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Drivers' Speeding Responses to Dummy Traffic Police: A Behavioral Assessment along the Sallaghari–Suryabinayak Section of the Araniko Highway

by

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DEPARTMENT OF CIVIL ENGINEERING

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The undersigned certify that they have read and recommended to Institute of Engineering for acceptance, a thesis entitled **"Drivers' Speeding Responses to Dummy Traffic Police: A Behavioral Assessment along the Sallaghari–Suryabinayak Section of the Araniko Highway"** submitted by Bikesh Lage in partial fulfillment of the requirement for degree of Master of Science in Transportation Engineering.

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ABSTRACT

Speeding is a major contributing factor to road crashes in Nepal, accounting for approximately 35% of fatalities in the Kathmandu Valley. Traditional enforcement methods such as radar guns and CCTV surveillance are limited by high costs and restricted operational coverage. This study evaluates the effectiveness of dummy traffic police, a low-cost behavioral deterrent, in reducing vehicle speeds along the Sallaghari–Suryabinayak section of the Araniko Highway. The study employed an automated speed estimation framework integrating YOLOv8 for vehicle detection and DeepSORT for multi-object tracking to analyze 38,656 vehicles across three phases: baseline, intervention (dummy deployment), and post-intervention. A binary logistic regression model was developed to assess the effect of dummy presence on the likelihood of speeding.

The results show that the presence of dummy traffic police significantly reduced the odds of speeding by approximately 68% (OR = 0.32, $p < 0.05$). However, a noticeable waning effect was observed, where the probability of speeding increased by about 5% per day following deployment, indicating behavioral adaptation as drivers recognized the absence of actual enforcement. Furthermore, vehicle type and lane position were significant predictors of speeding behavior; two-wheelers were 53% more likely to speed than cars, while vehicles in the right lane were nearly 13 times more likely to exceed speed limits compared to those in the shoulder. Given its low cost and ease of implementation, this intervention contributes to a broader understanding of behavioral policing strategies and traffic enforcement effectiveness. Future research should further explore the influence of dummy traffic police on a wider range of driver behaviors across different traffic environments and geographical contexts.

Keywords: Road Safety, Speeding Behavior, Dummy Traffic Police, Computer Vision (CV), YOLOv8, DeepSORT, Binary Logistic Regression

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LIST OF ABBREVIATIONS

CV	Computer Vision
AUC	Area Under the Curve
ROC	Receiver Operating Characteristic
MLE	Maximum Likelihood Estimation
LR	Log Likelihood Ratio
R^2	Coefficient of Determination
mAP	Mean Average Precision
ROI	Region of Interest
VS code	Visual Studio code
YOLO	You Only Look Once
DeepSORT	Deep Simple Online and Real-time Tracking
β	Regression Coefficient
OR	Odds Ratio
p	Probability value

CHAPTER 1: INTRODUCTION

1.1. Background

Road traffic deaths and injuries remain a major global public health and development challenge, accounting for an estimated 1.19 million deaths worldwide in 2021. The risk of road traffic death is three times higher in low-income countries than in high-income countries, despite these countries having less than 1% of the world's motor vehicles (WHO, 2023).

Nepal, in particular, experiences one of the highest road traffic fatality rates in Asia, with an estimated 28.2 deaths per 100,000 populations, compared to 15 deaths per 100,000 populations in India (ATO, 2025). According to Nepal Police records, road crashes have shown an increasing trend in recent years as shown in Figure 1.1. A total of 2,502 fatalities were reported in the fiscal year 2081/82, representing an increase from 2,369 deaths recorded in the previous fiscal year 2080/81. Reports from Nepal Police, as shown in Figure 1.2, further indicate that approximately 92.4% of all road crashes are attributed to driver-related factors, including violations of traffic rules, improper overtaking, over-speeding, driving under the influence of alcohol, mobile phone use while driving, and driving without a license. Among these factors, over-speeding and violations of traffic rules are identified as the leading causes of road crashes.

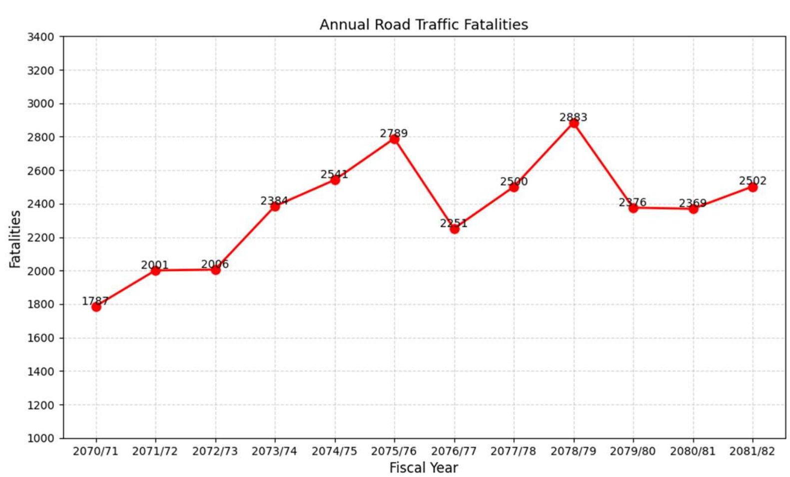

Figure 1.1: Road Crashes trend in Nepal (Source: Nepal Police)

Within the Kathmandu Valley, recent Nepal Police reports (2024) indicate that over-speeding is the predominant cause of road crashes, accounting for nearly 35% of all road fatalities. Despite the implementation of several measures to control speeding, including the deployment of radar guns, CCTV surveillance systems, and traffic signage, speeding violations remain prevalent, with more than 100 cases recorded daily on average within Kathmandu Valley.

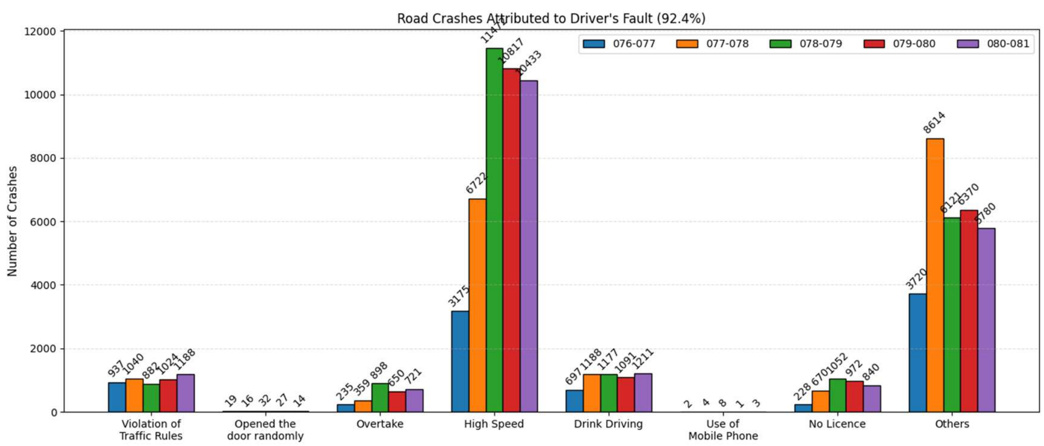

Figure 1.2: Road crashes attributed to Driver's Fault (Source: Nepal Police)

The Sallaghari–Suryabinayak section of the Araniko Highway, a six-lane urban corridor developed with support from the Japan International Cooperation Agency (JICA) in 2011, has emerged as one of the most critical crash-prone areas due to excessive speeding. Locations such as Thimi, Radhe Radhe, and Sallaghari have been identified as persistent crash hotspots along the Thimi–Suryabinayak section of the Araniko Highway, primarily due to speeding-related incidents (Adhikari, 2016; Aryal & Dhakal, 2024). The total number of crashes recorded at different locations along the Thimi–Suryabinayak section, as shown in Figure 1.3, indicates that several locations experience substantially higher crash frequencies than others, with Naya Thimi and Radhe Radhe recording the highest number of crashes (70 each), followed by Sallaghari (60) and Suryabinayak (56), highlighting the concentration of crash incidents along specific segments of the corridor.

Traffic violation records further highlight the prevalence of over-speeding along the study section. According to records from the Traffic Police Office, Chundevi, Bhaktapur, over-speeding accounted for 17,358 out of 29,914 recorded traffic violations along the Thimi–Sanga section of the Araniko Highway during fiscal year 2080/81, highlighting the widespread prevalence of speeding behavior within the study section.

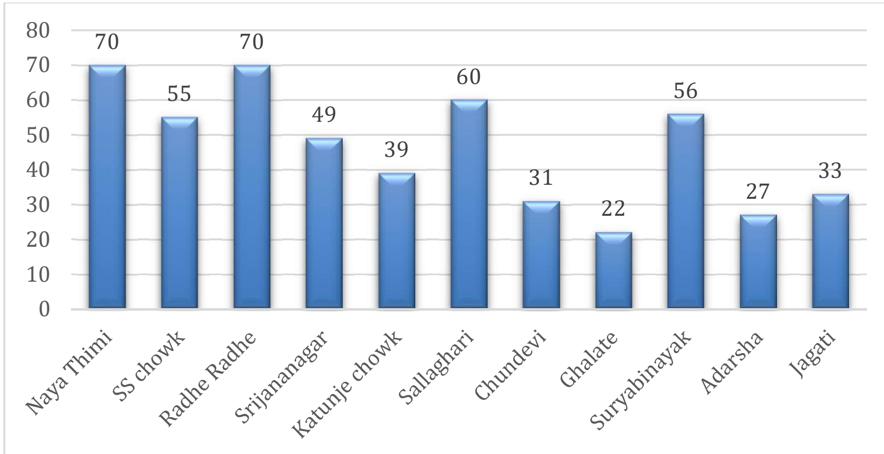

Figure 1.3: Total Number of Crashes between Shrawan, 2080 & Jestha, 2081

Traditional traffic monitoring approaches mainly rely on physical sensing devices, such as inductive loop detectors and radar-based speed sensors. Although these technologies provide relatively high measurement accuracy, they often involve high installation costs, maintenance challenges, and limited spatial coverage, which restrict their applicability for detailed vehicle behavior analysis in complex urban environments (Krajewski et al., 2018). In recent years, the rapid advancement of computer vision and deep learning technologies has created new opportunities for traffic monitoring and analysis. Object detection algorithms, particularly those from the You Only Look Once (YOLO) family, have demonstrated excellent performance in vehicle detection due to their high detection speed and computational efficiency, making them widely adopted in intelligent transportation applications (Redmon et al., 2015).

