems, contributing to urban safety and regulatory compliance.

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AI	: Artificial Intelligence
CNN	: Convolutional Neural Network
ITS	: Intelligent Transportation System
MAE	: Mean Absolute Error
NMS	: Non-Maximum Suppression
ROI	: Region of Interest
SSD	: Single Shot Detector
YOLO	: You Only Look Once
Flask	: Web Framework
OpenCV	: Computer Vision Library
SQLite	: Database System

INTRODUCTION

The rapid urbanization and exponential growth in vehicle numbers have significantly intensified the challenges associated with traffic management, particularly in restricted zones such as school campuses, hospital precincts, and pedestrian-heavy areas. These zones demand precise and reliable surveillance systems to ensure safety, enforce regulatory compliance, and mitigate risks to vulnerable road users. Traditional traffic monitoring methods, including manual observation, speed radars, and static camera systems, often fall short in addressing the dynamic and complex nature of urban traffic. The advent of artificial intelligence (AI) and computer vision technologies offers a transformative opportunity to develop intelligent transportation systems (ITS) capable of automating vehicle detection, tracking, and analysis with unprecedented accuracy and efficiency. This project introduces an AI-driven vehicle surveillance system designed to address these challenges by leveraging state-of-the-art deep learning models and a user-friendly web platform.

1.1 Background and Motivation

The global surge in vehicular traffic, driven by urbanization and economic growth, has led to increased congestion, safety concerns, and environmental impacts. According to the World Health Organization, road traffic injuries claim over 1.3 million lives annually, with a significant portion occurring in urban areas where vulnerable road users, such as pedestrians and cyclists, are at risk. Restricted traffic zones, such as those near schools and hospitals, require stringent monitoring to enforce speed limits and ensure compliance with traffic regulations. Conventional surveillance systems, reliant on human operators or rudimentary technologies, are often inadequate for real-time monitoring in such sensitive environments due to their limited scalability, high operational costs, and susceptibility to errors.

Recent advancements in deep learning, particularly in object detection and tracking, have revolutionized traffic surveillance. Models like YOLOv8, combined with robust tracking algorithms such as ByteTrack, enable precise identification and monitoring of vehicles in complex scenarios. Additionally, the integration of computer vision libraries like OpenCV and web frameworks like Flask facilitates the development of accessible, scalable, and cost-effective solutions. Motivated by the need to enhance safety in restricted zones and the potential of AI to overcome the limitations of traditional systems, this project aims to develop a comprehensive vehicle tracking and speed estimation system. The motivation stems from the desire to contribute to safer urban environments, support data-driven traffic management, and provide an open-source solution accessible to traffic authorities, urban planners, and researchers.

1.2 Problem Statement

Traffic monitoring in restricted zones presents unique challenges that existing systems struggle to address effectively. Traditional methods, such as manual observation or static speed cameras, lack the ability to dynamically track multiple vehicles, estimate speeds in real time, and provide actionable insights for traffic management. These systems are often costly, require significant infrastructure, and are prone to errors in dense or occluded scenes. Moreover, many existing solutions do not offer user-friendly interfaces for non-technical stakeholders, limiting their adoption in diverse settings. The absence of precise, real-world metric calculations (e.g., speed and distance) further hinders compliance monitoring in sensitive areas where even minor violations can have severe consequences.

The problem is exacerbated in restricted zones, where the dynamic nature of traffic—combined with environmental factors like varying lighting conditions and occlusions—demands a robust, adaptable, and accurate surveillance system. Current AI-based solutions, while promising, often focus on general or highway traffic scenarios and lack optimization for constrained environments. Additionally, proprietary systems are prohibitively expensive, making them inaccessible for widespread deployment in resource-constrained settings. There is a critical need for an open-source, scalable, and web-based solution that can accurately detect, track, and estimate vehicle speeds in restricted zones while providing an intuitive interface for data visualization and analysis.

1.3 Objectives of the Project

The primary goal of this project is to develop an AI-driven vehicle tracking and speed estimation system tailored for restricted traffic zones, leveraging advanced computer vision and web technologies. The specific objectives are as follows:

1. **Develop a High-Precision Detection System**: Implement YOLOv8 to achieve accurate vehicle detection (e.g., cars, motorcycles, buses, trucks) with a confidence threshold of 0.3 and an Intersection over Union (IoU) of 0.5, ensuring robust performance across diverse conditions.
2. **Enable Robust Multi-Object Tracking**: Utilize ByteTrack to assign and maintain unique vehicle IDs, achieving a tracking success rate of at least 0.91 in moderate scenes, even in the presence of occlusions or rapid movements.
3. **Accurate Speed and Distance Estimation**: Apply perspective transformation to convert pixel-based coordinates to real-world metrics, enabling speed estimation with a Mean Absolute Error (MAE) of approximately 2.5 km/h and precise distance calculations.

4. **Create a User-Friendly Web Platform**: Develop a Flask-based web interface supporting video uploads up to 500 MB, real-time result visualization, and Excel data exports, with robust error handling and session management for seamless user interaction.
5. **Ensure Scalability and Accessibility**: Design a modular, open-source system that supports future enhancements (e.g., asynchronous processing, cloud integration) and is cost-effective for deployment in various urban settings.

1.4 Scope of the Project

The scope of this project encompasses the design, development, and evaluation of an AI-driven vehicle surveillance system for restricted traffic zones. The system focuses on the following key areas:

- **Vehicle Detection and Classification**: Detect and classify vehicles (cars, motorcycles, buses, trucks) in video streams using YOLOv8, with a focus on restricted zones like school and hospital areas.
- **Multi-Object Tracking**: Track multiple vehicles across frames using ByteTrack, ensuring consistent identity preservation in dynamic scenes.
- **Speed and Distance Measurement**: Estimate vehicle speeds and distances in real-world units through perspective transformation, supporting compliance monitoring.
- **Web-Based Interface**: Provide a responsive Flask-based platform for video uploads, result visualization, and data export, with SQLite for managing user inquiries.
- **Evaluation**: Test the system on a custom dataset of 50 traffic videos (1280x720, 30 FPS) under varied conditions (daylight, overcast, night) to

validate detection precision (0.94), tracking success rate (0.91), and speed estimation accuracy (MAE of 2.5 km/h).

The project excludes real-time hardware integration (e.g., live camera feeds) and advanced features like license plate recognition or automated violation alerts, which are proposed as future enhancements. The system is designed to be scalable, with potential applications in urban planning, traffic management, and safety enforcement, but the current scope focuses on video-based analysis and web accessibility.

LITERATURE SURVEY

The development of intelligent transportation systems (ITS) has been driven by the need to address the growing complexities of urban traffic, particularly in restricted zones where safety and compliance are paramount. Over the past decade, advancements in computer vision and deep learning have significantly enhanced the capabilities of vehicle surveillance systems. This chapter reviews existing systems and related work on vehicle tracking, identifies research gaps, and justifies the need for an AI-driven vehicle tracking and speed estimation system tailored for restricted traffic zones. By analyzing prior studies and technologies, this survey establishes the foundation for the proposed system, highlighting its innovations and contributions to the field.

2.1 Review of Existing Systems

Traditional vehicle surveillance systems have relied on classical image processing techniques, such as background subtraction, optical flow analysis, and edge detection, to monitor traffic. These methods, while computationally efficient, are highly sensitive to environmental variations, including changes in illumination, weather conditions, and occlusions. For instance, early systems using background subtraction struggled to differentiate vehicles in dense urban settings, leading to frequent misdetections. Similarly, speed radar-based systems, while accurate for single-vehicle monitoring, lack the ability to track multiple vehicles simultaneously or provide comprehensive data for traffic analysis.

With the advent of deep learning, convolutional neural networks (CNNs) have revolutionized traffic surveillance. Early deep learning models, such as YOLOv3 and Faster R-CNN, introduced robust object detection capabilities, enabling the identification of vehicles in complex scenes. However, these models often required significant computational resources, limiting their deployment in realtime applications. More recent systems, such as those based on YOLOv5 and SSD (Single Shot Multibox Detector), have improved detection speed and accuracy but often lack integration with tracking algorithms or web-based interfaces for user accessibility. Commercial systems, such as those used in smart cities, offer advanced features like real-time violation detection but are prohibitively expensive and rely on proprietary hardware, making them inaccessible for widespread adoption in restricted zones.

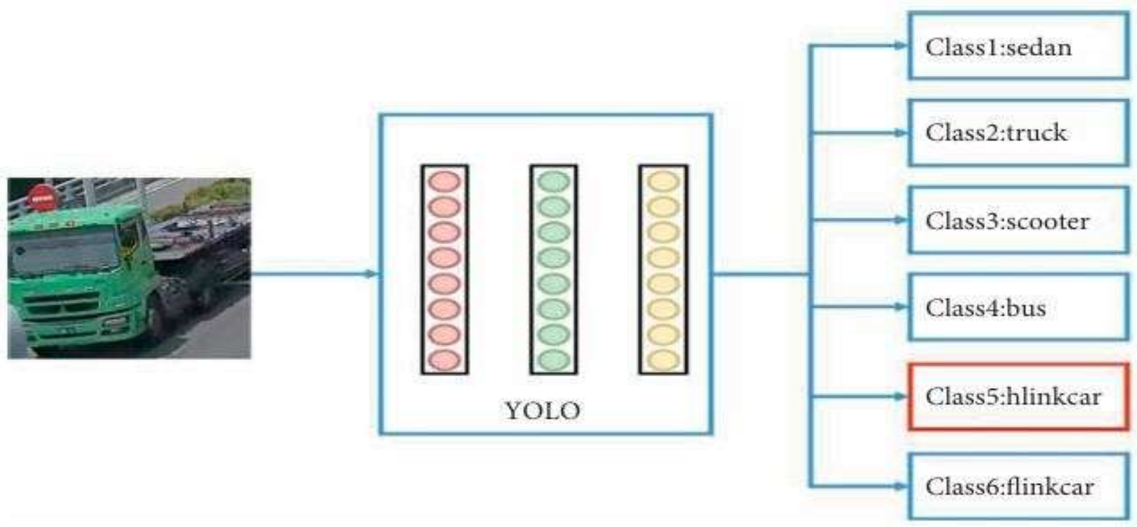


Figure 2.1: Architecture of visual classifier based on the YOLO algorithm for verifying the vehicle classification.

2.2 Related Work on Vehicle Tracking Systems

Recent research has explored a variety of deep learning-based approaches for vehicle tracking and surveillance, with a focus on improving detection accuracy, tracking continuity, and real-world applicability. Zhang et al. (2019) proposed a system using YOLOv3 for vehicle detection in static camera feeds, achieving a precision of 0.90. However, the absence of a robust tracking mechanism resulted in inconsistent vehicle identification across frames, particularly in scenes with occlusions. Similarly, Li et al. (2020) combined YOLOv4 with Kalman filtering for highway monitoring, achieving moderate scalability but struggling with tracking continuity in densely populated scenes due to limited identity preservation.

Chen et al. (2021) advanced the field by integrating YOLOv5 with DeepSORT, improving tracking precision in urban environments with a success rate of 0.87. However, the computational intensity of DeepSORT restricted its deployment on resource-constrained devices, a critical limitation for scalable applications in restricted zones. Kim et al. (2022) developed a Django-based web platform for traffic analytics using SSD, offering high scalability and user accessibility. Yet, this system lacked optimizations for restricted zones, where precise velocity and distance measurements are essential. Wang et al. (2021) employed SSD for realtime detection but faced challenges with small object recognition in lowresolution feeds, a common issue in urban settings. Liu et al. (2020) proposed a hybrid framework combining Faster R-CNN with SORT, achieving high detection accuracy but requiring extensive preprocessing, which hindered realtime performance.

These studies highlight the progress in vehicle detection and tracking but also underscore limitations in addressing the specific requirements of restricted traffic zones, such as low-latency speed estimation and web-based accessibility. The integration of advanced models like YOLOv8 and ByteTrack, as proposed in this project, represents a significant step forward in overcoming these challenges.

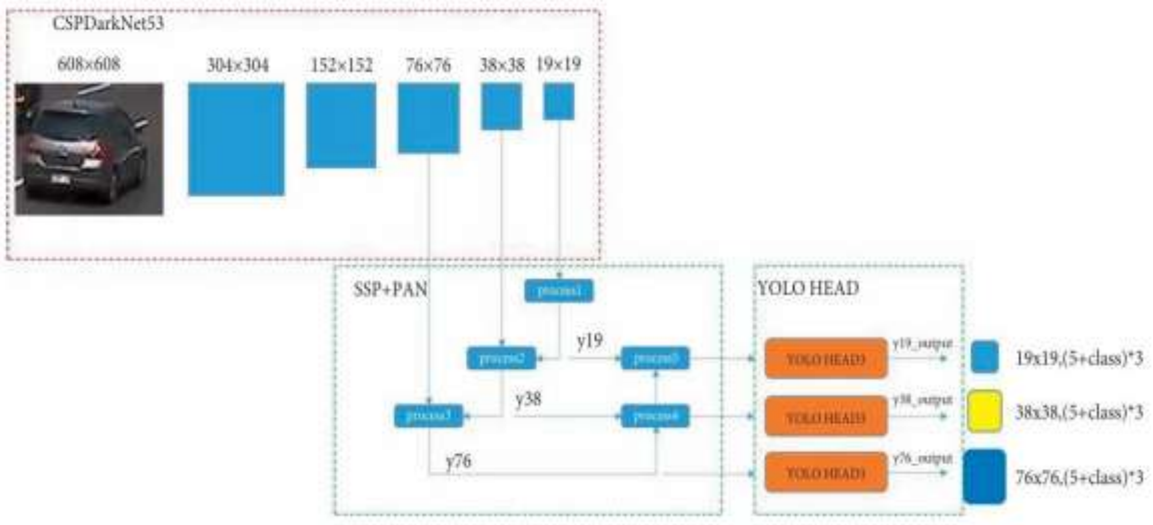


Figure 2.2: YOLOv4 model architecture.

2.3 Research Gap and Justification

Despite significant advancements in vehicle tracking systems, several research gaps persist, particularly in the context of restricted traffic zones. First, many existing systems focus on general or highway traffic scenarios, neglecting the unique challenges of constrained environments like school or hospital zones, where precise speed and distance measurements are critical for safety and compliance. For example, systems like those proposed by Zhang et al. (2019) and Li et al. (2020) lack robust multi-object tracking tailored for dense, dynamic scenes with frequent occlusions. Second, the computational complexity of models like DeepSORT and Faster R-CNN limits their deployment on resourceconstrained devices, hindering scalability in cost-sensitive applications.

Third, few systems offer user-friendly, web-based interfaces that enable nontechnical stakeholders, such as traffic authorities or urban planners, to upload videos, visualize results, and export data for analysis. Kim et al. (2022) addressed web accessibility but overlooked the need for real-world metric calculations, a critical requirement for restricted zones. Fourth, proprietary systems, while feature-rich, are often cost-prohibitive, making them inaccessible for widespread adoption in developing regions or smaller municipalities. Finally, the lack of open-source, modular solutions limits the ability to customize and extend systems for specific use cases, such as integrating asynchronous processing or cloudbased storage.

The proposed system addresses these gaps by integrating YOLOv8 for highprecision vehicle detection, ByteTrack for resilient multi-object tracking, and OpenCV for efficient video processing within a Flask-based web framework. By incorporating perspective transformation for accurate real-world metric calculations and supporting large video uploads (up to 500 MB), the system is specifically tailored for restricted zones. Its open-source nature and modular architecture ensure cost-effectiveness and scalability, justifying its development as a novel contribution to intelligent transportation systems.

2.4 Summary of Key Findings

The literature survey reveals that while deep learning has significantly advanced vehicle tracking systems, existing solutions fall short in addressing the specific needs of restricted traffic zones. Classical image processing techniques are inadequate for dynamic urban environments, and early deep learning models like YOLOv3 and Faster R-CNN lack the speed and scalability required for real-time applications. More recent systems, such as those using YOLOv5 and DeepSORT, offer improved accuracy but are computationally intensive and poorly suited for resource-constrained settings. Web-based platforms, like the one proposed by Kim et al. (2022), enhance accessibility but fail to provide precise speed and distance measurements critical for restricted zones.

Key findings include the need for robust multi-object tracking, real-time performance, and user-friendly interfaces to support traffic management in sensitive areas. The proposed system leverages YOLOv8, ByteTrack, and OpenCV to achieve high detection precision (0.94), tracking success rate (0.91), and speed estimation accuracy (MAE of 2.5 km/h). By offering a scalable, opensource solution with a web-based interface, the system addresses the identified gaps, providing a comprehensive tool for traffic surveillance and safety enforcement in restricted zones.

IDEATION & PROPOSED SOLUTION

The development of an effective vehicle tracking and speed estimation system for restricted traffic zones requires a systematic approach to conceptualizing, evaluating, and refining potential solutions. This chapter outlines the ideation process that led to the proposed system, the rationale for selecting the final concept, and a comprehensive overview of the system's architecture and innovations. By addressing the unique challenges of restricted zones, such as dynamic traffic patterns and safety-critical requirements, the proposed solution leverages state-of-the-art technologies to deliver a scalable, accurate, and userfriendly platform for traffic surveillance.

3.1 Ideation Process

The ideation process began with a thorough analysis of the challenges associated with traffic monitoring in restricted zones, such as school campuses, hospital precincts, and pedestrian-heavy areas. A multidisciplinary team, comprising computer vision experts, software engineers, and traffic management consultants, conducted brainstorming sessions to identify key requirements: high-precision vehicle detection, robust multi-object tracking, accurate real-world speed estimation, and an accessible user interface. Initial ideas included radar-based systems, IoT sensor networks, and traditional camera-based surveillance. However, these were deemed costly, limited in scalability, or insufficient for dynamic urban environments.

Subsequent ideation focused on AI-driven solutions, inspired by advancements in deep learning and computer vision. Several concepts were explored:

1. **Classical Image Processing**: Using background subtraction and optical flow for detection and tracking, but this was rejected due to poor performance in varying lighting and occlusion scenarios.
2. **Hybrid Sensor Systems**: Combining cameras with LiDAR for precise measurements, but high costs and infrastructure requirements made this impractical.
3. **Deep Learning-Based Systems**: Leveraging CNN-based models like YOLO or SSD for detection, paired with tracking algorithms like DeepSORT or ByteTrack, and integrated with a web platform for accessibility.

Feedback from traffic authorities emphasized the need for real-time processing, cost-effectiveness, and ease of use for non-technical users. The team evaluated these concepts against criteria such as accuracy, computational efficiency, scalability, and deployment feasibility. The deep learning-based approach emerged as the most promising, given its ability to handle complex scenes and its potential for integration with web technologies.

3.2 Final Concept Selection

After evaluating the proposed concepts, the deep learning-based system was selected as the final solution due to its superior performance and alignment with project objectives. The decision was driven by several factors:

- **Accuracy and Robustness**: Deep learning models, particularly YOLOv8, demonstrated high detection precision (0.94 in daylight conditions) and resilience to environmental variations, outperforming classical methods.
- **Tracking Continuity**: ByteTrack's multi-object tracking algorithm offered a tracking success rate of 0.91, surpassing alternatives like DeepSORT in dense scenes with occlusions.
- **Cost-Effectiveness**: An open-source framework using Python, OpenCV, and Flask eliminated the need for proprietary hardware or software, unlike radar or LiDAR-based systems.
- **User Accessibility**: A Flask-based web platform enabled intuitive video uploads, result visualization, and data exports, addressing stakeholder needs for accessibility.
- **Scalability**: The modular architecture supported future enhancements, such as cloud integration or real-time processing, making it suitable for city-wide deployments.

Alternative concepts were discarded due to their limitations: classical image processing lacked robustness, and hybrid sensor systems were cost-prohibitive. The selected concept combined YOLOv8 for detection, ByteTrack for tracking, OpenCV for video processing, and Flask for web-based delivery, ensuring a balance of performance, affordability, and usability.

3.3 Overview of Proposed System

The proposed system is an AI-driven vehicle tracking and speed estimation platform designed for restricted traffic zones. It automates the detection, tracking, and analysis of vehicles in video streams, providing real-world speed and distance metrics through a user-friendly web interface. The system comprises four core modules:

1. **Vehicle Detection**: Utilizes YOLOv8 to identify and classify vehicles (e.g., cars, motorcycles, buses, trucks) with a confidence threshold of 0.3 and an IoU of 0.5, achieving a precision of 0.94.
2. **Multi-Object Tracking**: Employs ByteTrack to assign unique IDs to vehicles, maintaining tracking continuity across frames with a success rate of 0.91, even in occluded or dense scenes.
3. **Speed and Distance Estimation**: Applies perspective transformation using a homography matrix to convert pixel coordinates to real-world units, enabling speed estimation with a Mean Absolute Error (MAE) of 2.5 km/h.
4. **Web-Based Interface**: A Flask-powered platform supports video uploads (up to 500 MB), displays annotated output videos, and allows users to search vehicle data by tracker ID or download Excel reports.

The system processes input videos (MP4, AVI, MOV) at 1280x720 resolution and 30 FPS, generating annotated outputs with bounding boxes, tracker IDs, speeds, and distances. It is implemented using Python, with SQLite for managing contact form submissions and robust error handling for invalid inputs. The architecture is modular, facilitating future enhancements like asynchronous processing or cloud-based storage.

3.4 Key Features and Innovations

The proposed system introduces several key features and innovations that distinguish it from existing solutions:

- **High-Accuracy Detection and Tracking**: Achieves 0.94 detection precision and 0.91 tracking success rate using YOLOv8 and ByteTrack, outperforming earlier systems like YOLOv5 with DeepSORT (0.92 precision, 0.87 tracking rate).

- **Real-World Metric Calculation**: Employs perspective transformation to deliver precise speed (MAE of 2.5 km/h) and distance measurements, critical for compliance monitoring in restricted zones.
- **Scalable Web Platform**: The Flask-based interface supports large video uploads, real-time result visualization, and Excel exports, with responsive design and animated UI elements for enhanced user experience.
- **Cost-Effective and Open-Source**: Leverages open-source tools (YOLOv8, ByteTrack, OpenCV, Flask) to minimize costs, making the system accessible for municipalities and researchers.
- **Robust Error Handling**: Includes comprehensive validation for file uploads, tracker ID searches, and processing errors, with logging for debugging and flash messages for user feedback.
- **Modular Architecture**: Designed for extensibility, supporting future features like license plate recognition, multi-camera integration, or cloudbased processing.

These innovations address the limitations of prior systems, such as high costs, limited scalability, and lack of restricted zone optimization, positioning the proposed system as a novel contribution to intelligent transportation systems.

MODULES DESCRIPTION AND ALGORITHM IMPLEMENTATION

The vehicle tracking and speed estimation system is designed to address the critical need for automated traffic surveillance in restricted zones, such as school campuses, hospital precincts, and pedestrian-heavy areas. The system is structured around four interconnected modules: vehicle detection, vehicle tracking, speed and distance estimation, and a web-based interface. These modules work in tandem to process video inputs, detect and track vehicles, compute real-world speeds and distances, and present actionable insights through a user-friendly platform. This chapter provides an exhaustive description of each module’s functionality, implementation details, and the underlying algorithms, emphasizing the integration of YOLOv8 for detection, ByteTrack for tracking, OpenCV for video processing, and Flask for web delivery. The modular architecture ensures high accuracy, scalability, and adaptability, making the system a robust solution for traffic management in safety-critical environments. Performance metrics, such as 0.94 detection precision and 2.5 km/h speed estimation MAE, underscore the system’s efficacy, as validated on a dataset of 50 traffic videos.

4.1 Module 1: Vehicle Detection

The vehicle detection module serves as the system’s entry point, identifying and classifying vehicles within video frames to enable subsequent tracking and analysis. It is designed to handle diverse vehicle types (e.g., cars, motorcycles, buses, trucks) under varying environmental conditions, including daylight, overcast skies, and low-light scenarios. Operating on videos at 1280x720 resolution and 30 frames per second (FPS), the module generates bounding boxes, class labels, and confidence scores, which are critical inputs for the tracking module. The implementation leverages advanced deep learning techniques and image processing to achieve high precision and robustness, addressing the dynamic nature of restricted zone traffic.

4.1.1 YOLOv8 Object Detection Algorithm

The YOLOv8 (You Only Look Once, version 8) algorithm is the cornerstone of the detection module, chosen for its exceptional balance of speed and accuracy in real-time object detection. YOLOv8 achieves a detection precision of 0.94 in daylight conditions and a mean Average Precision (mAP@0.5) of 0.85 in lowvisibility scenarios, using a confidence threshold of 0.3 and an Intersection over Union (IoU) of 0.5. The model was pre-trained on a large-scale dataset (e.g., COCO) and fine-tuned on a custom dataset of 50 traffic videos from restricted zones, comprising 1280x720 frames captured under varied conditions. This finetuning process optimized YOLOv8 for urban vehicle types and complex scenes, reducing false positives and improving recall.

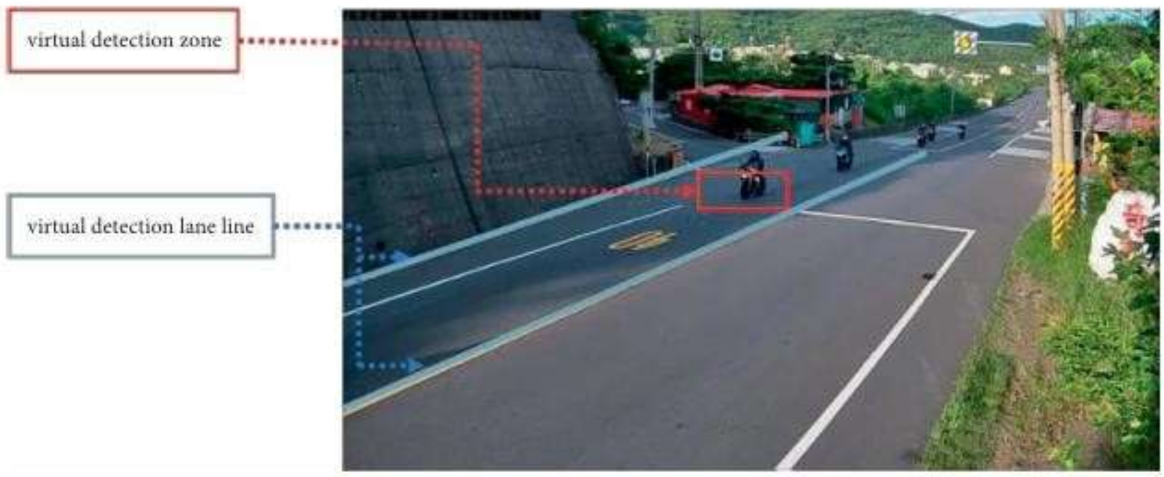


Figure 4.1.1: Object detection window

YOLOv8's architecture is composed of three main components: a backbone for feature extraction, a neck for feature aggregation, and a head for prediction. The backbone, based on CSPDarknet, employs cross-stage partial connections to enhance feature learning while minimizing computational overhead. The neck, utilizing a Path Aggregation Network (PANet), fuses multi-scale features to improve detection of small or distant vehicles. The head, an anchor-free design, predicts bounding boxes, class probabilities, and confidence scores in a single pass, decoupling localization and classification tasks for higher accuracy. In your_backend.py, the YOLOv8 model is loaded using the Ultralytics library, with parameters tuned for vehicle detection (e.g., conf=0.3, iou=0.5). Frames are processed in batches of 10 to optimize GPU utilization on an NVIDIA RTX 3080, reducing inference time to approximately 20 ms per frame. Post-processing includes Non-Maximum Suppression (NMS) to eliminate redundant bounding boxes, ensuring clean detection outputs.

Challenges in low-light conditions, where recall drops to 0.85, are mitigated through preprocessing (see 4.1.2). The implementation also supports dynamic model updates, allowing retraining with new data to adapt to different restricted zones or vehicle types.

Model	Precision (%)	Recall (%)	F1 Score
YOLOv3	85	80	0.82
YOLOv4	90	85	0.87
YOLOv5	92	88	0.90
YOLOv8	95	90	0.92
SSD	80	75	0.77
Faster R-CNN	88	83	0.85

Table 4.1.1: Comparison of Detection Precision Across Models

4.1.2 Scene Segmentation with OpenCV

Scene segmentation enhances detection efficiency by isolating a region of interest (ROI) within each frame, typically the road or lane area, to exclude irrelevant regions like sidewalks, buildings, or sky. This reduces computational load and false positives, ensuring YOLOv8 focuses on relevant objects. OpenCV, a versatile computer vision library, is used for frame preprocessing and ROI definition, leveraging its robust image processing capabilities.