Although speed enforcement tools such as radar guns and CCTV surveillance systems have been deployed along Thimi–Suryabinayak secion since 2014, their high cost, limited operational range, and maintenance requirements restrict their large-scale application. Similarly, the continuous presence of police personnel on all roadways is not feasible due to limited manpower and competing operational duties. According to the Office of the Auditor General Nepal report for FY 2023/2024, only 1,113 traffic police officers were deployed to manage traffic in the Kathmandu Valley, with each officer responsible for approximately 1,787 registered vehicles. This disproportionate ratio highlights a substantial shortage of enforcement personnel and the associated challenges in maintaining consistent traffic regulation.

In addition to conventional enforcement strategies, awareness-oriented initiatives have also been implemented in Nepal. In 2020, the Metropolitan Traffic Police Division installed several dummy traffic police figures at major intersections across the Kathmandu Valley as part of a public awareness campaign on traffic rules and regulation, as shown in Figure 1.4.

Figure 1.4: Dummy Traffic Police as awareness tool

These life-sized cutouts displayed safety messages and information about traffic fines to remind drivers of traffic regulations. These perceived enforcement tools mimic the visual presence of law enforcement and can temporarily influence driver behavior. However, there remains limited research evaluating the effectiveness and behavioral persistence of dummy traffic police in addressing speeding behavior within the Nepalese road context.

1.2. Problem Statement

Despite the implementation of conventional enforcement measures–including radar-based monitoring and CCTV surveillance, over-speeding remains a critical safety concern along the Sallaghari–Suryabinayak section of the Araniko Highway. The high capital investment required for these technologies, coupled with the limited availability of traffic personnel, has resulted in significant monitoring gaps. Consequently, large segments of the highway remain unchecked, allowing dangerous driving behaviors to persist. This situation highlights an urgent need for the development of low-cost speed enforcement solutions that can provide continuous and wider spatial coverage.

1.3. Research Objectives

The primary objective of this study is to assess drivers' speeding responses to the presence of dummy traffic police along an urban highway section. The specific objectives of the study are presented below:

1. To assess drivers' speeding behavior in the presence and absence of dummy traffic police.
2. To develop a logistic regression model for predicting drivers' speeding behavior under dummy traffic police deployment.

1.4. Scope of Study

The scope of this study are as following:

1. The study focuses exclusively on the Sallaghari–Suryabinayak urban highway section of the Araniko Highway, analyzing speed behavior over a straight, uninterrupted segment with sufficient sight distance
2. Speeds are measured using computer vision (CV)**,** while LiDAR gun is used to determine the reference speed measurement.
3. Only off-peak, free-flow traffic conditions (12-1 PM) are analyzed to avoid congestion-related speed variations.
4. The research assesses the impacts of fixed-location dummy traffic police.

1.5. Limitation of Study

Following are the limitations of the study:

1. Night-time and peak-hour speed behaviors are not analyzed.
2. The impact of existing speed-reducing interventions was not accounted for during the analysis.
3. Study limited to one urban arterial section; generalization may require further study.

1.6. Organization of Report

The thesis is organized into five chapters, as outlined below:

Chapter 1: Introduction presents the background of road safety issues in Nepal, highlighting the problem of over-speeding along the Sallaghari–Suryabinayak section of the Araniko Highway. It outlines the research problem, objectives of the study, and the scope and limitations of the research.

Chapter 2: Literature Review reviews national and international studies related to driver speeding behavior, perceived enforcement strategies, dummy police interventions, and the methodological approaches adopted in previous research.

Chapter 3: Methodology describes the research design, selection of the study area, data collection procedures, variable preparation, the logistic regression modeling, and model evaluation strategies.

Chapter 4: Results and Discussion presents and interprets the findings of the logistic regression analysis, examines the behavioral impact of dummy traffic police deployment, and analyzes the potential short-term decay pattern in driver compliance.

Chapter 5: Conclusion and Recommendations summarizes the key findings of the study and provides recommendations for improving speed management and traffic safety based on the research outcomes.

CHAPTER 2: LITERATURE REVIEW

2.1. Overview of Road Safety and Speeding Issues

Road traffic crashes continue to be a major public health concern worldwide, with over-speeding consistently recognized as one of the leading contributing factors. Increases in average speed are directly linked to both the likelihood of a crash and the severity of its consequences. For instance, a 1% increase in mean speed can lead to roughly a 4% increase in the risk of fatal crashes and a 3% increase in serious injury crashes (WHO, 2023). The Nilsson Power Model further illustrates this relationship, showing that fatal crashes increase with the fourth power of speed. This indicates that even small increases in mean speed can result in disproportionately higher fatal crash risk (Nilsson, 2004).

2.2. Human Factors and Driving Speeding Behavior

Human factors have a strong influence on how drivers choose their speed. Many drivers depend on their own judgement and the flow of surrounding traffic rather than strictly following the posted speed limit. Their choices are also shaped by personal attitudes and by the level of enforcement they believe is present on the road (Haglund & Åberg, 2000). Drivers often increase their speed when they perceive the road environment to be safer or less controlled (Vaa, 2014). This behavior reflects risk compensation, where a lower perceived level of risk leads drivers to adopt higher speeds. Overall, these findings suggest that speeding behavior is strongly influenced by driver perception and beliefs about the road environment, rather than by the posted speed limit alone.

2.3. Effectiveness of Inanimate Enforcement Tools

Several studies have evaluated the impact of inanimate enforcement tools, such as dummy traffic police or police cutouts, on driver speeding behavior. It has been shown that the perceived presence of law enforcement, even without actual enforcement, can effectively reduce speeding behavior (Rhodes & Pivik, 2011; Simpson et al., 2020). Drivers tend to respond to cues of enforcement and often adjust their speed when they believe they are being observed. In addition, the strategic placement of unmanned police vehicles along roadways has been found to lead to measurable reductions in traffic speed (Kaplan et al., 2000). These findings suggest that visible signs of enforcement, whether real or simulated, can influence driver behavior; however, the impact may diminish over time if the cues are not consistently reinforced or if drivers recognize them as non-functional.

2.4. Use of Computer Vision (CV) in Speed Studies

Recent advanced computer vision technologies introduce numerous studies and researches in vision-based vehicle speed measurement. The main objective is to utilize traffic monitoring cameras for vehicle speed estimation without requiring additional speed sensors (Sangsuwan & Ekpanyapong, 2024). In recent years, the rapid development of computer vision and deep learning technologies has provided new opportunities for traffic flow monitoring. Object detection algorithms such as the YOLO (You Only Look Once) series have demonstrated excellent performance in vehicle recognition due to their efficient detection capabilities, gradually becoming the mainstream method for object detection in traffic scenarios (Redmon et al., 2015). YOLO is substantially faster than most convolutional neural networks since it conducts classification and bounding box regression in a single step (Abdel-Aty et al., 2023). Among the different versions of YOLO, YOLOv8s provides improved detection accuracy compared to earlier versions such as YOLOv3 and YOLOv5s, particularly in detecting small or partially occluded objects that are commonly encountered in complex traffic environments. In addition, the DeepSORT algorithm combines deep appearance features with Kalman filtering to enable robust multi-object tracking, even under varying illumination conditions (Mu et al., 2025).

2.5. Analytical Approaches in Speeding Research

Researchers have applied a range of analytical methods to understand speeding behavior and its relationship with road safety outcomes. Statistical regression models are widely used to examine how traffic speed influences crash risk and driver behavior. For example, the relationship between changes in traffic speed and accident frequency has been modeled using the power model proposed by Nilsson (Nilsson, 2004) and later refined through statistical analysis (Elvik, 2013). In studies of driver behavior, regression techniques such as logistic regression have been used to examine the probability of speeding under different roadway and enforcement conditions (Simpson et al., 2020). In recent years, advances in computer vision and automated traffic monitoring have enabled the collection of detailed vehicle trajectory and speed data from video footage, allowing more precise behavioral analysis (Abdel-Aty et al., 2023). Such analytical approaches provide valuable insights into the determinants of speeding and support the development of effective speed management strategies.

2.6. Speeding and Enforcement Context in Nepal

Speeding is recognized as one of the major contributing factors to road traffic crashes in Nepal. Rapid urbanization, increasing vehicle ownership, and mixed traffic conditions have made speed management a significant challenge on both urban and highway networks. According to the World Health Organization, excessive or inappropriate speed increases both the likelihood of crashes and the severity of injuries, making speed control an essential component of road safety strategies. In Nepal, road traffic regulation and enforcement are primarily governed by the Motor Vehicles and Transport Management Act, 2049 (1993) and its 1997 Regulations, while operational enforcement is carried out by the Nepal Traffic Police. Traffic police commonly use manual enforcement methods such as roadside monitoring, handheld radar guns, and visual observation to detect speeding vehicles. In recent years, Automatic Number Plate Recognition (ANPR) systems with speed detection capabilities have been deployed at a few locations across the country. However, these systems involve high capital investment along with recurring operational and maintenance costs due to their reliance on specialized hardware, software licensing, and continuous system operation. As a result, their implementation remains limited, restricting wider spatial coverage of speed enforcement.

2.7. Research Gap

The reviewed literatures indicate that speeding is one of the major contributors to road traffic crashes and crash severity worldwide. Previous studies have shown that drivers' speeding behavior is influenced by factors such as road conditions, perceived risk, and the presence of enforcement measures. Research on inanimate enforcement interventions, including dummy traffic police and police cutouts, suggests that the perceived presence of enforcement can temporarily reduce vehicle speeds, although the effect may diminish over time.

In the Nepalese context, speeding remains a major road safety concern, while enforcement is still largely dependent on manual monitoring and radar-based speed checks. Although dummy traffic police have occasionally been used as an awareness measure, limited research has been conducted to evaluate their effectiveness in influencing drivers' speeding behavior. Therefore, this study aims to address these gaps through a data-driven assessment of drivers' speeding responses to dummy traffic police deployment along a major highway section.