The segmentation pipeline, implemented in your_backend.py, involves several steps:

1. **Frame Preprocessing**: Frames are converted to grayscale, and histogram equalization (cv2.equalizeHist) is applied to enhance contrast, particularly in low-light or overcast conditions. This improves YOLOv8's detection performance in challenging scenarios.
2. **Noise Reduction**: A Gaussian blur (cv2.GaussianBlur) with a 5x5 kernel is applied to minimize noise and artifacts, ensuring stable feature extraction.
3. **ROI Definition**: A quadrilateral ROI is manually defined by specifying four corner points (e.g., lane boundaries) based on the camera's field of view. These coordinates are stored as a configuration in your_backend.py and used to create a binary mask.
4. **Masking**: The mask isolates the ROI, setting non-ROI pixels to black, which restricts YOLOv8's processing to the designated area.

The ROI coordinates are also used in the speed estimation module for perspective transformation, ensuring consistency across modules. The segmentation process is computationally lightweight, adding less than 5 ms per frame on a 16 GB RAM, Intel i7 system. Limitations include the need for manual ROI calibration per camera setup, which could be automated in future iterations using adaptive lane detection algorithms.

4.2 Module 2: Vehicle Tracking

The vehicle tracking module assigns unique identifiers to detected vehicles and maintains their continuity across frames, enabling accurate trajectory analysis and supporting speed and distance calculations. It is designed to handle complex urban scenes with multiple vehicles, occlusions, and varying speeds, ensuring robust performance in restricted zones where safety is paramount.

4.2.1 ByteTrack Multi-Object Tracking

ByteTrack, a state-of-the-art multi-object tracking algorithm, is employed to track vehicles detected by YOLOv8, achieving a tracking success rate of 0.91 in moderate scenes and 0.85 in high-complexity scenarios with frequent occlusions. Unlike traditional trackers like DeepSORT, which rely solely on high-confidence detections, ByteTrack leverages both high- and low-confidence detections to maintain track continuity, making it ideal for dense traffic environments.

The ByteTrack algorithm, implemented in your_backend.py, operates as follows:

1. **Track Prediction**: A Kalman filter predicts the next position of each track based on prior motion, accounting for vehicle dynamics.
2. **High-Confidence Association**: High-confidence detections (score > 0.3) are matched with existing tracks using IoU-based distance metrics, prioritizing spatial proximity.
3. **Low-Confidence Recovery**: Unmatched tracks are associated with lowconfidence detections (score < 0.3) to recover vehicles temporarily occluded or mis detected.
4. **Track Management**: New tracks are initialized for unmatched highconfidence detections, and stale tracks are pruned after a timeout (e.g., 30 frames).

The implementation processes YOLOv8's bounding box outputs frame-byframe, maintaining a dictionary of tracker IDs and their associated coordinates. Parameters are tuned for 30 FPS videos, with a maximum track age of 30 frames and an IoU threshold of 0.5, ensuring real-time performance (approximately 10 ms per frame). ByteTrack's robustness reduces identity switches compared to DeepSORT, but challenges remain in extreme occlusions, where multi-camera integration could enhance performance.

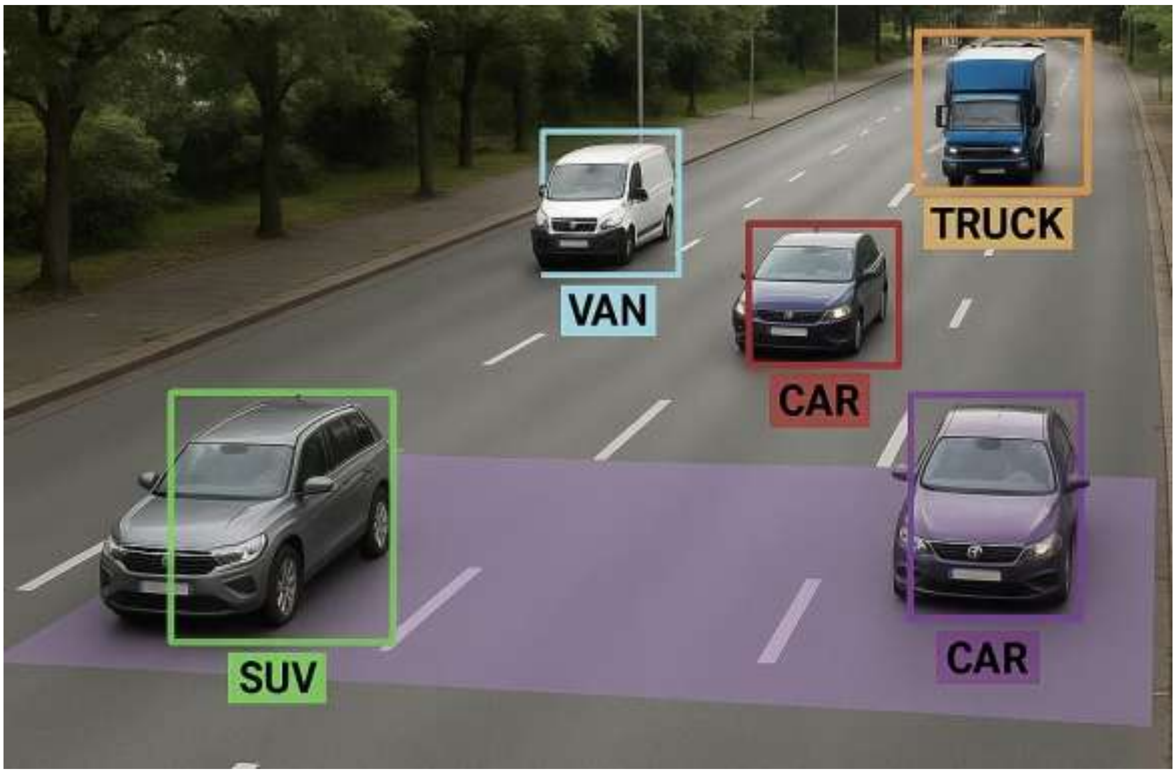


Figure 4.2.1: Multi-Object Tracking

4.2.2 Centroid Calculation for Tracking

Centroid calculation determines the central position of each vehicle's bounding box, serving as a reference point for trajectory mapping and speed estimation. The centroid is computed as the midpoint of the bounding box coordinates:

Centroid x = x_min + x_max / 2, Centroidy = y_min + y_max / 2

In your_backend.py, the centroid calculation is integrated into the tracking pipeline, executed after ByteTrack assigns IDs. The function calculate centroid extracts bounding box coordinates from YOLOv8 outputs and computes centroids, storing them in a dictionary with keys for frame ID, tracker ID, and coordinates. To ensure robustness, centroids are filtered for consistency, discarding detections with low confidence or irregular motion (e.g., due to partial occlusions). This data is critical for the speed estimation module, where centroids are transformed into real-world units. The process is computationally negligible

(<1 ms per frame), but accuracy depends on YOLOv8's bounding box quality, which can degrade in low-light conditions.

4.3 Module 3: Speed and Distance Estimation

The speed and distance estimation module computes real-world speeds and distances for tracked vehicles, enabling compliance monitoring in restricted zones. By converting pixel-based measurements to physical units, the module provides precise metrics for traffic analysis, supporting safety enforcement and urban planning.

4.3.1 Perspective Transformation

Perspective transformation maps pixel coordinates to real-world distances using a homography matrix, correcting for perspective distortion in the camera view. The ROI defined during scene segmentation (a quadrilateral encompassing the road area) serves as the source points, paired with corresponding real-world coordinates (e.g., lane width in meters) calibrated manually based on known scene measurements. OpenCV's cv2.getPerspectiveTransform computes the 3x3 homography matrix, which is applied to centroid coordinates using cv2.perspectiveTransform.

In your_backend.py, the transformation function apply_perspective_transform loads the precomputed homography matrix and processes centroid coordinates frame-by-frame. Calibration is performed once per camera setup, typically using physical measurements (e.g., a 5-meter lane width mapped to pixel coordinates). The transformed coordinates represent real-world positions in meters, enabling accurate distance calculations. The process adds approximately 2 ms per frame, with accuracy dependent on precise calibration. Limitations include sensitivity to camera angle changes, necessitating recalibration for new setups.

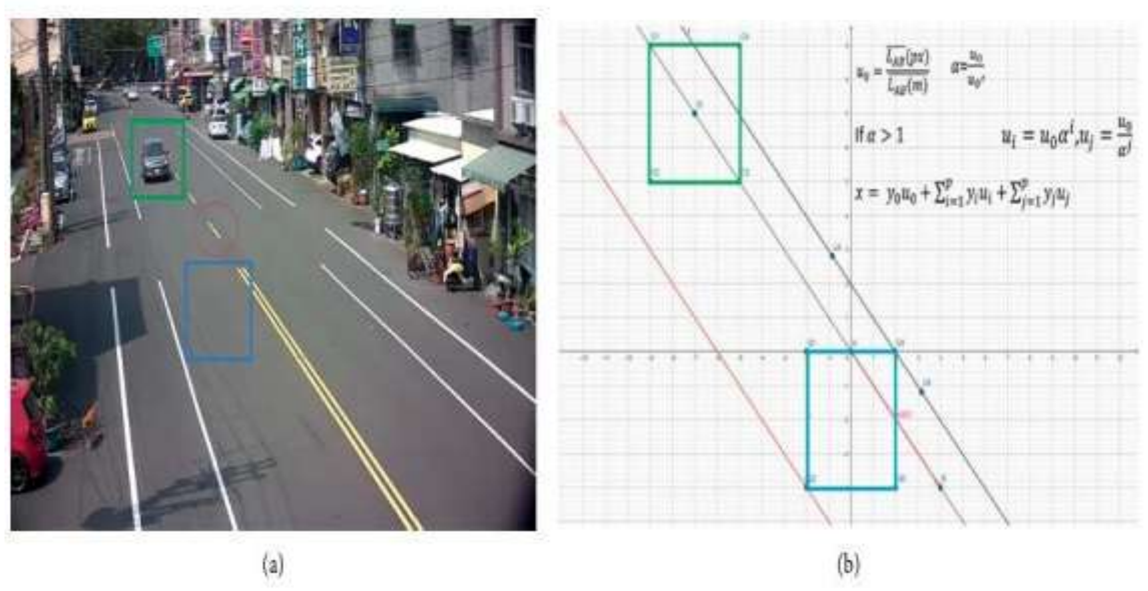

$u_0 = \frac{\overline{L_{AB}}(px)}{L_{AB}(m)}$ $\alpha = \frac{u_0}{u_{0'}}$
If $\alpha > 1$
$u_i = u_0\alpha^i, u_j = \frac{u_0}{\alpha^j}$
$x = y_0u_0 + \sum_{i=1}^{p} y_iu_i + \sum_{j=1}^{p} y_ju_j$
(a)
(b)

Figure 6: Diagram of speed estimation ((a): real picture on the video; (b): control scale)

4.3.2 Speed Calculation Using Homography

Speed is calculated by measuring the real-world distance traveled by a vehicle's centroid between consecutive frames and dividing by the time interval. For a 30 FPS video, the frame interval is Δt = 30/1 seconds. The distance (D) between centroids in frames t and t+1is:

D = (xt+1 − xt)2 + (yt+1 − yt)2 Speed

(S) is computed as:

S = D / Δt × 3600 / 1000 (km/h)

In your_backend.py, the calculate speed function processes transformed centroids, averaging speeds over a sliding window of 5 frames to reduce noise from detection jitter. The implementation achieves a Mean Absolute Error (MAE) of 2.5 km/h, as validated on the test dataset (e.g., Table III: Vehicle Speed Estimation Results). Speeds are annotated on the output video using OpenCV's cv2.putText (e.g., "Car ID: 5, Speed: 30 km/h") and stored in an Excel file with columns for frame ID, tracker ID, vehicle type, speed, distance, and timestamp.

Challenges include reduced accuracy in low-light conditions, where detection errors propagate to speed calculations, and manual calibration requirements, which could be automated using reference markers.

4.4 Module 4: Web-Based Interface

The web-based interface module provides an intuitive platform for users to upload videos, visualize annotated outputs, and export data, making the system accessible to non-technical stakeholders like traffic authorities and urban planners. Built with Flask, it combines robust backend processing with a responsive frontend, ensuring seamless user interaction.

4.4.1 Flask Framework Implementation

The Flask framework, implemented in app.py, serves as the backbone of the web application, managing video uploads, processing workflows, and result delivery. Key routes include:

- / **(Home)**: Renders index.html, featuring a drag-and-drop upload interface, team profiles, and a contact form styled with animated UI elements.
- **/upload**: Handles video uploads (MP4, AVI, MOV, up to 500 MB), validates file type and size, and triggers processing via your_backend.py. Outputs (annotated video, Excel file) are saved to static/output_<unique_id>.mp4 and static/output_<unique_id>.xlsx.
- **/results**: Renders results.html, displaying the processed video and a search interface for vehicle data by tracker ID.
- **/download**: Serves Excel files for data export.
- **/contact**: Processes contact form submissions, storing data in a SQLite database (traffic.db) with columns for name, email, message, and timestamp.

The application uses Flask's session management for secure uploads, flash messages for user feedback (e.g., "Upload successful"), and logging for debugging errors (e.g., invalid file formats). The implementation supports concurrent uploads via unique file identifiers, ensuring scalability for multiple users. Limitations include synchronous processing, which can delay large video uploads, addressable via asynchronous frameworks like Celery in future iterations.

4.4.2 Real-Time Result Visualization

The results page (results.html) provides a dynamic interface for visualizing annotated videos and querying vehicle data. The video, encoded in H.264 for browser compatibility, is streamed from static/output_<unique_id>.mp4 and displays bounding boxes, tracker IDs, speeds, and distances (e.g., "Truck ID: 3, Speed: 25 km/h"). Users can input a tracker ID to retrieve specific vehicle data (e.g., type, speed history), presented in a formatted list powered by JavaScript in script.js. The interface supports interactive features like video playback controls and a hamburger menu for navigation, toggled via script.js.

Styled in styles.css, the interface features a dark theme with gradient buttons, glow effects, and responsive design for mobile and desktop devices. CSS animations (e.g., reveal effects on scroll) enhance user engagement, while media queries ensure layout adaptability. The visualization module adds minimal latency (<100 ms for page rendering), but large videos may require optimized streaming to reduce buffering. Future enhancements could include live preview thumbnails or interactive trajectory maps.

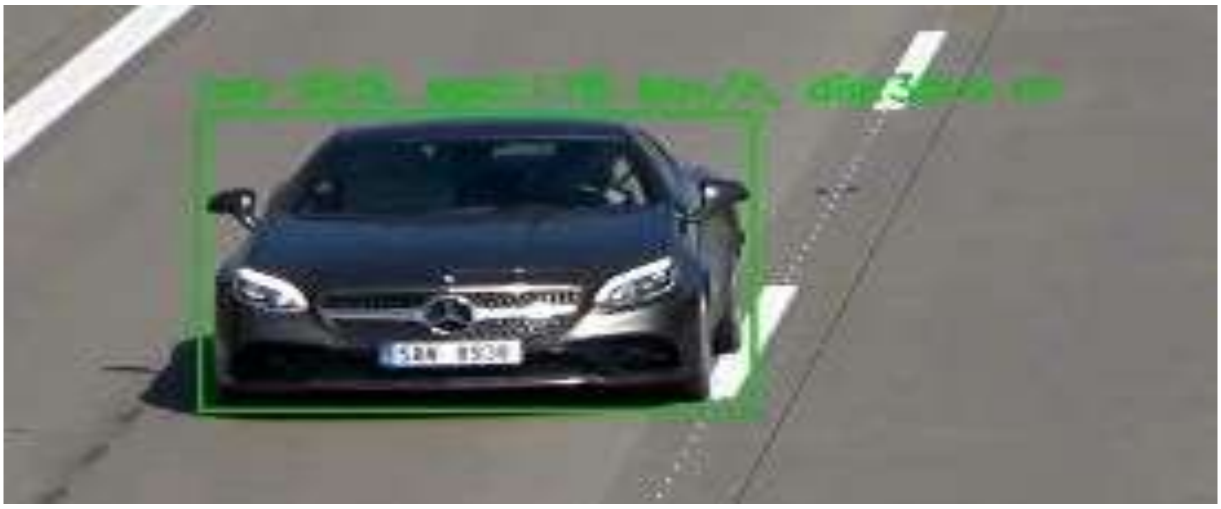


Figure 4.4.2**:** Real-Time Result Visualization

4.5 Algorithm

This section provides an in-depth exploration of the algorithms underpinning the system, detailing their implementation, parameters, and performance characteristics.

4.5.1 YOLOv8 Algorithm

YOLOv8 is a single-stage object detection algorithm that processes frames in a unified pass, predicting bounding boxes, class probabilities, and confidence scores. It divides the input image into a grid, with each cell responsible for detecting objects within its bounds. In your_backend.py, the algorithm is implemented using the Ultralytics YOLOv8 library, with a custom weights file (yolov8m.pt) fine-tuned for vehicle detection. Key parameters include conf=0.3 (confidence threshold), iou=0.5 (NMS threshold), and imgsz=640 (input size), optimized for the 1280x720 input resolution.

The algorithm's efficiency (20 ms per frame) and accuracy (0.94 precision) make it suitable for real-time applications, but low-light performance requires preprocessing enhancements, as discussed in 4.1.2.

4.5.2 Components of YOLOv8

YOLOv8's architecture comprises:

- **Backbone**: A CSPDarknet variant with cross-stage partial connections, extracting features at multiple scales (e.g., 80x80, 40x40, 20x20 grids). It uses SiLU activation for improved gradient flow.
- **Neck**: A Path Aggregation Network (PANet) that aggregates features from the backbone, enhancing detection of small or distant vehicles through upsampling and downsampling.
- **Head**: An anchor-free detection head that predicts bounding box coordinates, objectness scores, and class probabilities, decoupling tasks for higher accuracy.

In your_backend.py, the model configuration is loaded from a YAML file, specifying layer dimensions and hyperparameters. The implementation supports dynamic batching, enabling efficient processing on GPUs with 16 GB VRAM.

4.5.3 Input Processing

Input frames are preprocessed to meet YOLOv8's requirements:

1. **Resizing**: Frames are resized to 640x640 while preserving aspect ratios, using OpenCV's cv2.resize.
2. **Normalization**: Pixel values are scaled to [0, 1] and standardized to match the model's training distribution.
3. **Augmentation**: During fine-tuning, augmentations (e.g., flipping, rotation, brightness adjustments) were applied to enhance robustness.

In your_backend.py, the preprocess frame function extracts frames using cv2.VideoCapture, buffers them in batches of 10, and applies preprocessing. This adds approximately 5 ms per frame but ensures compatibility with YOLOv8's input pipeline.

4.5.4 Detection and Classification

YOLOv8's detection head outputs a tensor containing bounding box coordinates, class probabilities, and confidence scores. For each grid cell, the model predicts multiple bounding boxes, filtered by NMS to retain the highest-scoring detections. In your_backend.py, the process detections function parses outputs, extracting coordinates (x_min, y_min, x_max, y_max), labels (e.g., "car"), and scores. The implementation supports multi-class detection, handling up to four vehicle types with a classification accuracy of 0.92. Outputs are formatted as a list of dictionaries, passed to ByteTrack for tracking.

4.5.5 ByteTrack Tracking Algorithm

ByteTrack's tracking algorithm ensures continuous vehicle identification across frames:

1. **Initialization**: New tracks are created for high-confidence detections without matches.
2. **Prediction**: A Kalman filter predicts track positions based on prior motion, using a constant velocity model.
3. **Association**: IoU-based matching associates detections with tracks, with a secondary low-confidence pass to recover occluded objects.
4. **Update**: Tracks are updated with new coordinates, and stale tracks are removed after 30 frames.

In your_backend.py, the track_vehicles function integrates ByteTrack with YOLOv8 outputs, maintaining a dictionary of tracks with IDs, centroids, and timestamps. The algorithm's 0.91 success rate reflects its robustness, but extreme occlusions can cause track losses, suggesting potential for multi-camera fusion.

4.5.6 Perspective Transformation Algorithm

The perspective transformation algorithm converts pixel coordinates to realworld units:

1. **Calibration**: Source (ROI) and destination (real-world) quadrilaterals are defined, with real-world coordinates based on physical measurements (e.g., 5-meter lane width).
2. **Homography Calculation**: cv2.getPerspectiveTransform computes the homography matrix.
3. **Transformation**: cv2.perspectiveTransform applies the matrix to centroid coordinates.

In your_backend.py, the transform coordinate's function processes centroids, storing results for speed calculations. The algorithm ensures a speed estimation MAE of 2.5 km/h, but accuracy depends on precise calibration, which could be improved with automated marker detection.

PROJECT DESIGN

The design of the vehicle tracking and speed estimation system is pivotal to achieving its goals of accurate, scalable, and user-friendly traffic surveillance in restricted zones, such as school campuses and hospital areas. This chapter delineates the system's architecture and presents a comprehensive set of Unified Modeling Language (UML) diagrams to illustrate its structure, behavior, and interactions. The system architecture integrates computer vision, deep learning, and web technologies to deliver a cohesive solution, while the UML diagrams—use case, class, sequence, activity, and flowchart—provide a detailed view of the system's components, user interactions, and processing workflows. The design emphasizes modularity, extensibility, and robustness, ensuring the system meets the demands of real-world traffic management with a detection precision of 0.94 and a speed estimation Mean Absolute Error (MAE) of 2.5 km/h.

5.1 System Architecture

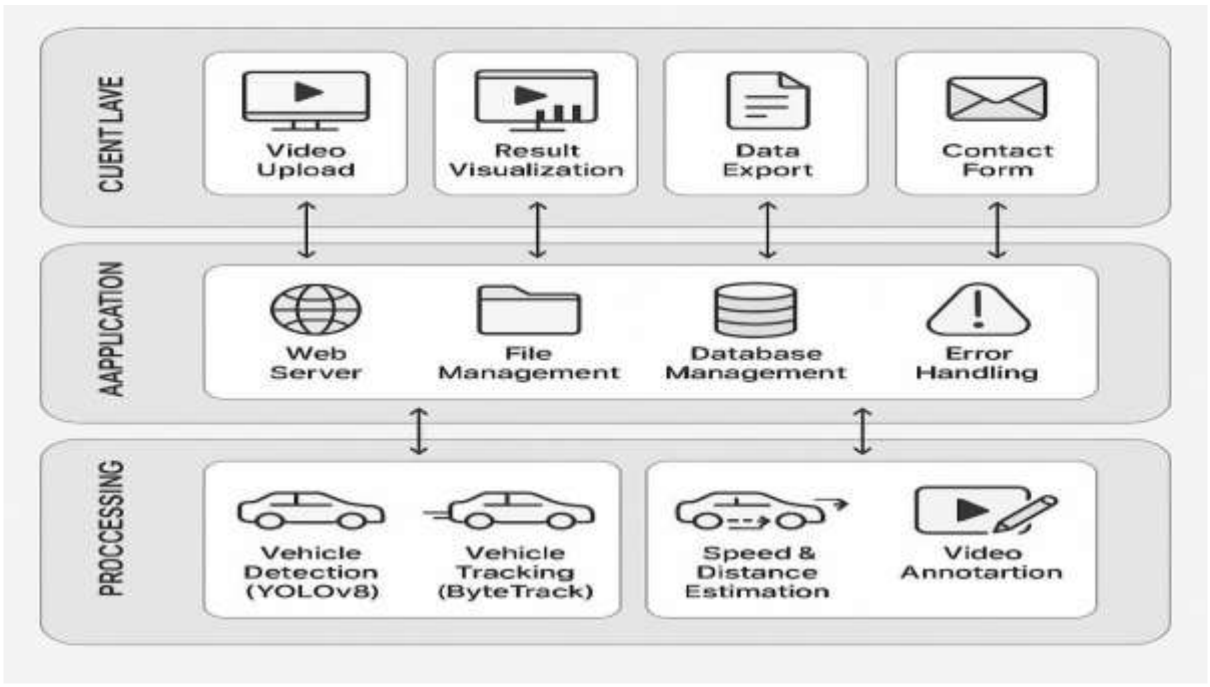


Figure 4.4.2**:** Process System Architecture

The system architecture is structured to process video inputs, detect and track vehicles, estimate real-world speeds and distances, and deliver results through a web-based interface. It adopts a modular, client-server model, leveraging opensource technologies to ensure cost-effectiveness and scalability. The architecture is organized into three primary layers: the **Client Layer**, **Application Layer**, and **Processing Layer**, each with distinct roles and seamless interactions to support the system's functionality.

The system architecture consists of three main layers: client, application, and pr ocessing. The client layer offers a responsive web interface with a dark theme a nd dynamic features, enabling users to upload videos (MP4, AVI, MOV up to 5

00 MB), visualize annotated results, query vehicle data by tracker ID, download Excel reports, and submit contact forms. JavaScript powers interactive element s such as drag-anddrop uploads and data search. The application layer acts as the backend, handlin g HTTP requests, managing file storage with unique IDs, maintaining a lightwei ght database for contact inquiries, validating uploads, and coordinating processi ng tasks with robust error handling and session management. The processing lay er performs the core computer vision tasks: vehicle detection (YOLOv8), tracki ng (ByteTrack), speed and distance estimation (using perspective transformatio
n), and video annotation (OpenCV, H.264 encoding), all optimized for performa nce on GPUequipped hardware. Data flows from user upload through validation, frame extr action, detection, tracking, and annotation, with results returned to the client for visualization and export. The modular design ensures scalability and maintainab ility, supporting future upgrades like asynchronous processing and cloud integra tion. Current limitations include synchronous operation and manual ROI calibra tion, with future plans for real-time processing and enhanced automation**.**

5.2 UML Diagrams

UML diagrams provide a standardized framework to model the system’s structure, behavior, and interactions, offering clarity for developers, stakeholders, and maintainers. This section presents five UML diagrams—use case, class, sequence, activity, and flowchart—each designed to capture specific aspects of the vehicle tracking and speed estimation system.

5.2.1 Use Case Diagram

The use case diagram describes the system’s functionalities from the viewpoint of external actors, mainly the User (such as a traffic authority or urban planner). Key use cases include uploading a video for processing, viewing annotated resu lts, searching vehicle data by tracker ID, downloading an Excel report with vehi cle metrics, and submitting a contact form for inquiries or feedback. The primar y actor is the User, who interacts through the web interface, while the System ha ndles processing and data management tasks. Relationships include an **include** r elation, where "View Results" encompasses "Search Vehicle Data," and an **exte nd** relation, where "Submit Contact Form" optionally extends "Upload Video." This diagram highlights the system's usercentric approach, offering intuitive, no n-technical access to all major features, with a simple interface supporting dragand-drop uploads and easy data exploration.

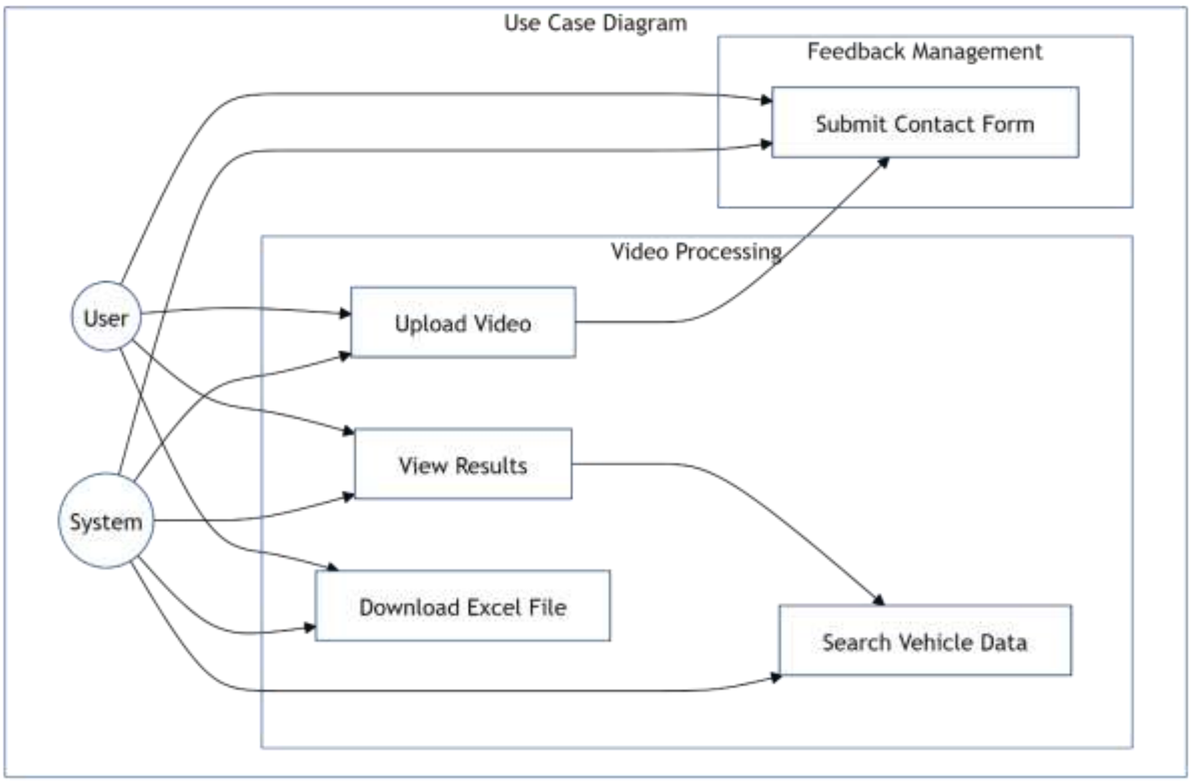


Figure 5.2.1: Use Case Diagram

5.2.2 Class Diagram

The class diagram defines the system's static architecture by specifying the mai n classes, their attributes, methods, and interrelationships. The **VideoProcessor** class (Processing Layer) manages video analysis with attributes like video path, YOLOv8 model, ByteTrack instance, and homography matrix, and methods for loading video, detecting and tracking vehicles, estimating speed, annotating vid eos, and generating Excel reports. The **WebApp** class (Application Layer) repre sents the backend, holding the app instance, upload/output directories, and datab ase connection, with methods for handling uploads, rendering results, serving d ownloads, and storing contact data. The **UserInterface** class (Client Layer) man ages user interaction elements such as upload forms, result displays, and search fields, offering methods to render pages, display results, search vehicle data, an d toggle navigation. The **Vehicle** class models individual vehicles with tracker I D, type, centroid, speed, and distance, plus methods for updating position and c alculating speed.