CHAPTER 3: METHODOLOGY

3.1. Research Design

This study adopts a behavioral observational research design supported by logistic regression analysis to statistically examine the influence of dummy traffic police on driver speeding behavior. The overall research framework integrates sequential field observations, video graphic data collection, speed extraction, and statistical modeling. The conceptual structure of the research design is illustrated below in Figure 3.1.

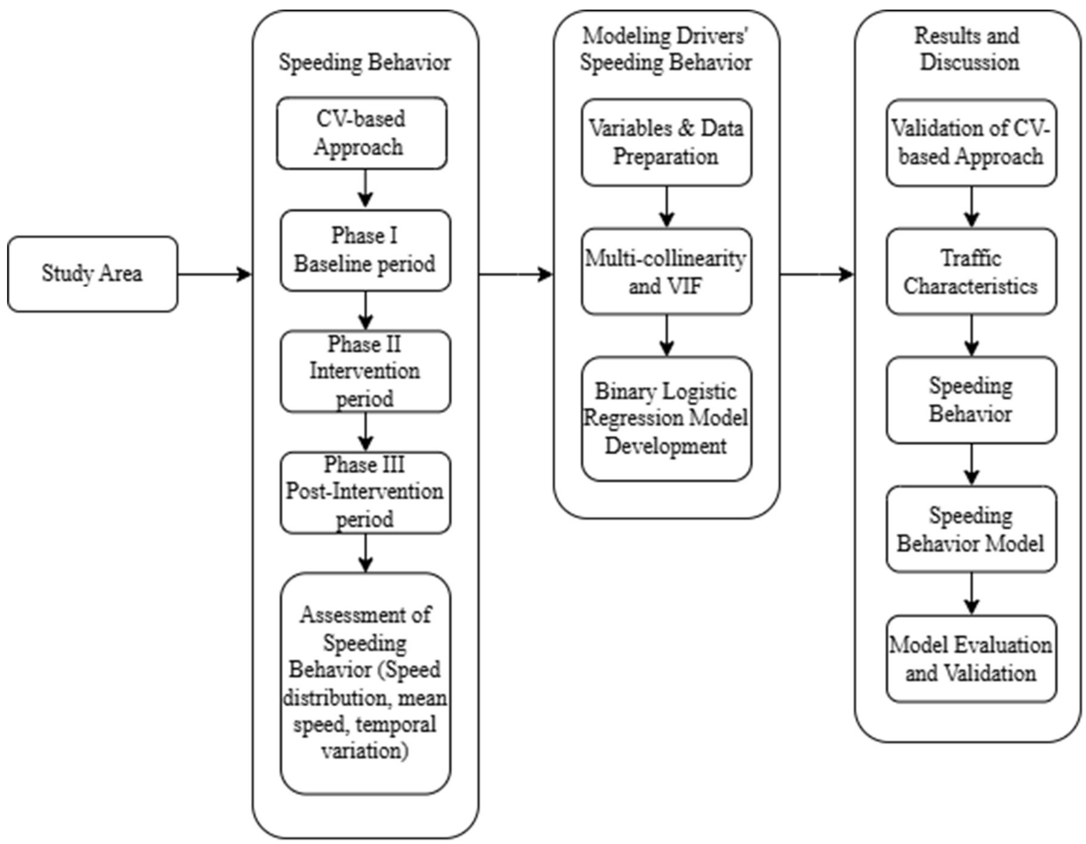

Figure 3.1: Research design

3.2. Tools

Traffic videos were recorded using a GoPro Hero Session camera at 30 frames per second (fps) with a resolution of 1920 × 1080 pixels. Video processing and model development were carried out using Python in Visual Studio (VS) Code environment on a laptop with 12th Gen Intel Core i5, 16 GB RAM, and NVIDIA GeForce RTX 3050 GPU.

Vehicle detection and classification were performed using YOLOv8, while DeepSORT was used for vehicle tracking. OpenCV handled image processing, and Pandas and NumPy were used for data preprocessing. Logistic regression modeling was conducted using Scikit-learn, and visualizations were generated using Matplotlib. Microsoft Excel was used for preliminary data organization and verification. A life-sized human-like mannequin dressed in a traffic police uniform was deployed along the study section to simulate traffic police presence. The tools used during the study are summarized in Table 3.1.

Table 3.1: Tools used in the study

S.N.	Category	Name	Tools
1	Hardware	Video Recording device	GoPro Hero Session
2		Computer	Laptop with 12th Gen Intel Core i5 processor, 16 GB RAM, 64-bit Windows operating system, and NVIDIA GeForce RTX 3050 GPU
3	Software	Programming Language	Python (3.11)
4		Development Environment	Visual Studio Code (VS code)
5		Data Organization	Microsoft Excel
6	Python Libraries	Vehicle Detection	Ultralytics YOLOv8
7		Vehicle Tracking	DeepSORT
8		Image Processing	OpenCV
9		Data Processing	Pandas, NumPy
10		Statistical Modeling	Scikit-learn, Statsmodels
11		Data Visualization	Matplotlib
12	Material	Speed Enforcement tool	Human-like mannequin, Dummy Traffic Police, Life sized (6’2”)

3.3. Study Area

For this study, the Sallaghari–Suryabinayak section of the Araniko Highway, particularly near Chundevi, was selected as the study location, as shown in Figure 3.2. The site was chosen based on several criteria, including a straight road segment with uninterrupted traffic flow, absence of major intersections, adequate sight distance, and a history of relatively high crash occurrences. Records from Nepal Police indicate that the Sallaghari–Suryabinayak road segment consistently reports a higher number of crashes, particularly in the areas of Sallaghari, Chundevi, and Ghalate, as illustrated in Figure 1.3 above.

This straight road segment functions as a speeding pocket, encouraging higher vehicle speeds along the stretch and influencing driver behavior at nearby intersections. The presence of pedestrian crossings at Sallaghari and Ghalate further increases the safety sensitivity of this section, highlighting the need for effective speed management. Moreover, crashes associated with over-speeding in this section have repeatedly threatened the safety of nearby residents and public property, including incidents involving vehicle overturning and breaches of existing safety barriers.

Figure 3.2: Study area

3.4. Speeding Behavior

To assess drivers' speeding behavior, a computer vision (CV)-based approach was applied to estimate vehicle speeds along with vehicle class and lane position. The videographic survey was conducted for a total period of 21 days under three distinct traffic conditions: normal conditions (baseline), during the presence of dummy traffic police (intervention), and after the removal of the dummy (post-intervention). An analysis of speeding behavior was then carried out, focusing on speed distribution, mean speed, and temporal variations in speeding behavior across conditions with and without dummy traffic police.

3.4.1 Computer Vision (CV)-based Approach

A CV–based framework was used to automatically detect vehicles, track their movement, and estimate their speeds from video data. The system follows a sequential pipeline consisting of video input, vehicle detection, vehicle tracking, virtual line crossing detection, speed computation, and structured data output, as shown in Figure 3.3.

Initially, video recordings collected from the study area were processed frame by frame using OpenCV. Each frame was then passed through a custom-trained object detection model based on YOLOv8 to identify vehicles and classify them into predefined categories. DeepSORT subsequently assigned unique IDs to the detected vehicles and tracked them across consecutive frames. Two virtual reference lines, separated by a known distance, were used to determine the time taken by each vehicle to traverse the segment. This time interval was then used to compute the vehicle speed. The computed speed, along with the vehicle type and lane position, were stored for further analysis.

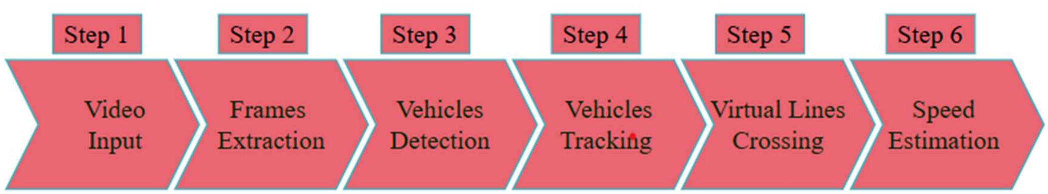

Figure 3.3: CV-based speed estimation framework

a) Dataset Preparation

To develop a robust vehicle detection model suitable for local traffic conditions, a custom dataset was prepared using frames extracted from recorded videos of the study area. Video frames were extracted at a rate of 30 fps to ensure adequate temporal coverage. The original dataset consisted of 939 annotated images, containing a total of 5,305 labeled objects across six vehicle classes: 2-Wheelers (3,148), Car (898), Utility (425), Bus (340), Truck (267), and Microbus (209).

The images were annotated using Roboflow, where bounding boxes were manually drawn around each vehicle, as shown in Figure 3.4. The annotation process was carefully carried out to ensure that the dataset accurately represented real-world traffic characteristics, including heterogeneous vehicle composition, varying lighting conditions, and occlusions commonly observed in the study section.

Roboflow is a cloud-based CV platform that facilitates dataset management, image annotation, preprocessing, and model training. It provides an intuitive interface for labeling images and supports multiple annotation formats compatible with modern deep learning frameworks. In this study, it was used to annotate images, manage dataset versions, and export the dataset in a format suitable for model training.

To enhance model generalization and robustness under varying field conditions, data augmentation techniques were applied. These included exposure variation (−10% to +10%) to simulate lighting changes, blur up to 2.5 pixels to account for motion and focus variations, and noise addition up to 0.1% of pixels to replicate real-world image distortions. Additionally, auto-orientation preprocessing was applied to ensure consistent image alignment. As a result of these augmentations, the dataset size increased to 2,435 images. The augmented dataset was split into training, validation, and testing subsets and then exported in a YOLOv8-compatible format for efficient model training and deployment.