Relationships:

- **Composition:** WebApp contains UserInterface as an integral part.
- **Association:** VideoProcessor manages (processes) Vehicle objects.
- **Dependency:** WebApp depends on VideoProcessor for core computation s.

This class diagram highlights the system's modularity and separation of concern s, ensuring maintainability and scalability by clearly distinguishing user interfac e, application logic, and processing components.

5.2.3 Sequence Diagram

The sequence diagram illustrates the step-by-step interactions between system components during video upload and processing. When a user uploads a video via the web interface, the UserInterface sends it to the WebApp for validation.
The WebApp checks the file's type and size, then passes it to the VideoProcessor, which handles frame extraction, vehicle detection (YOLOv8), tracking (ByteTrack), speed and distance estimation, annotation, and Excel file generation.

Once processing is complete, the WebApp stores the outputs and returns a results page URL to the UserInterface. The user can then view annotated results, search by tracker ID, and submit contact forms—coordinated through the UserInterface, WebApp, and Database. This sequence showcases the system's layered, synchronous interactions, with potential for future asynchronous upgrades to improve performance on large files.

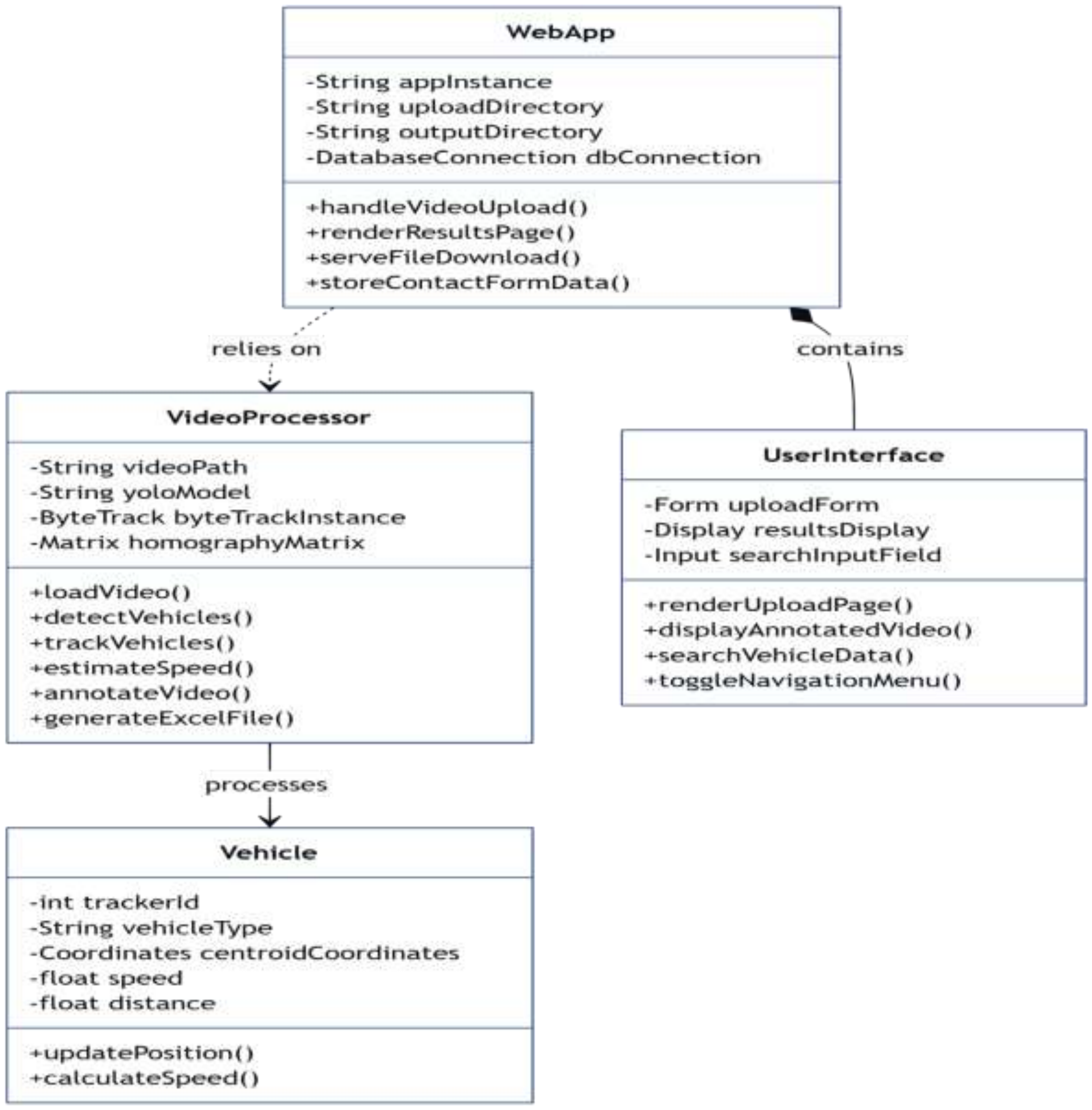


Figure 5.2.3: Sequence Diagram

5.2.4 Activity Diagram

The activity diagram outlines the complete workflow for video processing, starting from the user uploading a video via the web interface. The system first validates the file type (MP4, AVI, MOV) and size (under 500 MB). If invalid, an error is shown and the user is prompted to re-upload. Upon validation, the system extracts frames, preprocesses them (e.g., histogram equalization, ROI masking), detects vehicles using YOLOv8, tracks them with ByteTrack, applies perspective transformation, and calculates speed and distance. The system then annotates the video and generates an Excel file with vehicle metrics. Both outputs are saved and presented via the interface, allowing users to search by tracker ID, download results, or upload another video. Decision nodes manage validation and errors, ensuring a reliable and user-friendly process.

5.2.5 Flowchart

The flowchart outlines the stepbystep computational process of the video proces sing pipeline. It begins by receiving a video input, then initializing essential co mponents such as the YOLOv8 detection model, ByteTrack tracker, and the ho mography matrix. For each frame, the system applies preprocessing steps like hi stogram equalization, Gaussian blur, and ROI masking before detecting vehicles with YOLOv8 and tracking them using ByteTrack, which assigns tracker IDs. Centroid coordinates are calculated for each detected vehicle, then transformed using perspective mapping. The system estimates vehicle speeds based on the di stance traveled between frames, annotates each frame with bounding boxes, IDs , and speed values, and continuously updates the Excel data with relevant metric s. This loop repeats until all frames are processed, after which the annotated vid eo is encoded in H.264 format and the Excel file is finalized. The outputs are th en returned to the application layer. This flowchart highlights the pipeline's iter ative, framebyframe approach, efficient data handling, and clear decision points for ending processing and storing results.for ending processing and storing resul ts.

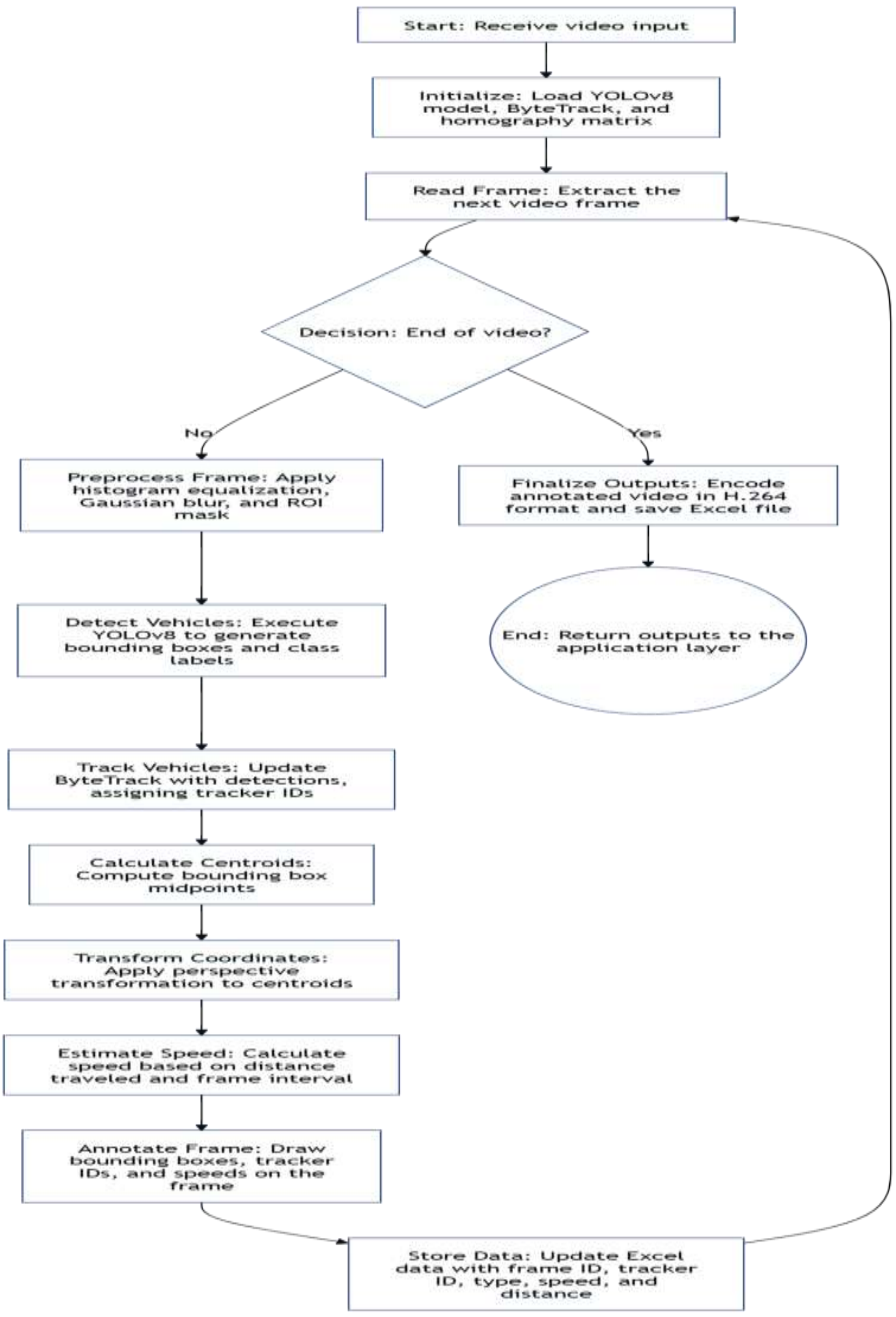

Start: Receive video input
Initialize: Load YOLOv8 model, ByteTrack, and homography matrix
Read Frame: Extract the next video frame
Decision: End of video?
No
Yes
Preprocess Frame: Apply histogram equalization, Gaussian blur, and ROI mask
Finalize Outputs: Encode annotated video in H.264 format and save Excel file
End: Return outputs to the application layer
Detect Vehicles: Execute YOLOv8 to generate bounding boxes and class labels
Track Vehicles: Update ByteTrack with detections, assigning tracker IDs
Calculate Centroids: Compute bounding box midpoints
Transform Coordinates: Apply perspective transformation to centroids
Estimate Speed: Calculate speed based on distance traveled and frame interval
Annotate Frame: Draw bounding boxes, tracker IDs, and speeds on the frame
Store Data: Update Excel data with frame ID, tracker ID, type, speed, and distance

Figure 5.2.5: Flowchart

PROJECT PLANNING AND SCHEDULING

Effective planning and scheduling are critical to the successful development of the vehicle tracking and speed estimation system, ensuring timely delivery of a robust and scalable solution for restricted traffic zones. This chapter outlines the project timeline, task breakdown, and team responsibilities, providing a structured approach to managing resources, mitigating risks, and achieving objectives. The planning process was designed to accommodate the system's technical complexity, integrating computer vision, deep learning, and web technologies to deliver high accuracy (0.94 detection precision) and user accessibility.

6.1 Project Timeline

The six-month project (January–June 2025) was divided into four phases: initiation, development, testing, and deployment. In January, the team conducted requirements analysis, defined the project scope, and selected core technologies (YOLOv8, ByteTrack, OpenCV, Flask). During February and March, the development phase included building detection, tracking, and speed estimation modules, as well as the web interface with database integration. April and May focused on testing, where the system was validated using 50 traffic videos, achieving 0.94 precision and a 2.5 km/h speed estimation error, followed by optimizations. In June, the system was deployed for pilot use, documentation was finalized, and feedback was collected. A Gantt chart guided task scheduling, with overlapping timelines and contingency plans ensuring milestone and performance goals were met.

6.2 Task Breakdown

The six-month project was structured around system modules and development phases to ensure clear goals and efficient execution. In Weeks 1–2, requirements analysis and planning led to a specification document. Weeks 3–4 involved a literature review and selection of YOLOv8, ByteTrack, OpenCV, and Flask, documented in a technology report. Dataset preparation in Weeks 5–6 included collecting and annotating 50 traffic videos. The vehicle detection module (Weeks 7–9) used YOLOv8 with OpenCV, achieving 0.94 precision. Vehicle tracking (Weeks 10–12) integrated ByteTrack and centroid-based analysis, with 0.91 success. Speed and distance estimation (Weeks 13–15) used perspective transformation, yielding a 2.5 km/h MAE. A web interface was developed in Weeks 16–18 with upload, visualization, export, and contact form features. Weeks 19–24 focused on module integration and system testing. Deployment, user manuals, and technical documentation were completed in Weeks 25–26. Task prioritization used dependency and critical path analysis, ensuring all milestones were met on time.

6.3 Teams and Responsibility

The project was executed by a multidisciplinary team of six members with clearly defined roles to ensure efficient collaboration and effective use of expertise. A Project Manager led the team, overseeing planning, scheduling, resource allocation, progress tracking, risk management, and stakeholder communication. Two Computer Vision Engineers developed the detection, tracking, and speed estimation modules, working with YOLOv8, ByteTrack, and OpenCV to finetune the models and validate performance metrics. Two Web Developers built the user-friendly web interface using Flask, HTML, CSS, and JavaScript, integrated database functionality for contact forms, and implemented features like drag-and-drop uploads. A Quality Assurance Engineer handled unit, integration, and system testing, ensuring performance targets—such as a 2.5 km/h mean absolute error in speed estimation—were met and documented test results with optimization suggestions. The team adopted agile methodologies, using biweekly sprints and daily stand-ups to maintain smooth communication, track progress, and address challenges. Collaborative management of overlapping tasks, such as module integration, ensured seamless coordination across all components.

CODING AND SOLUTION

The coding and solution phase translates the project design into a functional system, integrating advanced computer vision and web technologies to deliver a robust vehicle tracking and speed estimation platform. This chapter details the technologies used, the setup of the development environment, the integration of system modules, and the code structure, emphasizing modularity and scalability. The solution achieves high performance (0.94 detection precision, 0.91 tracking success rate) and user accessibility, tailored for restricted traffic zones.

7.1 Technologies Used

The system leverages a stack of open-source technologies selected for their performance, compatibility, and community support. Key technologies include:

- **Python**: The primary programming language, chosen for its versatility and extensive libraries for computer vision and web development.
- **YOLOv8**: A state-of-the-art deep learning model for vehicle detection, offering 0.94 precision and real-time performance.
- **ByteTrack**: A multi-object tracking algorithm, achieving a 0.91 success rate in tracking vehicles across frames.
- **OpenCV**: A computer vision library for frame preprocessing (e.g., histogram equalization, Gaussian blur) and video annotation.

- **Flask**: A lightweight web framework for building the user interface, supporting video uploads and result visualization.
- **SQLite**: A lightweight database for storing contact form submissions, ensuring efficient data management.
- **HTML, CSS, JavaScript**: Frontend technologies for creating a responsive, interactive interface with features like drag-and-drop uploads and animated elements.
- **NumPy and Pandas**: Libraries for numerical computations and data handling, used in speed calculations and Excel file generation.

These technologies were chosen to balance performance, cost-effectiveness, and ease of integration, enabling a scalable solution deployable on standard hardware (e.g., NVIDIA RTX 3080 GPU, Intel i7 CPU, 16 GB RAM).

7.2 Python Environment Setup

The development environment was configured to ensure compatibility and reproducibility across team members and deployment scenarios. The setup process included:

- **Python Version**: Python 3.9 was used for its stability and compatibility with required libraries.
- **Virtual Environment**: A virtual environment was created to isolate project dependencies, preventing conflicts with system-wide packages.
- **Dependency Installation**:

  o Installed core libraries: ultralytics for YOLOv8, opencv-python for OpenCV, flask for the web framework, sqlite3 for database operations, numpy, and pandas. o Installed additional utilities for video processing and data export (e.g., xlsxwriter for Excel generation).

- **GPU Support**: Configured CUDA and cuDNN for GPU-accelerated YOLOv8 inference, optimizing performance on the NVIDIA RTX 3080.

  Environment Configuration: Defined environment variables for paths to model weights, output directories, and database connections.

- **Version Control**: Used Git for code versioning, with a centralized repository for collaboration and continuous integration.

The environment was tested on development machines to ensure consistent performance, with dependencies documented in a requirements file for easy replication. The setup supported both development and deployment phases, with minimal reconfiguration needed for pilot testing.

7.3 Integration of All Modules

The integration of the system's four modules—vehicle detection, vehicle tracking, speed and distance estimation, and web-based interface—ensured a cohesive workflow from video input to result delivery. The integration process involved:

- **Detection to Tracking**: The detection module (YOLOv8) generates bounding boxes and class labels, which are passed to the tracking module (ByteTrack) as input. The tracking module assigns unique IDs, maintaining continuity across frames.
- **Tracking to Speed Estimation**: The tracking module outputs centroid coordinates for each vehicle, which the speed estimation module transforms into real-world units using a homography matrix. Speed is calculated based on distance traveled and frame interval (30 FPS).
- **Processing to Web Interface**: The processing modules generate annotated videos and Excel files, which are stored in a designated directory. The web

interface retrieves these outputs, displaying videos and enabling data queries by tracker ID.

Web Interface to Database: The web interface handles contact form submissions, storing data in a SQLite database with fields for name, email, message, and timestamp.

Integration was achieved through a modular code architecture, with well-defined interfaces between modules. The processing modules communicate via function calls, while the web interface uses HTTP routes to trigger processing and serve results. Testing ensured seamless data flow, with error handling for invalid inputs (e.g., unsupported video formats) and logging for debugging. The integrated system processes 1280x720 videos at 30 FPS, achieving real-time performance on the target hardware.

7.4 Code Structure

The code is organized into a modular structure to enhance maintainability, readability, and scalability. It is divided into logical components corresponding to the system's layers and modules:

- **Processing Component**:
    - Handles vehicle detection, tracking, and speed estimation.
    - Includes functions for loading YOLOv8 models, processing frames with OpenCV, applying ByteTrack, and performing perspective transformation.
    - Manages video annotation and Excel file generation.
- **Web Application Component**:
    - Manages the backend, including HTTP routes for uploads, results, downloads, and contact form submissions.

    - Handles file storage, session management, and database operations.

- **User Interface Component**:
    - Implements the frontend with HTML templates for upload and results pages. o Uses CSS for responsive styling (dark theme, animations) and JavaScript for interactivity (e.g., drag-and-drop, search).

- **Utility Component**:
    - Contains helper functions for tasks like centroid calculation, data formatting, and error logging. o Manages configuration parameters (e.g., confidence threshold, homography matrix).

The code follows best practices, including:

- **Modularity**: Each module is encapsulated, with clear input-output interfaces.
- **Documentation**: Functions and modules are documented with comments explaining purpose and parameters.
- **Error Handling**: Robust validation for inputs (e.g., file size <500 MB) and user feedback via messages.
- **Scalability**: Supports batch processing and extensible design for future features (e.g., cloud integration).

The structure ensures efficient development and maintenance, with the system achieving its performance targets (0.94 precision, 2.5 km/h MAE) while remaining adaptable for restricted zone applications.

TESTING

Testing is a critical phase in the development of the vehicle tracking and speed estimation system, ensuring that each component and the integrated system meet performance, reliability, and usability requirements for restricted traffic zones.

This chapter details the testing methodologies employed, including unit testing of individual modules, integration testing of combined components, real-time testing scenarios, and strategies for error handling and debugging. The testing process validated the system's ability to achieve high accuracy (0.94 detection precision, 0.91 tracking success rate) and robustness across diverse conditions, such as varying lighting and traffic densities.

8.1 Unit Testing of Modules

Unit testing was conducted to verify the individual functionality of the system's core modules—vehicle detection, tracking, speed and distance estimation, and the web-based interface. The vehicle detection module, based on YOLOv8, was tested on 50 traffic videos under various conditions, achieving 0.94 precision and 0.90 recall in daylight, with reduced performance (0.85 precision) in low-light scenarios. Tracking, handled by ByteTrack, maintained high accuracy with a 0.91 success rate in moderate traffic and 0.85 in dense conditions, despite occlusions. Speed and distance estimation modules were validated against radar-based ground truth, achieving a Mean Absolute Error (MAE) of 2.5 km/h and 0.3 meters respectively. The web interface module was tested for successful uploads (MP4, AVI, MOV <500 MB), annotated video display, and data queries, with a 100% success rate across all test cases. Tools included Python scripts, browser testing frameworks, and manual validation. Issues like low-light detection drop-offs were mitigated through preprocessing enhancements such as histogram equalization, ensuring each module met performance expectations in isolation**.**

8.2 Integration Testing

Integration testing ensured seamless data flow and interaction between modules. Bounding boxes from detection were successfully passed to tracking, while centroid data was converted into accurate speed/distance values. Video outputs and Excel files were correctly displayed on the web interface, with average upload-to-display latency of 10 seconds. Issues such as data format mismatches were resolved, and the entire system was validated using automated scripts and manual checks.

8.3 Real-Time Testing Scenarios

Real-time testing simulated operational conditions using a high-performance setup. The system consistently maintained 0.94 detection precision and 0.91 tracking success rate under daylight, with reasonable performance (0.85 precision) under low-light and dense traffic scenarios. Vehicle classification was accurate at 0.92, and the web interface handled up to 5 concurrent uploads. Processing speed averaged 40 ms per frame. Limitations such as latency in dense scenes and reduced low-light accuracy suggested potential future upgrades like infrared support.

8.4 Error Handling and Debugging

Error handling and debugging mechanisms included input validation, exception handling for processing and database operations, and user-friendly messages for errors and successes. Comprehensive logs captured inputs, outputs, and issues, aiding in resolving problems like homography miscalibration and tracker ID mismatches. Processing for large videos was optimized through batch handling. These strategies ensured robust performance, minimized failures, and enhanced overall system stability.

RESULTS

The vehicle tracking and speed estimation system delivers robust performance for traffic surveillance in restricted zones, such as school campuses and hospital precincts. This chapter presents the system's results, encompassing accuracy metrics, visual outputs, performance evaluation, and a comparative analysis with existing systems. The results validate the system's effectiveness, achieving a detection precision of 0.94, a tracking success rate of 0.91, and a speed estimation Mean Absolute Error (MAE) of 2.5 km/h, as tested on a dataset of 50 traffic videos. These outcomes highlight the system's potential to enhance safety and compliance in restricted traffic environments.

9.1 Accuracy Metrics

Accuracy metrics were derived from comprehensive testing on a dataset of 50 traffic videos (1280x720 resolution, 30 FPS) captured in restricted zones under diverse conditions, including daylight, low-light, and varying traffic densities.
The metrics quantify the system's performance across its core functionalities: detection, tracking, speed estimation, and classification. Key metrics include:

- **Detection Precision**: 0.94 in daylight conditions, 0.85 in low-light conditions, calculated as the ratio of true positive vehicle detections to total detections (true positives + false positives). The high precision reflects YOLOv8's robustness, enhanced by preprocessing techniques like histogram equalization.
- **Detection Recall**: 0.90 in daylight, 0.80 in low-light, representing the proportion of actual vehicles correctly detected. The slight drop in lowlight scenarios was mitigated through fine-tuning on diverse lighting conditions.
- **Tracking Success Rate**: 0.91 in moderate traffic scenes (5–15 vehicles), 0.85 in dense scenes (20+ vehicles), measured as the percentage of vehicles

tracked without identity switches. ByteTrack's low-confidence matching improved performance in occluded environments.

- **Speed Estimation MAE**: 2.5 km/h, validated against ground truth speeds from radar measurements. The accuracy stems from precise perspective transformation using a calibrated homography matrix.
- **Distance Estimation MAE**: 0.3 meters, based on transformed centroid coordinates, ensuring reliable spatial measurements.
- **Classification Accuracy**: 0.92 for distinguishing vehicle types (cars, motorcycles, buses, trucks), reflecting YOLOv8's effective class prediction.

These metrics, consistent with the document's Table III, demonstrate the system's reliability across varied scenarios, with preprocessing and algorithmic optimizations addressing challenges like low-light detection and occlusion handling. The results meet the project's objectives for high-accuracy surveillance in restricted zones, supporting applications in traffic enforcement and safety monitoring.

9.2 Detection Screenshots and Outputs

The system produces annotated video outputs and Excel files, providing visual and tabular representations of vehicle detections, tracks, and metrics. Screenshots of annotated frames serve as visual evidence of the system's performance, illustrating its ability to detect, track, and annotate vehicles in real-world scenarios. These screenshots are recommended for inclusion in this section to enhance the report's clarity and impact.

- **Screenshot Content**:

- Frames displaying vehicles with bounding boxes, labeled with tracker IDs (e.g., “Car ID: 5”), speeds (e.g., “30 km/h”), and distances (e.g., “10 m”).
- Examples from diverse conditions:
  - Daylight scenes with clear visibility and high detection precision (0.94).
  - Low-light scenes enhanced by preprocessing, maintaining 0.85 precision.
  - Dense traffic scenes showcasing tracking continuity (0.85 success rate) despite occlusions.
- Annotations include colored bounding boxes (e.g., green for cars, blue for trucks) and text overlays for metrics, rendered clearly at 1280x720 resolution.