Figure 3.4: Image Annotation using Roboflow

b) Model Training

The vehicle detection model was trained using the YOLOv8 architecture with a custom training approach to better capture local traffic patterns. The annotated dataset was used for training with 100 epochs, a batch size of 16, and an input image resolution of 640 × 640 pixels. The trained model demonstrated strong detection performance, achieving an overall precision of 0.763, recall of 0.795, mAP@0.5 of 0.825, and mAP@0.5:0.95 of 0.594. The obtained performance metrics are consistent with findings from previous studies on traffic object detection using YOLO-based models, where precision and recall values typically range between 0.6 and 0.9, and mAP values commonly fall between 0.6 and 0.8 depending on dataset complexity (Aloufi et al., 2023; Doria Usta et al., 2025). Class-wise results indicated higher detection accuracy for cars and buses, while comparatively lower performance was observed for motorcycles, likely due to higher variability and occlusion in heterogeneous traffic conditions.

c) Vehicle Detection

YOLO processes each frame in a single pass and identifies objects by predicting bounding boxes, and class labels simultaneously, making it highly efficient and suitable for video-based traffic analysis. Each frame was processed to identify vehicles along with their bounding boxes, and class labels. The model was capable of detecting multiple vehicles simultaneously within a frame, enabling analysis under mixed traffic conditions. The output of this stage formed the foundation for tracking and speed estimation processes in the following stages. To ensure data reliability, only vehicles that successfully crossed both reference lines were considered.

d) Vehicle Tracking

Vehicle tracking was performed to maintain the identity of each detected vehicle across consecutive frames by assigning a unique ID to every vehicle. This ensures that each vehicle is consistently tracked throughout its movement in the video, which is essential for accurate speed estimation. The tracking process was implemented using DeepSORT, with predefined parameters including max_age = 15, n_init = 5, max_iou_distance = 0.5, and max_cosine_distance = 0.3. These parameters help control tracking stability by allowing temporary missed detections, confirming valid tracks, and ensuring accurate matching between detections across frames.

e) Region of Interest (ROI) and Reference Lines

A specific region of interest (ROI) was defined within the video frame to focus the analysis on the roadway segment relevant to speed measurement. Within this region, two virtual reference lines (blue and red) were drawn perpendicular to the direction of traffic flow, separated by a distance of 20 m, as shown in Figure 3.5.

The dummy traffic police were positioned at a sufficient distance from approaching drivers to allow perception and reaction before reaching the blue line, as shown in Figure 3.6. It was assumed that vehicles travel at a constant speed between the two reference lines. Given the posted speed limit of 50 km/h, the time required to traverse the 20 m distance is approximately 1.44 seconds, and for higher speeds, this duration would be even shorter. Furthermore, along this section, the dummy traffic police could not be clearly distinguished from the blue line, reducing the likelihood of drivers accelerating within the region of interest. This suggests that the distance of the dummy traffic police from the blue line is more critical than its distance from the red line. The use of fixed reference lines provides a simple and effective calibration approach, enabling pixel-based motion in the video to be translated into real-world speed measurements.

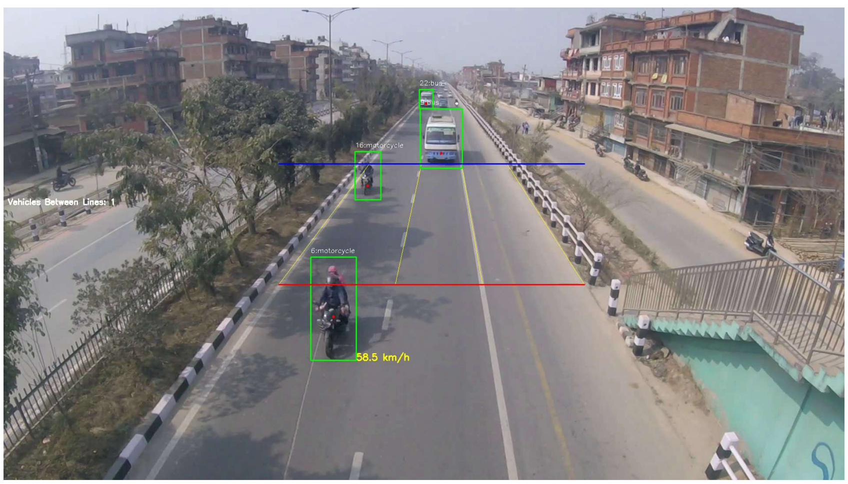

Figure 3.5: Region of Interest and Line Crossing Logic

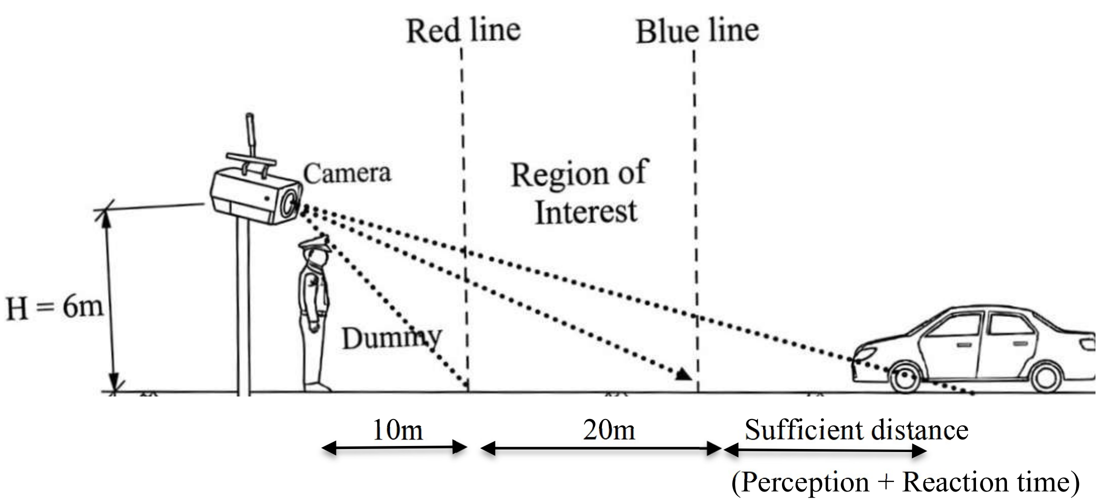

Figure 3.6: Layout of ROI and dummy placement

f) Line Crossing Logic

The detection of vehicle crossing events was based on the movement of the centroid of the bounding box associated with each tracked vehicle. A crossing event was registered when the centroid of a vehicle transitioned from one side of a reference line to the other between consecutive frames. Specifically, if the centroid position in the previous frame was located before the reference line and in the current frame it was located beyond the line, the vehicle was considered to have crossed that line. To avoid duplicate detections, each vehicle ID was allowed to trigger a crossing event only once per reference line.

g) Speed Estimation Method

Speed estimation was based on the time taken by a vehicle to travel between the two reference lines. When a tracked vehicle crosses the first line, the corresponding frame number is recorded. Similarly, the frame number is recorded when the same vehicle crosses the second line.

The time taken by a vehicle to traverse the known distance was computed using the difference in frame numbers corresponding to line crossing events, as shown in Equation (3.1) and was calculated using the video frame rate (frames per second, fps) which was maintained at 30.

$$\text{Time} = \frac{Frame\ Difference}{FPS} \tag{3.1}$$

Thereafter, the speed is computed using the known distance between the lines, as shown in Equation (3.2).

$$\text{Speed} = \frac{Distance}{Time} \tag{3.2}$$

The resulting speed is then converted into kilometers per hour (km/h) and displayed simultaneously in the video frame, as shown in Figure 3.7.

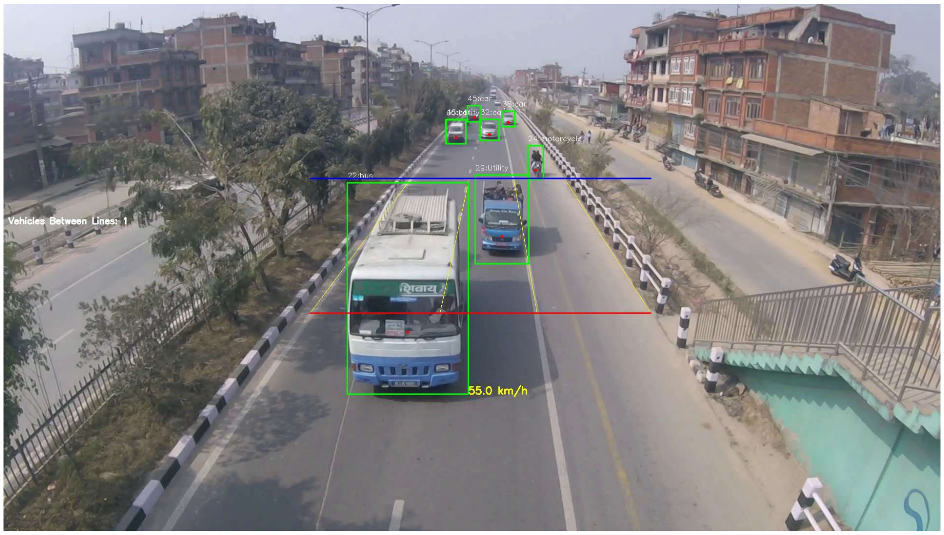

Figure 3.7: Output frame showing speed of vehicle

h) Lane Identification and Vehicle Classification

In addition to speed estimation, the system also extracted lane position and vehicle type information. Lane identification was performed by analyzing the horizontal position of the vehicle's bounding box within the frame. Based on predefined spatial boundaries, vehicles were classified as traveling in either the left lane or right lane or shoulder. Vehicle classification was directly obtained from the detection model, which assigns each detected object to a predefined class. This enabled the analysis of speed behavior across different vehicle categories and lane positions.

i) Speed Calibration Using LiDAR Gun

To calibrate the CV–based speed estimates, simultaneous measurements were obtained using a LiDAR speed gun during video data collection, as shown in Figure 3.8. The LiDAR device recorded spot speeds of sample of vehicles across different classes randomly, as illustrated in Figure 3.9, while the same vehicles were captured in the video for CV-based estimation. The LiDAR speed gun provides direct speed readings of moving vehicles and is considered a reliable reference for field-based speed measurement. The recorded video was later processed through the CV-based speed estimation system, and the estimated speeds were matched with the corresponding LiDAR gun readings. Matched observations were used to develop a linear regression model relating CV-estimated speeds to LiDAR-measured speeds, yielding the calibration equation, as shown in Equation (3.3).

$$\text{Speed}_{\text{LiDAR}} = 0.977 + 0.952 \times \text{Speed}_{\text{CV}} \tag{3.3}$$

Model performance was evaluated using standard error metrics to assess the accuracy of the CV-based speed estimates relative to LiDAR measurements, as presented in Table 3.2. Based on these results, the derived calibration equation was later applied to adjust the CV-based speed estimates, improving the overall accuracy and reliability of the speed estimation system.