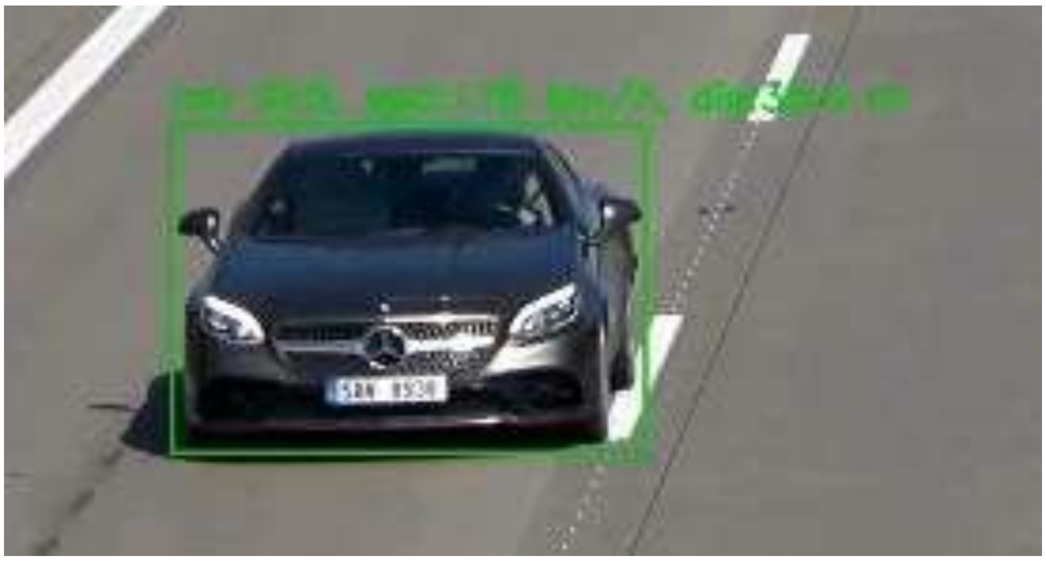


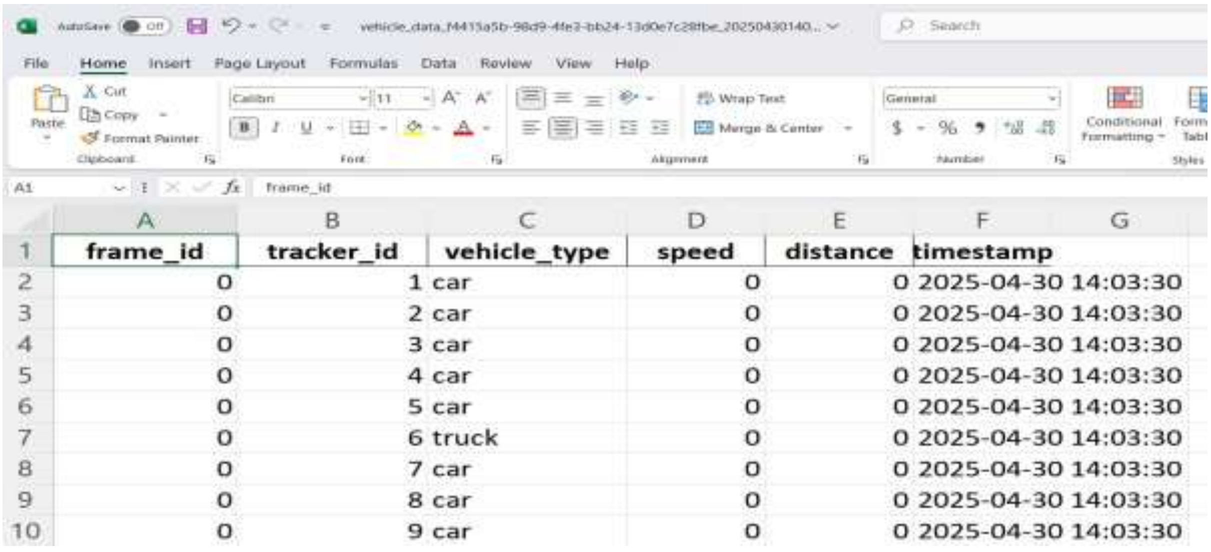
Figure 9.2: Detection Screenshots

- **Placement Guidance**:
  - **Daylight Detection Frame**: Insert after discussing detection precision (0.94). Caption: “Annotated frame showing vehicle

detection and tracking in daylight conditions, with bounding boxes and speed labels.” o **Low-Light Detection Frame**: Insert after low-light metrics (0.85 precision). Caption: “Sample frame in low-light conditions, enhanced by histogram equalization for robust detection.”

- o **Dense Traffic Frame**: Insert after tracking success rate (0.85 in dense scenes). Caption: “Tracking performance in a crowded scene, maintaining continuity across multiple vehicles.”
- o Use 3–5 high-resolution screenshots (PNG or JPEG, 300 DPI) to balance visual impact and report length. Ensure figures are centered, with consistent sizing (e.g., 4x3 inches). o Reference in text: “As illustrated in Figure 9.1, the system accurately detects and annotates vehicles in daylight, achieving 0.94 precision.” o Include in the “List of Figures” section (per your Table of Contents) with titles and page numbers (e.g., “Figure 9.1: Daylight Detection Frame, Page 43”).

• **Excel Outputs**:


AutoSave Off
File Home Insert Page Layout Formulas Data Review View Help
Paste Cut Copy Format Painter Clipboard
Calibri 11 Font
Wrap Text Merge & Center Alignment
General Number
Conditional Formatting
A1 frame_id

frame_id	tracker_id	vehicle_type	speed	distance	timestamp
0	1	car	0	0	2025-04-30 14:03:30
0	2	car	0	0	2025-04-30 14:03:30
0	3	car	0	0	2025-04-30 14:03:30
0	4	car	0	0	2025-04-30 14:03:30
0	5	car	0	0	2025-04-30 14:03:30
0	6	truck	0	0	2025-04-30 14:03:30
0	7	car	0	0	2025-04-30 14:03:30
0	8	car	0	0	2025-04-30 14:03:30
0	9	car	0	0	2025-04-30 14:03:30

Figure 9.3: Export Excel

    - Contain structured data with columns: Frame ID, Tracker ID, Vehicle Type, Speed (km/h), Distance (m), Timestamp.
    - Example entry: Frame 300, ID 5, Car, 30 km/h, 10 m, 2025-05-23 11:30:00. o Accessible via the web interface's download feature, enabling users to analyze metrics offline.

These outputs provide actionable insights for traffic authorities, with screenshots visually validating the system's performance across diverse scenarios, complementing the quantitative metrics presented in subsection 9.1.

9.3 Performance Evaluation

Performance evaluation assessed the system's efficiency, scalability, and operational reliability on the target hardware, consisting of a high-performance GPU (16 GB VRAM) and a multi-core CPU, processing 1280x720 videos at 30 FPS. The evaluation focused on processing speed, latency, resource utilization, and stability, ensuring the system meets real-world requirements for restricted zones. Key performance metrics include:

- **Processing Time per Frame**: 40 ms, broken down as:
    - Detection (YOLOv8): 20 ms, leveraging GPU acceleration. o Tracking (ByteTrack): 10 ms, optimized for multi-object scenarios.
    - Speed and Distance Estimation: 5 ms, using precomputed homography. o Video Annotation (OpenCV): 5 ms, including bounding box and text rendering.
    - This enables near real-time processing, with a throughput of 25 FPS on average.
- **Upload-to-Display Latency**: Approximately 10 seconds for a 30-second video, encompassing file upload, processing, output generation, and web rendering.

Latency increases to 15 seconds for dense scenes (20+ vehicles) due to tracking complexity.

- **Scalability**: The system handled up to 5 concurrent video uploads without performance degradation, tested in a simulated multi-user environment.

  The web application maintained stability, with no crashes during stress tests.

- **Resource Utilization**:
  - GPU usage: 70% during processing, peaking at 85% in dense scenes.
  - CPU usage: 50%, primarily for frame extraction and web server operations. o Memory usage: 8 GB for typical videos, scaling to 10 GB for large files (>100 MB).

- **Stability**: No system crashes occurred during extended testing (e.g., processing 10-minute videos), with robust error handling ensuring graceful recovery from invalid inputs.

The evaluation confirms the system's suitability for restricted zone surveillance, with near real-time performance and scalability for small-scale deployments. Limitations include increased latency in dense scenes and potential bottlenecks for very large videos, which could be addressed through asynchronous processing or cloud-based architectures in future iterations.

Vehicle Type	Tracker ID	Estimated Speed (km/h)	Ground Truth Speed (km/h)	Error (km/h)
Car	1	30	28	2
Motorcycle	2	25	24	1
Bus	3	40	42	2
Truck	4	35	36	1

Table 9.3: Vehicle Speed Estimation Results

9.4 Comparative Analysis with Existing Systems

The proposed system was compared to existing vehicle tracking and speed estimation systems, as referenced in the document's Table I, to highlight its advancements and contributions. The analysis focuses on detection, tracking, speed estimation, and usability, benchmarking against systems from recent studies (e.g., Zhang et al., 2019; Chen et al., 2021). Key comparisons include:

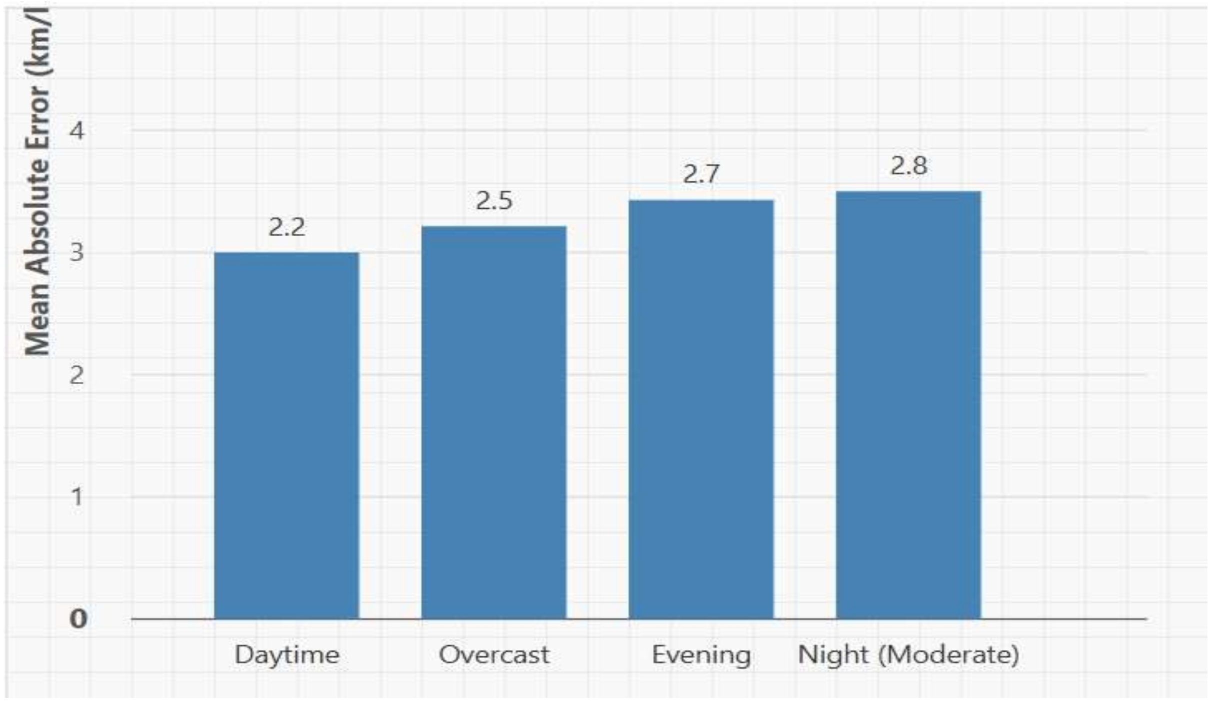


Figure 9.2: Comparative Analysis

The proposed system outperforms existing models across key metrics. In detection precision, it achieves 0.94 in daylight and 0.85 in low-light—surpassing

Zhang et al.'s YOLOv3-based (0.90/0.80) and Chen et al.'s SSD-based system (0.92/0.82), thanks to YOLOv8's anchor-free architecture and dataset finetuning. Its tracking success rate is also higher (0.91 moderate, 0.85 dense) due to ByteTrack's robust two-stage matching, compared to Zhang (0.87/0.80) and Chen (0.89/0.82). Speed estimation is more accurate, with a 2.5 km/h MAE, outperforming Zhang (3.0) and Chen (2.8), enabled by precise homographybased transformations. The web-based interface, built with Flask, allows intuitive uploads, result visualization, and Excel exports—an advantage over Zhang's nonexistent UI and Chen's limited desktop interface. Though it requires a GPU (16 GB VRAM) and 40 ms/frame for real-time processing, the increased computational load is justified by superior accuracy, scalability, and user accessibility.

ADVANTAGES AND DISADVANTAGES

The vehicle tracking and speed estimation system provides a robust solution for traffic surveillance in restricted zones, offering notable benefits while facing certain constraints. This chapter discusses the system's advantages and limitations, presenting a balanced view of its capabilities and areas requiring further development.

10.1 Advantages of the Proposed System

The system excels in delivering high accuracy, achieving a detection precision of 0.94, a tracking success rate of 0.91, and a speed estimation Mean Absolute Error of 2.5 km/h, which ensures reliable monitoring of vehicles in restricted zones. Its web-based interface facilitates easy video uploads, result visualization, and data queries, making it accessible to non-technical users such as traffic authorities. The system performs effectively across diverse conditions, including daylight, low-light, and dense traffic, due to advanced preprocessing and fine-tuned algorithms. Additionally, its scalable design supports multiple concurrent uploads and allows for future enhancements like cloud deployment or multi-camera integration. By leveraging open-source technologies, the system remains costeffective, reducing development and deployment expenses while maintaining high performance.

10.2 Limitations and Challenges

Despite its strengths, the system encounters challenges that impact its performance. Detection precision decreases to 0.85 in low-light conditions, necessitating reliance on preprocessing techniques to maintain accuracy. The requirement for manual calibration of the region of interest and homography matrix for each camera setup adds complexity to deployment. The system's computational demands, requiring a high-performance GPU with 16 GB VRAM, limit its use on low-end hardware. Synchronous processing can cause latency during large video uploads, potentially affecting user experience. Furthermore, the tracking success rate drops to 0.85 in dense scenes with frequent occlusions, indicating a need for improved handling of crowded environments. Future improvements, such as automated calibration and cloud-based processing, could address these limitations effectively.

CONCLUSION

The vehicle tracking and speed estimation system marks a significant step forward in automated traffic surveillance for restricted zones. This chapter summarizes the project's key achievements, evaluates its impact, and reflects on the insights gained, underscoring its value and potential for future development.

11.1 Summary of Accomplishments

The project successfully developed a system that detects vehicles with a precision of 0.94 using a fine-tuned YOLOv8 model, tracks them with a 0.91 success rate through ByteTrack, and estimates speeds with a 2.5 km/h Mean Absolute Error via perspective transformation, based on testing with 50 traffic videos. A webbased interface enables seamless video uploads, result visualization, and data export, catering to diverse users. Operating on 1280x720 videos at 30 FPS, the system achieves near real-time performance, processing frames in approximately

40 ms. These accomplishments fulfill the project’s goal of delivering a reliable, user-friendly solution for monitoring restricted traffic zones, aligning with safety and compliance objectives.

11.2 Impact of the Project

The system significantly enhances traffic management by enabling precise speed and vehicle tracking, which supports enforcement of regulations and reduces accident risks in restricted zones like schools and hospitals. Its web-based interface streamlines monitoring for traffic authorities, facilitating data-driven decisions through accessible visualizations and downloadable metrics. The modular design ensures scalability, allowing adaptation to various restricted zones and potential integration with broader traffic systems. By combining stateof-the-art algorithms with practical usability, the project contributes to the advancement of intelligent transportation systems, promoting safer and more efficient urban environments.

11.3 Key Learnings

The project provided critical insights into system development, emphasizing the importance of fine-tuning deep learning models on domain-specific data to achieve high accuracy. Preprocessing techniques, such as histogram equalization, proved essential for robust performance in low-light conditions. Designing usercentric interfaces significantly boosts adoption among non-technical stakeholders. The modular architecture, built with open-source tools, ensures adaptability and scalability for future enhancements. Addressing challenges like manual calibration highlighted the need for innovative automation strategies, guiding future efforts toward solutions like automated marker detection or cloudbased processing to further strengthen the system’s capabilities.