Table 3.2: CV speed validation

Metrics	Value
Mean Absolute Error (MAE)	2.50 km/h
Root Mean Square Error (RMSE)	3.05 km/h
Mean Percentage Error (MPE)	0.25%
Mean Absolute Percentage Error (MAPE)	4.90 %

Figure 3.8: Speed data collection using LiDAR

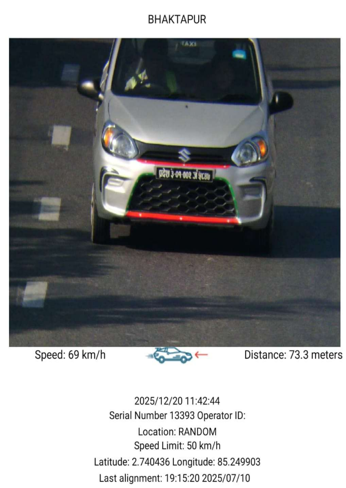

Figure 3.9: Sample Data Recording

3.4.2 Phase I: Baseline Period

The baseline period aimed to document normal driver behavior under uninterrupted traffic conditions. Video recordings were taken during the off-peak hour, between 12:00 PM and 1:00 PM, when traffic flow is relatively stable and less affected by congestion-induced speed variations. Before the start of the video recordings, numbers of markings were made on the pavement, to identify the known physical distance marks on the video recording. Recordings were conducted over six (6) days to ensure adequate representation of routine driving patterns. This baseline dataset served as the control condition against which the effects of dummy police deployment were evaluated.

3.4.3 Phase II: Intervention Period

During the intervention period, the dummy was deployed at the designated location near the overhead pedestrian bridge at Chundevi, Bhaktapur, as shown in Figures 3.10 and 3.11. The dummy was placed on the shoulder of the carriageway and positioned to ensure clear visibility from a sufficient distance, allowing approaching drivers to notice it well in advance.

Continuous video recording was carried out over a period of twelve (12) days to capture driver responses under varying traffic conditions. The duration for which the dummy was deployed was selected to adequately capture short-term behavioral adaptation while ensuring consistency in data collection. Previous studies have adopted similar intervention durations, ranging from approximately 10 days to 2–3 weeks, to evaluate changes in driver behavior. In this context, a 12-day observation period was considered sufficient to capture the initial reduction in speeding behavior as well as the subsequent trend of behavioral adaptation. During this period, daily changes in the proportion of vehicles exceeding the threshold speed limit were monitored and recorded to assess behavioral adaptation among drivers.

Figure 3.10: Dummy Traffic Police

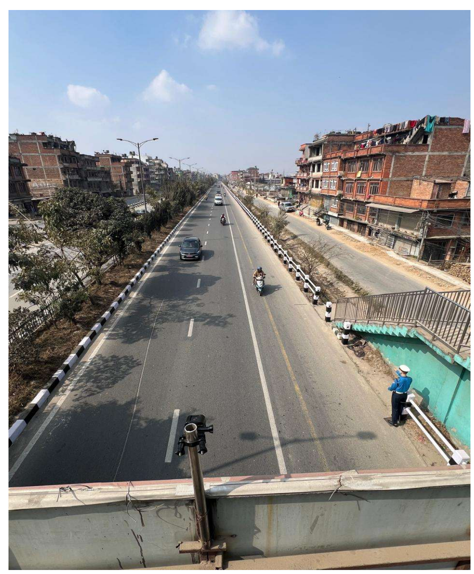

Figure 3.11: Video Recording under Dummy Presence

3.4.4 Phase III: Post-Intervention Period

Following the completion of the intervention period, the dummy traffic police was removed to assess the after-effect of dummy. Three (3) additional days of video recording were conducted under the same time-of-day and traffic flow conditions as in the baseline period. The post-intervention duration was intentionally kept shorter, as the objective was to capture the immediate behavioral response following the removal of the dummy rather than long-term adaptation. This phase helped to determine whether driver behavior reverts immediately to pre-intervention patterns or whether a residual speed-reducing effect remains for a short period. Figure 3.12 shows the number of days in each phase of the study.

Day	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
Phase	Baseline Period (No dummy)						Intervention Period (Dummy deployed)												Post-Intervention Period (No dummy)		

Figure 3.12: Phase Vs Day of dummy traffic deployment

3.4.5 Analysis of Speeding Behavior

Video recordings from different phases were processed using the CV-based vehicle detection and speed estimation model discussed earlier. To assess driver speeding behavior under the presence and absence of the dummy traffic police, a set of speeding characteristics was defined based on standard traffic flow analysis approaches. These included: (i) speed distribution across different study phases (baseline, intervention, and post-intervention), which helps in examining the spread and dispersion of vehicle speeds and identifying shifts in the overall speed profile; (ii) mean speed across phases, used to compare central tendencies and evaluate the extent of reduction or increase in average speeds due to the intervention; and (iii) temporal variation in speed across phases, which captures day-to-day fluctuations in driving behavior and allows for the assessment of behavioral adaptation over time. In addition, the proportion of vehicles exceeding the predefined threshold speed was monitored across all phases to directly quantify speeding behavior. Together, these indicators provide a comprehensive framework to evaluate the effectiveness of the dummy traffic police in influencing driver behavior under varying traffic conditions.

3.5. Modeling Driver's Speeding Behavior

Using data extracted from videographic analysis, a binary logistic regression model was developed to predict drivers' speeding behavior under conditions of dummy traffic police deployment. Binary logistic regression was selected due to its appropriateness for modeling dichotomous outcomes and its capacity to quantify the influence of multiple explanatory variables in terms of odds ratios. In this model, the dependent variable represents speeding behavior, defined as a binary outcome distinguishing between speeders and non-speeders. The independent variables include enforcement condition, vehicle type, lane position, and relevant temporal factors.

3.5.1 Variables and Data Preparation

The data extracted from the videographic analysis included vehicle speed, vehicle class (2-wheelers, cars, utility vehicles, buses, trucks, and microbuses), and lane position (shoulder, left, and right). Among these, vehicle speed and vehicle classification are commonly used variables in previous studies to evaluate speeding behavior and traffic composition. In contrast, lane position was incorporated as a site-specific variable to capture the lateral distribution of vehicles across the carriageway, which is particularly relevant under the heterogeneous traffic conditions observed in the study area. For the logistic regression model, speeding was considered the dependent variable, while the presence of dummy traffic police, vehicle class, and lane position were treated as independent variables (predictors). Additionally, two temporal variables namely- time since dummy deployment and time after dummy removal, were included to assess the time-dependent effects of dummy traffic police on speeding behavior. The posted speed limit along the Koteshwor–Suryabinayak section of the Araniko Highway is 50 km/h, however, enforcement typically begins at speeds of 60 km/h or higher. Accordingly, a threshold of 60 km/h was adopted in this study, classifying vehicles traveling at 60 km/h or above as speeders and those below as non-speeders.

In binary logistic regression, only the dependent variable must be binary, while independent variables can be binary, categorical, or continuous. As shown in Table 3.3, speeding and dummy traffic presence were encoded as binary variables, vehicle class and lane position were treated as categorical predictors using one-hot encoding, and time since dummy deployment and time after dummy removal were treated as continuous variables. Vehicles traveling at 60 km/h or above were coded as 1 for speeding and 0 otherwise. Similarly, dummy traffic presence was coded as 1 when deployed at the site and 0 when absent.

Under one-hot encoding, each category was represented by a separate binary indicator variable. For vehicle class, multiple binary indicators were created, with car designated as the reference category. Each indicator variable took the value 1 if a vehicle belonged to that specific class and 0 otherwise. This encoding allowed categorical predictors to be incorporated appropriately into the logistic regression framework. Similarly, separate binary indicator variables were created for each lane category (i.e., left lane and right lane), with the shoulder designated as the reference category. Continuous time variables were entered directly, coded sequentially (1, 2, 3…) for periods after dummy deployment or removal and 0 otherwise, allowing the model to estimate how the likelihood of speeding changed incrementally over time.

Table 3.3: Coding the Variables

Variables	**Encoding Approach**
Speeding	Binary (No=0, Yes=1)
Dummy traffic presence	Binary (No=0, Yes=1)
Time since dummy deployment	Continuous (1,2,3,…..)
Time after dummy removal	Continuous (1,2,3,…..)
Vehicle class	One-hot encoding
Lane position	One-hot encoding

After all variables were appropriately encoded, a single analytical dataset consisting combined data from all three phases was prepared and finalized for analysis, as shown in Table 3.4, ensuring that binary, categorical, and continuous predictors were correctly formatted for input into the logistic regression model.

Table 3.4: Sample Dataset

Speeding (1=yes/ 0=no)	Dummy Traffic Police Presence	Time since dummy deployment (days)	Time after dummy removal (days)	2-wheelers	Bus	Truck	Utility	Micro	Left lane	Right lane
0	0	0	0	1	0	0	0	0	1	0
1	0	0	0	0	1	0	0	0	0	1
1	1	3	0	1	0	0	0	0	1	0
0	1	5	0	0	0	1	0	0	0	1

Table 3.4: Sample Dataset (continued)

Speeding (1=yes/ 0=no)	Dummy Traffic Police Presence	Time since dummy deployment (days)	Time after dummy removal (days)	2-wheelers	Bus	Truck	Utility	Micro	Left lane	Right lane
1	1	7	0	0	0	0	0	1	1	0
0	1	7	0	0	0	0	1	0	0	1
1	1	8	0	1	0	0	0	0	0	1
0	1	10	0	1	0	0	0	0	0	1
1	0	0	1	0	0	0	0	0	1	0
1	0	0	2	0	0	1	0	0	1	0

3.5.2 Multi-collinearity and Variance Inflation Factor (VIF)

Multi-collinearity happens when two or more independent variables in a regression model are highly correlated with each other. It is the property of predictors, not the model performance. It does not reduce the predictive power of the model much, but with its presence, coefficients become unstable, standard errors become large, p-values become unreliable, and small data changes can cause large coefficient changes.

VIF is a numerical measure used to detect multi-collinearity. It tells how much the variance of a regression coefficient is inflated because of correlation with other predictors. Mathematically, VIF for variable X_i is presented in Equation (3.4).

$$X_i = \frac{1}{1 - R^2_i} \tag{3.4}$$

where, R^2_i is obtained by regressing X_i on all other independent variables. So, basically, if X_i is highly explained by other predictors, R^2_i is high and VIF becomes large. Generally, a variable need to be removed when VIF>10 as it refers to serious multi-collinearity. Table 3.5 presents the results of the VIF test for multi-collinearity among the predictor variables.

Table 3.5: VIF of Variables

Predictor Variables	VIF
Dummy Traffic Police Presence	5.90
Time since dummy deployment	4.47
Time after dummy removal	1.29
2-Wheelers	2.62
Bus	1.15
Truck	1.13

Table 3.5: VIF of Variables (continued)

Predictor Variables	VIF
Utility	1.19
Microbus	1.05
Left lane	2.07
Right lane	1.80

The results indicate that most variables exhibited low to moderate VIF values, generally below 5, suggesting no serious multi-collinearity concerns. The VIF value for the variable "Dummy Traffic Police Presence" was found to be 5.90, which is slightly above the commonly accepted threshold of 5. This indicates a moderate level of correlation with other independent variables in the model. The most plausible source of this correlation is the inclusion of the time-related variables, particularly time since dummy deployment. Conceptually, this relationship is expected, as the duration since deployment can only increase when the dummy police is present. Therefore, the observed multi-collinearity reflects a structural and logically consistent relationship between the variables rather than an issue arising from random correlation.

3.5.3 Binary Logistic Regression Model for Speeding Behavior

Binary logistic regression is a statistical method used to model the relationship between a binary dependent variable and a set of independent variables. It estimates the probability of occurrence of an event based on independent variables by applying a logistic function. Unlike linear regression, which is used for continuous outcomes, binary logistic regression is specifically designed for categorical variables with two possible outcomes (e.g. 0/1 or yes/no). For instance, $Y_i = 1$ if vehicle "i" is classified as a speeder, and $Y_i = 0$ otherwise. The general form of the binary logistic regression model is presented in Equation (3.5).

$$log\left(\frac{P(Yi=1)}{P(Yi=0)}\right) = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \beta_3 X_{i3} + \ldots\ldots\ldots + \beta_n X_{ik} \tag{3.5}$$

where, $log\left(\frac{P(Yi=1)}{P(Yi=0)}\right)$ = log-odds of speeding,

β_n = regression beta coefficients,

X_n = independent variables,

Similarly, the actual probability of speeding applying the logistic (sigmoid) function is presented in Equation (3.6).

$$p = \frac{1}{1 + e^{-Z}} \tag{3.6}$$

where, $Z = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \beta_3 X_{i3} + \ldots\ldots\ldots + \beta_n X_{ik}$

For this study, the binary regression model is presented in Equation (3.7).

$$log\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1\,(Dummy) + \beta_2(Time\ since\ deployment) + \beta_3(Time\ after\ removal) + \beta_4(2 - wheeler) + \beta_5(Bus) + \beta_6(Truck) + \beta_7(Utility) + \beta_8(Microbus) + \beta_9(Left\ lane) + \beta_{10}(Right\ lane) \tag{3.7}$$

To evaluate model performance and avoid overfitting, the compiled dataset was divided into training and testing subsets using a stratified 80:20 split. Stratification was applied based on the dependent variable (speeding) to preserve the original proportion of speeders and non-speeders in both subsets. The training dataset (80%) was used to estimate the logistic regression model parameters, while the testing dataset (20%) was reserved for out-of-sample validation.

The model was implemented in Python using the stats models library. A generalized linear model (GLM) with a binomial family and logit link function was specified. Since the dependent variable exhibited class imbalance, inverse-frequency class weights were computed and incorporated into the estimation procedure to ensure balanced learning between speeding and non-speeding observations. The model was fitted using the training dataset, and predicted probabilities were generated for the testing dataset. Model performance was subsequently evaluated using classification accuracy, confusion matrix, ROC-AUC, and precision-recall metrics.

CHAPTER 4: RESULTS AND DISCUSSION

4.1. Validation of CV-based Vehicle Detection

4.1.1 Validation of Counting Accuracy

The counting accuracy of the CV-based vehicle detection system was validated using a 24-minute validation video recorded from the study section. Manual observation of the video was considered as the ground truth and compared with the predicted counts obtained from the CV-based detection model. The comparison was performed for each vehicle class, including 2-wheelers, car, bus, utility, microbus, and truck. A total of 739 vehicles were manually observed, while the system correctly counted 720 vehicles, resulting in an overall counting accuracy of 97.43%, which is consistent with previous studies (Yamamoto et al., 2025). Among the vehicle classes, motorcycles exhibited the highest traffic volume with a counting accuracy of 98.41%, while buses were detected with 100% accuracy, as shown in Table 4.1.

Table 4.1: Comparison of manual and predicted counts

Vehicle class	Ground Truth counts	True Positives	Counting Accuracy (%)
2-wheelers	503	495	98.41
Car	118	117	99.15
Bus	34	34	100.00
Utility	45	40	88.89
Microbus	11	7	63.64
Truck	28	27	96.43
Total	739	720	97.43

4.1.2 Validation of Classification Accuracy

The classification results, as shown in Table 4.2, demonstrated high overall accuracy, with precision, recall, and F1-score of 0.99, 0.97, and 0.98, respectively, consistent with findings reported in the literature (Yamamoto et al., 2025). The model performed consistently well for major classes such as 2-wheelers, cars, buses, and trucks, showing balanced precision and recall. Slightly lower recall for micro (0.64) and utility vehicles (0.89) indicates some missed detections, likely due to visual similarity. Overall, the results validate the reliability of the model, with minor scope for improvement in less represented classes.

Table 4.2: Classification Performance

Vehicle class	Ground Truth counts	Predicted counts	True Positives	Precision	Recall	F1 score
2-wheelers	503	495	495	1.00	0.98	0.99
Car	118	123	117	0.95	0.99	0.97
Bus	34	35	34	0.97	1.00	0.99
Utility	45	42	40	0.95	0.89	0.92
Microbus	11	7	7	1.00	0.64	0.78
Truck	28	27	27	1.00	0.96	0.98
Total	739	729	720	0.99	0.97	0.98

4.2. Traffic Characteristics

This section provides a descriptive analysis of traffic characteristics, offering an overall understanding of the prevailing traffic conditions across the study period. The analysis includes vehicle composition, which captures the distribution of different vehicle categories, and lane distribution, which reflects the lateral positioning of vehicles across the carriageway.

4.2.1 Vehicle Composition

The vehicle composition of the dataset is illustrated in Figure 4.1, using a stacked bar chart. The results indicate that the traffic stream is predominantly composed of 2-wheelers and cars, with proportions remaining relatively consistent across the three phases (2-wheelers: approximately 68–71%; cars: approximately 15–18%), while buses, trucks, microbuses, and utility vehicles constitute comparatively smaller shares (generally below 10% each). This distribution reflects typical mixed traffic conditions and highlights the dominance of lighter vehicles in the study area. The presence of different vehicle categories is important, as each type may exhibit distinct speed characteristics and behavioral patterns.

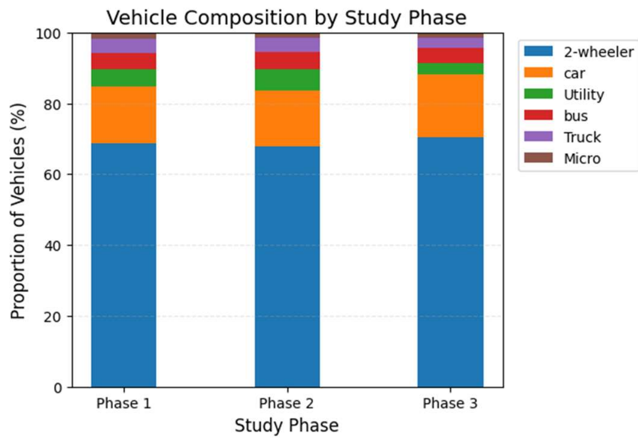

Figure 4.1: Phase-wise Vehicle Composition

4.2.2 Lane Distribution

The distribution of vehicles across lanes is presented in Figure 4.2, using a stacked bar chart. The results show that traffic distribution across lanes remains relatively consistent across the three phases. The proportion of vehicles in the left lane ranges from approximately 41.4% to 42.3%, followed by the right lane with values between 34.4% and 36.1%, and the shoulder lane with proportions ranging from 22.1% to 24.0%. This consistency indicates a stable lane preference pattern throughout the study period. A higher concentration of vehicles was observed in the left lane, followed by the right lane, compared to the shoulder lane.

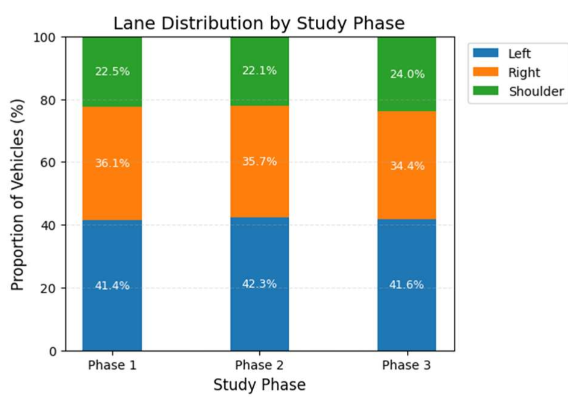

Figure 4.2: Phase-wise Lane Distribution of Vehicles

4.3. Speeding Behavior

This section presents the descriptive statistics of drivers' speeding characteristics, providing an overall understanding of speeding behavior across the study period. The analysis includes speed distribution, variations in mean speed, and temporal trends in speeding across different study phases.