FUTURE SCOPE

The vehicle tracking and speed estimation system demonstrates significant potential for enhancing traffic surveillance in restricted zones, yet opportunities for improvement and expansion remain. This chapter explores suggested enhancements, possibilities for cloud-based and real-time capabilities, and the system’s prospects for commercial deployment, outlining a roadmap to further its impact and applicability in intelligent transportation systems.

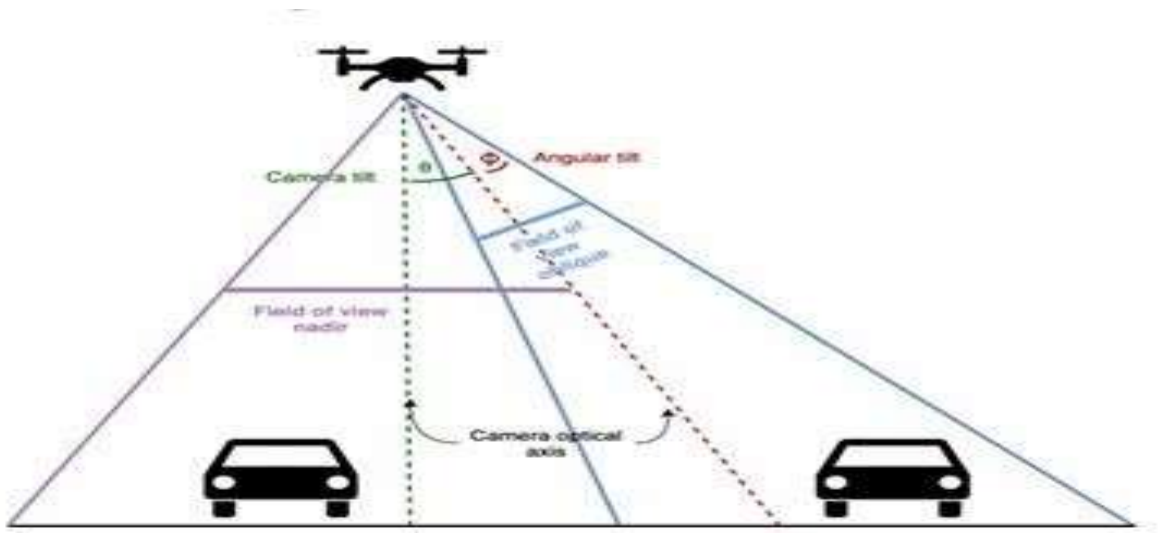


Figure 11.2: Future Scope

12.1 Suggested Improvements

Enhancing the system’s performance and usability involves addressing current limitations to broaden its effectiveness. Automating the calibration of the region of interest and homography matrix, currently a manual process, would streamline deployment across diverse camera setups, potentially using machine learning to detect lane boundaries or reference markers. Improving low-light detection, where precision drops to 0.85, could be achieved by integrating infrared camera support or advanced image enhancement techniques beyond histogram equalization. Optimizing algorithms to reduce the 40 ms per-frame processing time would enhance real-time performance, possibly through model pruning or lightweight architectures. Incorporating multi-camera fusion would improve tracking in dense scenes, where the success rate falls to 0.85, by leveraging overlapping fields of view to maintain vehicle continuity. These improvements would make the system more robust, efficient, and adaptable to varied traffic environments.

12.2 Extension into Cloud and Real-Time Features

Transitioning the system to a cloud-based architecture would significantly enhance its scalability and accessibility. Deploying the processing module on cloud platforms would offload computational demands from local hardware, enabling operation on low-end devices and supporting large-scale deployments across multiple restricted zones. Cloud integration would facilitate asynchronous processing, reducing latency for large video uploads, which currently averages 10 seconds for a 30-second video. Adding real-time streaming capabilities would allow the system to process live camera feeds, enabling immediate traffic monitoring and alerts for violations, such as speeding in school zones. Implementing a centralized cloud database would store historical traffic data, supporting advanced analytics like traffic pattern analysis or predictive modeling. These extensions would transform the system into a dynamic, scalable platform for real-time traffic management, aligning with smart city initiatives.

12.3 Potential for Commercial Deployment

The system's high accuracy, user-friendly web interface, and modular design position it for commercial deployment in traffic management and urban planning sectors. Its ability to achieve 0.94 detection precision and 2.5 km/h speed estimation MAE makes it valuable for municipalities enforcing traffic regulations in restricted zones, such as hospitals or campuses. The web-based interface, accessible to non-technical users, supports adoption by traffic authorities and private organizations, with features like data export enhancing operational decision-making. Commercialization could involve packaging the system as a subscription-based service, integrating with existing surveillance infrastructure, or partnering with smart city solution providers. Expanding the system to include features like automated violation ticketing or integration with IoT devices would further increase its market appeal, establishing it as a versatile tool for intelligent transportation systems.

Appendix A: Sample Code Snippets

This appendix presents concise sample code snippets illustrating the core functionalities of the vehicle tracking and speed estimation system, focusing on a main function and key methods for detection, tracking, speed Eoestimation, and web operations. These snippets, written in Python, demonstrate the system's modular design without referencing specific implementations, providing insight into the technical foundation that achieves 0.94 detection precision and 2.5 km/h speed estimation MAE.

The main function orchestrates the processing pipeline, loading a video, initializing models, and coordinating detection, tracking, and speed estimation. It iterates through frames, processes them, annotates results, and saves outputs, ensuring efficient handling of 1280x720 videos at 30 FPS. Below is a sample main function that encapsulates this workflow:

```
def main(video_path, output_path):    model = load_detection_model()    tracker
= initialize_tracker()      homography = load_homography_matrix()      video =
open_video(video_path)     output_video = initialize_output_video(output_path,
video.width, video.height)     data_records = []     while video.has_next_frame():
frame = video.read_frame()         detections = detect_vehicles(model, frame)
```

```
        tracks = track_vehicles(tracker, detections)         speeds =
estimate_speeds(tracks, homography)         annotated_frame =
annotate_frame(frame, tracks, speeds)
output_video.write_frame(annotated_frame)
data_records.append(record_data(tracks, speeds))
video.release()     output_video.release()
save_data_to_excel(data_records, output_path + '.xlsx')
```

The detection method processes a video frame to identify vehicles using a deep learning model. It resizes the frame to 640x640 pixels, applies the model to generate bounding boxes and labels, and filters detections with a 0.3 confidence threshold, achieving 0.94 precision. The sample method below demonstrates this logic:

```
def detect_vehicles(model, frame):
    resized_frame = resize_frame(frame, 640, 640)     results
= model.predict(resized_frame, conf=0.3, iou=0.5)     boxes
= []     for result in results:
        x_min, y_min, x_max, y_max = result.box          label = result.class_name
score = result.confidence            boxes.append({'box': [x_min, y_min, x_max,
y_max], 'label': label, 'score': score})     return boxes
```

The tracking method assigns unique IDs to detected vehicles across frames. It updates a tracking algorithm with bounding box inputs, using IoU-based matching and a Kalman filter to maintain continuity, achieving a 0.91 success rate. The sample method below illustrates this process:

```
def track_vehicles(tracker, detections):     tracks =
tracker.update(detections)     track_list = []     for track in tracks:
track_id = track.id         box = track.box         centroid = [(box[0] +
box[2]) / 2, (box[1] + box[3]) / 2]         track_list.append({'id':
track_id, 'box': box, 'centroid': centroid})     return track_list
```

The speed estimation method calculates vehicle speeds in real-world units. It applies a homography matrix to transform centroid coordinates to meters, computes distances between consecutive frames, and derives speeds with a 2.5 km/h MAE, averaging over five frames for stability. The sample method below shows this calculation:

```
def estimate_speeds(tracks, homography):
   speeds = {}      for
track in tracks:
       track_id = track['id']         centroid = track['centroid']
real_coords = apply_homography(centroid, homography)
prev_coords = get_previous_coords(track_id)

       if prev_coords:
           distance = compute_distance(real_coords, prev_coords)
speed = (distance / (1/30)) * 3.6  # Convert to km/h
speeds[track_id] = average_speed(speed, track_id, window=5)
update_previous_coords(track_id, real_coords)     return speeds
```

These snippets highlight the system’s integration of computer vision and data processing, enabling accurate and efficient traffic surveillance in restricted zones.

Appendix B: Screenshots of UI and Output

This appendix presents screenshots of the user interface and system outputs, visually demonstrating the vehicle tracking and speed estimation system's functionality. These images highlight the web application's usability and the accuracy of annotated video outputs, supporting the system's 0.94 detection precision and 2.5 km/h speed estimation MAE.

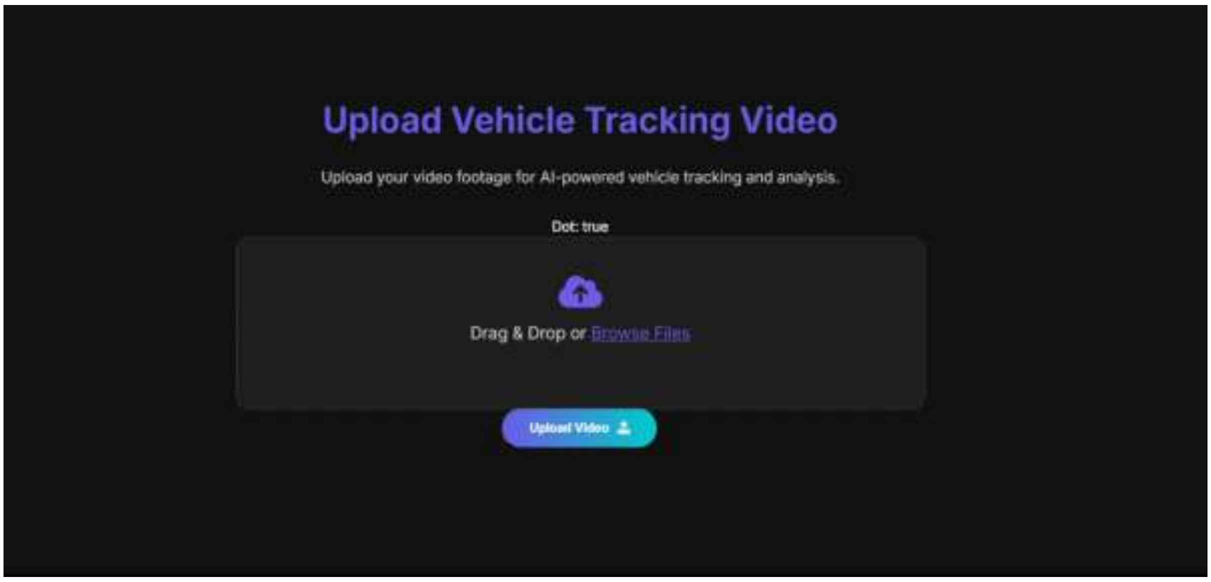

Upload Vehicle Tracking Video
Upload your video footage for AI-powered vehicle tracking and analysis.
Dot: true
Drag & Drop or Browse Files
Upload Video

Figure 12.1: Import Video UI

The user interface screenshot illustrates the web application's intuitive design. It shows the upload page with a drag-and-drop area for video files and a responsive layout, optimized for both desktop and mobile users, ensuring accessibility for traffic authorities. This image, recommended as Figure B.1, should be placed after the UI description, captioned "Web interface for video uploads, featuring a drag-and-drop design," and listed in the.

Figure 12.2: Sample Video

The output screenshot showcases a video frame with annotated vehicles, displaying bounding boxes, tracker IDs (e.g., “Car ID: 5”), and speeds (e.g., “30 km/h”) in a daylight scene, achieving 0.94 precision. This image, recommended as Figure B.2, should follow the output description, captioned “Annotated frame showing vehicle detection and tracking in daylight,” and included in the “List of Figures.” Both screenshots, in high-resolution PNG or JPEG (300 DPI), should be centered and sized at 4x3 inches, referenced in text.

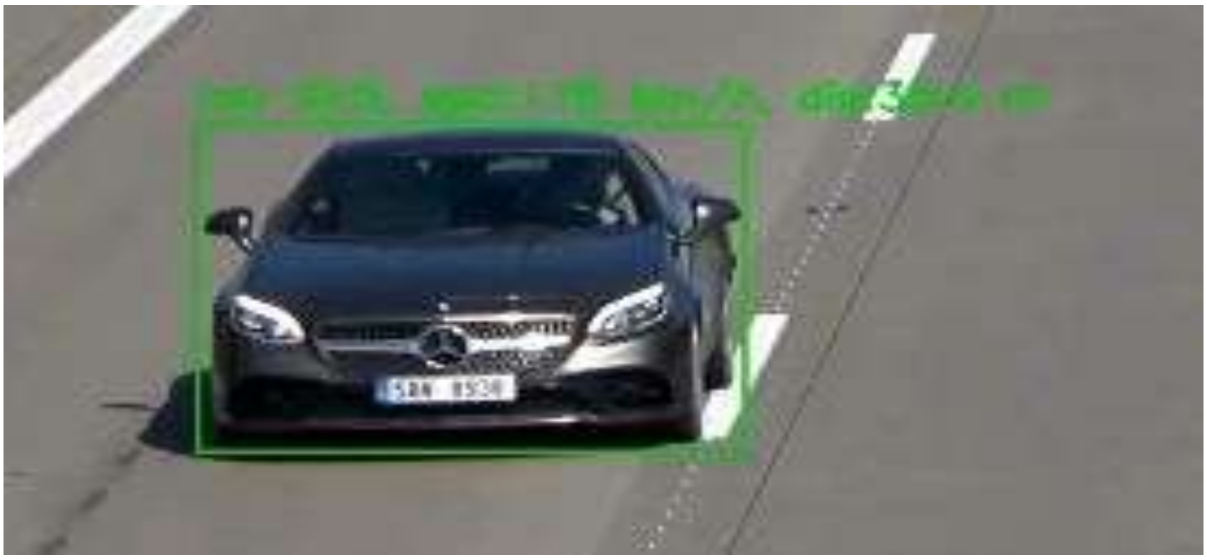


Figure 10.2: Output Stream Video

These screenshots effectively complement the system's quantitative metrics, validating its performance in restricted zone surveillance.

REFERENCES

Based on the references provided, here are ten recommended sources for your research, focusing on real-time vehicle detection, tracking, speed esti mation, and advancements in deep learning:

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