4.3.1 Speed Distribution Across Study Phases

During the baseline phase, the speed distribution exhibited a unimodal and approximately bell-shaped pattern, indicating relatively consistent driving behavior in the absence of any intervention, as shown in Figure 4.3. The majority of vehicles were concentrated within the speed range of 45–60 km/h, with the highest frequency observed around the 50–55 km/h class interval. The right tail of the distribution extended up to approximately 100 km/h, indicating the presence of a smaller proportion of high-speed vehicles. Overall, 26.62% of vehicles were observed to exceed the speeding threshold, which reflects a considerable level of speeding during the baseline condition.

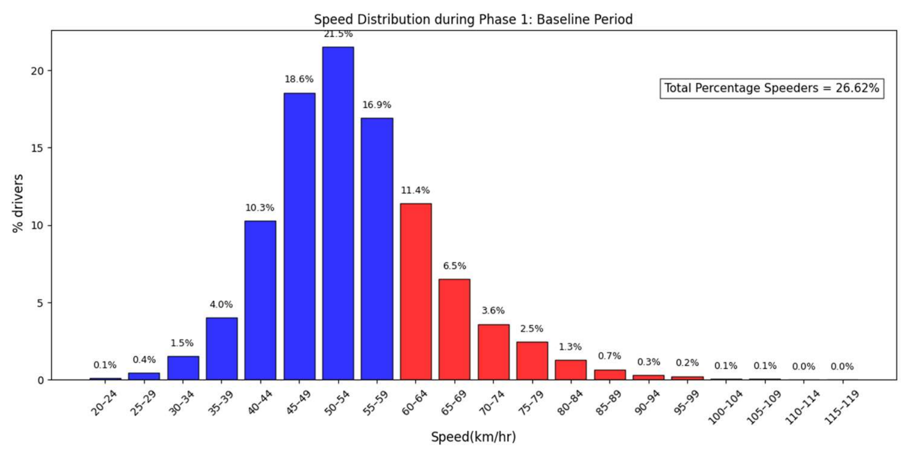

Figure 4.3: Speed Distribution during Phase 1 (Baseline Period)

During the intervention period, a clear shift in driving behavior was observed compared to the baseline condition. The speed distribution became more concentrated within the lower and mid-speed ranges, with the peak shifting slightly toward lower speed classes, as shown in Figure 4.4. There was a noticeable reduction in the proportion of vehicles traveling at higher speeds, indicating that fewer drivers were engaging in over-speeding behavior. The spread of the distribution also appeared slightly narrower, suggesting more uniform speeds among vehicles. This change reflected the influence of the dummy traffic police presence, which encouraged drivers to adopt more cautious and compliant driving behavior. Overall, the intervention period demonstrated a visible reduction in speed levels and improved speed discipline across the traffic stream, with only 14.66% of vehicles classified as speeders during this phase.

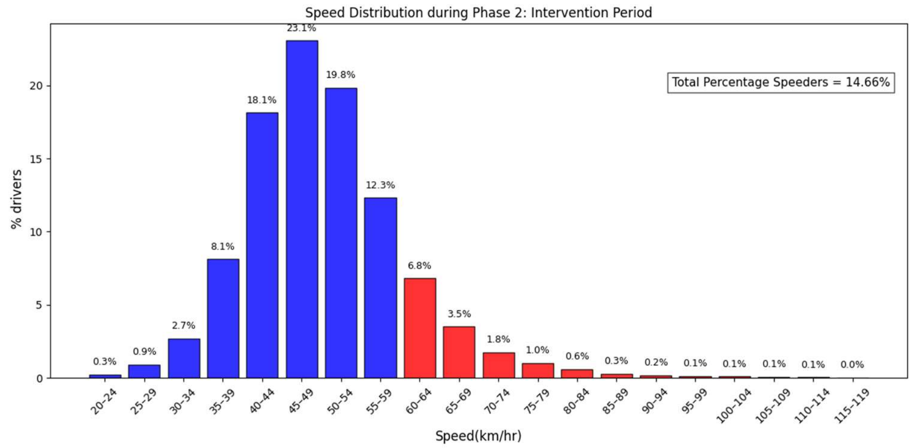

Figure 4.4: Speed Distribution during Phase 2 (Intervention Period)

During the post-intervention period, the speed distribution showed a tendency to shift back toward the baseline pattern, as shown in Figure 4.5. The peak of the distribution remained around the mid-speed range, but there was a gradual increase in the proportion of vehicles traveling at higher speeds compared to the intervention period. This indicates that, once the dummy traffic police were removed, drivers began to revert to their previous driving behavior. Consequently, 24.57% of vehicles were classified as speeders during the post-intervention phase, reflecting a approximate return to baseline speeding conditions.

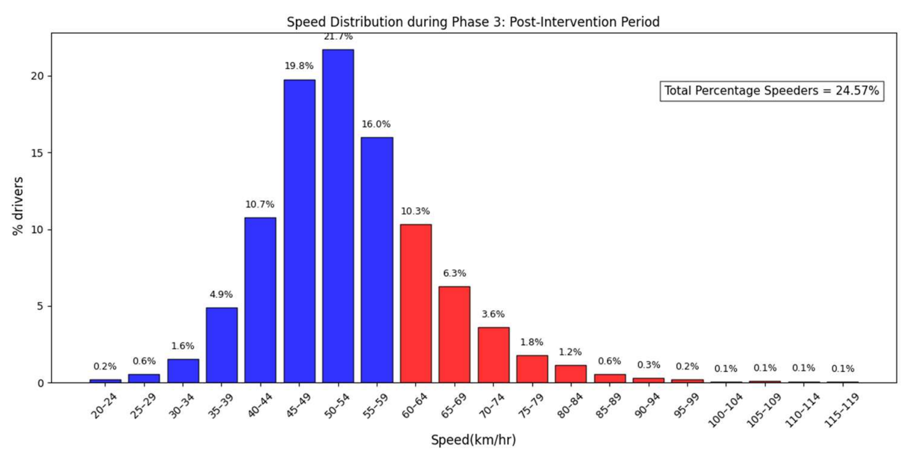

Figure 4.5: Speed Distribution during Phase 3 (Post-Intervention Period)

4.3.2 Mean Speed Across Study Phases

The variation in mean speed across the three study phases is presented using a bar chart, as shown in Figure 4.6. The result showed that the mean speed during the baseline phase was higher compared to the intervention phase. A noticeable reduction in mean speed was observed during the intervention phase, indicating that the presence of the dummy traffic police had a measurable impact on driver behavior. In the post-intervention phase, the mean speed increased again, suggesting a decline in the intervention effect after removal of the dummy. However, the extent of increase provides insight into whether the effect was temporary or partially sustained.

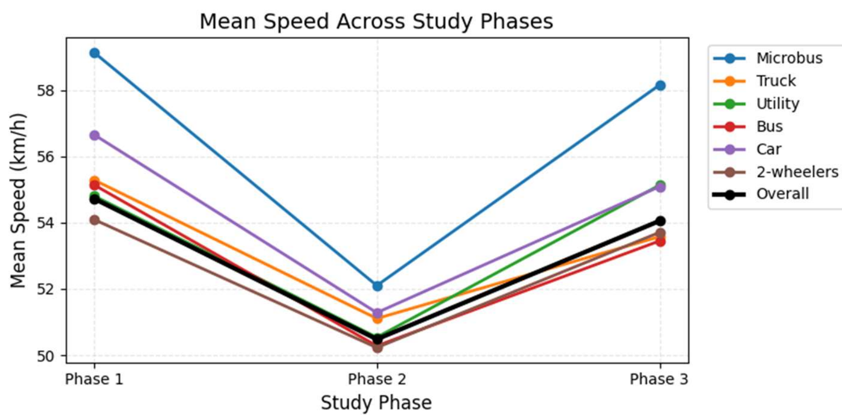

Figure 4.6: Mean Speed Across Study Phases

4.3.3 Temporal Variation in Speeding Behavior

The percentage of speeding vehicles over the 21-day study period is presented in Figure 4.7 using a line graph, which clearly illustrates the temporal variation in speeding behavior. During the baseline period (Days 1–6), the proportion of speeding vehicles remained relatively high and stable, ranging approximately between 23% and 31%.

With the introduction of the dummy traffic police on Day 7, a noticeable decline in speeding was observed, with the percentage reducing to around 14%. This reduction became more pronounced on Day 8, where the proportion further dropped to approximately 9%. During the early intervention phase, speeding levels remained comparatively low, generally fluctuating between 12% and 15%. However, as the intervention period progressed, a gradual increase in the percentage of speeding vehicles was observed, rising to approximately 17–21%. This trend indicates a waning effect, suggesting that drivers gradually adapted to the presence of the dummy traffic police over time.

Following the removal of the dummy traffic police during the post-intervention period (Days 19–21), the percentage of speeding vehicles increased further, ranging from approximately 21% to 29%, thereby indicating a return toward baseline conditions. Overall, this temporal pattern highlights both the immediate effectiveness of the intervention and its limited sustainability over an extended period.

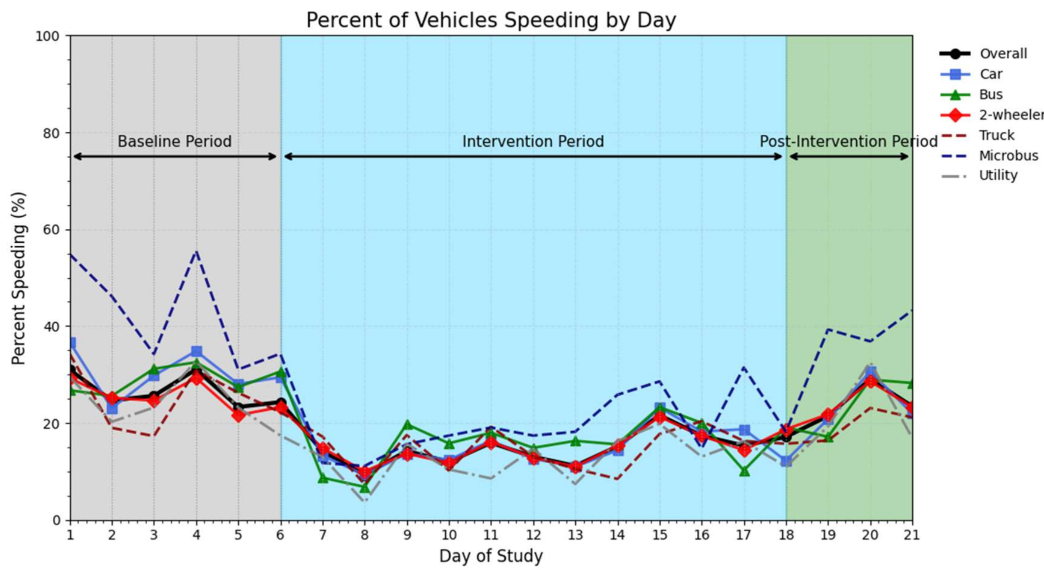

Figure 4.7: Day-wise Percentage of Vehicles Speeding

4.4. Speeding Behavior Model

A binary logistic regression model was developed to examine the influence of dummy traffic police presence, vehicle class, and lane position on the likelihood of speeding. The model coefficients, along with their standard errors (SE), statistical significance, and odds ratios (OR), are presented in Table 4.3.

Table 4.3: Results from Logistic Regression Modeling

Variable	Coef. (β)	SE	p-value	(OR=e^{β})	95% CI (Lower)	95% CI (Upper)
Constant	−1.8017	0.054	0.000	0.17	−1.908	−1.695
Dummy Traffic Police Presence	−1.1331	0.043	0.000	0.32	−1.217	−1.050
Time since dummy deployment	0.0511	0.005	0.000	1.05	0.041	0.061
Time after dummy removal	−0.0200	0.018	0.254	0.98	−0.054	0.014

Table 4.3: Results from Logistic Regression Modeling (continued)

Variable	Coef. (β)	SE	p-value	(OR=e^{β})	95% CI (Lower)	95% CI (Upper)
2-Wheelers	0.4274	0.034	0.000	1.53	0.361	0.494
Bus	0.4440	0.064	0.000	1.56	0.318	0.569
Truck	−0.1744	0.068	0.011	0.84	−0.308	−0.040
Utility	−0.2657	0.061	0.000	0.77	−0.385	−0.147
Microbus	0.5549	0.090	0.000	1.74	0.379	0.731
Left Lane	1.8744	0.045	0.000	6.52	1.786	1.963
Right Lane	2.5562	0.047	0.000	12.89	2.465	2.648

The p-value of one of the independent variables, namely Time after dummy removal, was found to be greater than 0.05 ($p > 0.05$), indicating that the time after dummy removal was statistically insignificant. Therefore, a reduced model was estimated by omitting this variable, as presented in Table 4.4.

Table 4.4: Results from Reduced Logistic Regression Modeling

Variable	Coef. (β)	SE	p-value	(OR=e^{β})	95% CI (Lower)	95% CI (Upper)
Constant	−1.8143	0.053	0.000	0.16	−1.918	−1.710
Dummy Traffic Police Presence	−1.1208	0.041	0.000	0.32	−1.202	−1.040
Time since dummy deployment	0.0511	0.005	0.000	1.05	0.041	0.061
2-Wheelers	0.4273	0.034	0.000	1.53	0.361	0.494
Bus	0.4442	0.064	0.000	1.56	0.319	0.570
Truck	−0.1729	0.068	0.011	0.84	−0.307	−0.039
Utility	−0.2646	0.061	0.000	0.77	−0.384	−0.145
Microbus	0.5542	0.090	0.000	1.74	0.378	0.730
Left Lane	1.8746	0.045	0.000	6.52	1.786	1.963
Right Lane	2.5565	0.047	0.000	12.89	2.465	2.648

Upon comparing the reduced model with the original model, only minimal changes were observed in the estimated coefficients and overall model performance. This indicates that the excluded variable had a negligible influence on the model. Therefore, the reduced model, as shown in Equation (4.1), was considered adequate and preferred for its simplicity.

$$log\left(\frac{p}{1-p}\right) = -1.8143 - 1.1208\,(Dummy) + 0.0511(Time\ since\ deployment) + 0.4273(2-wheeler) + 0.4442(Bus) - 0.1729\,\beta_6(Truck) - 0.2646\,(Utility) + 0.5542(Microbus) + 1.8746(Left\ lane) + 2.5565(Right\ lane) \tag{4.1}$$

Based on the final reduced model, the intercept term was negative and statistically significant ($\beta = -1.8143$, $p < 0.05$). This indicates that under baseline conditions, when all independent variables are at their reference categories (absence of dummy traffic police, car as vehicle class, and shoulder as lane position), the odds of speeding are low (OR = 0.16), suggesting a substantially reduced likelihood of speeding under baseline conditions relative to the neutral odds level (OR = 1).

4.4.1 Regression Coefficients

a) Effect of Dummy Traffic Police Presence

The presence of dummy traffic police showed a negative and highly significant coefficient ($\beta = -1.1208$, $p < 0.05$). The corresponding odds ratio (OR = 0.32) indicates that the presence of dummy traffic police reduces the odds of speeding by approximately 68% compared with situations where no dummy traffic police is present. This indicates that the perceived presence of enforcement substantially reduces the likelihood of speeding. In practical terms, drivers appear to respond to the visual cue of enforcement even when the enforcement is simulated through a stationary dummy traffic police. The result suggests that perceived monitoring can influence driver behavior and lead to safer speed choices.

b) Effect of Time Since Dummy Deployment

The variable representing time since dummy deployment showed a positive and statistically significant coefficient ($\beta = 0.0511$, $p < 0.05$). The estimated odds ratio (OR = 1.05) suggests that for each unit increase in time since deployment, the odds of speeding increase by approximately 5%. This finding indicates that the effectiveness of the dummy traffic police gradually diminishes over time. As drivers repeatedly encounter the same enforcement cue, they may begin to recognize that the enforcement is not active and gradually revert to their previous speeding behavior. This pattern reflects behavioral adaptation among drivers.

c) Effect of Vehicle Class

Vehicle type was found to significantly influence speeding behavior. 2-wheelers showed a positive and statistically significant coefficient ($\beta = 0.4273$, $p < 0.05$) with an odds ratio of 1.53, indicating that motorcycles are approximately 53% more likely to exceed the speed threshold compared to cars. This may be attributed to their higher maneuverability and acceleration capability, which allows riders to travel at higher speeds. Similarly, buses exhibited a positive and significant association with speeding ($\beta = 0.4442$, $p < 0.05$), with an odds ratio of 1.56, suggesting that buses are about 56% more likely to exceed the speed threshold compared to cars. This behavior may be influenced by operational pressures such as maintaining schedules and reducing travel time.

Microbuses demonstrated the strongest positive association among vehicle categories ($\beta = 0.5542$, $p < 0.05$), corresponding to an odds ratio of 1.74, indicating that they are approximately 74% more likely to exceed the speed threshold compared to cars. This finding may reflect the operational characteristics of microbus services, which often prioritize faster travel to maximize passenger turnover. In contrast, trucks showed a negative and statistically significant coefficient ($\beta = -0.1729$, $p < 0.05$) with an odds ratio of 0.84, indicating that trucks are approximately 16% less likely to exceed the speed threshold compared to cars. This behavior may be associated with vehicle weight, safety considerations, and operational restrictions. Similarly, utility vehicles also exhibited a negative and significant coefficient ($\beta = -0.2646$, $p < 0.05$) with an odds ratio of 0.77, suggesting that they are about 23% less likely to exceed the speed threshold relative to cars.

d) Effect of Lane Position

Lane position showed a strong and statistically significant effect on speeding. Compared with the shoulder (reference category), vehicles in both the left and right lanes had much higher probabilities of speeding. The left lane ($\beta = 1.8746$, $p < 0.05$) had an odds ratio of 6.52, while the right lane ($\beta = 2.5565$, $p < 0.05$) showed an even stronger effect with an odds ratio of 12.89, indicating the highest likelihood of exceeding the speed threshold.

4.4.2 Scenario-based Probability Analysis

Scenario-based predicted probabilities were computed to improve the interpretability of the logistic regression model. The intervention effect was evaluated by comparing pre-deployment (Dummy = 0) and post-deployment (Dummy = 1) conditions, while time since deployment was varied from 0 to 12 days. Figure 4.8 presents the predicted probabilities of speeding for predefined vehicle classes across different lanes under the pre-deployment condition (Dummy = 0).

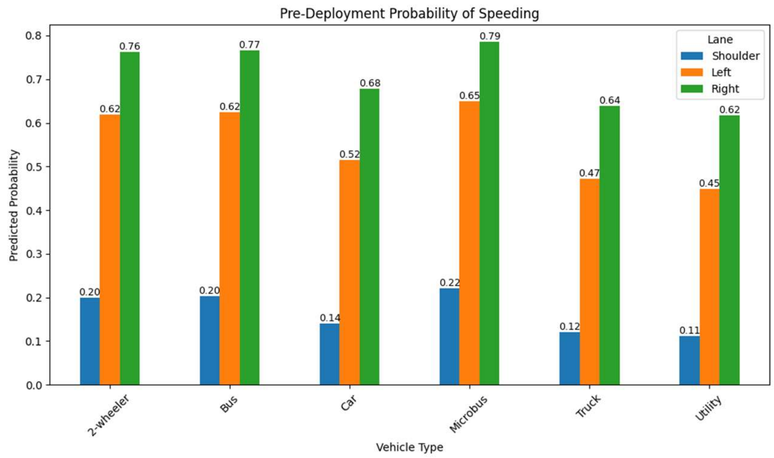

Figure 4.8: Pre-Deployment Probability of Speeding

Figures 4.9 present the variation in predicted probability during the post-deployment condition (Dummy=1) across different vehicle classes over the period of 1 to 12 days, with separate lines representing lane positions. The results indicate a noticeable reduction in predicted probability immediately after deployment, as observed by the drop from Day 0 to Day 1, followed by a gradual increasing trend over time.

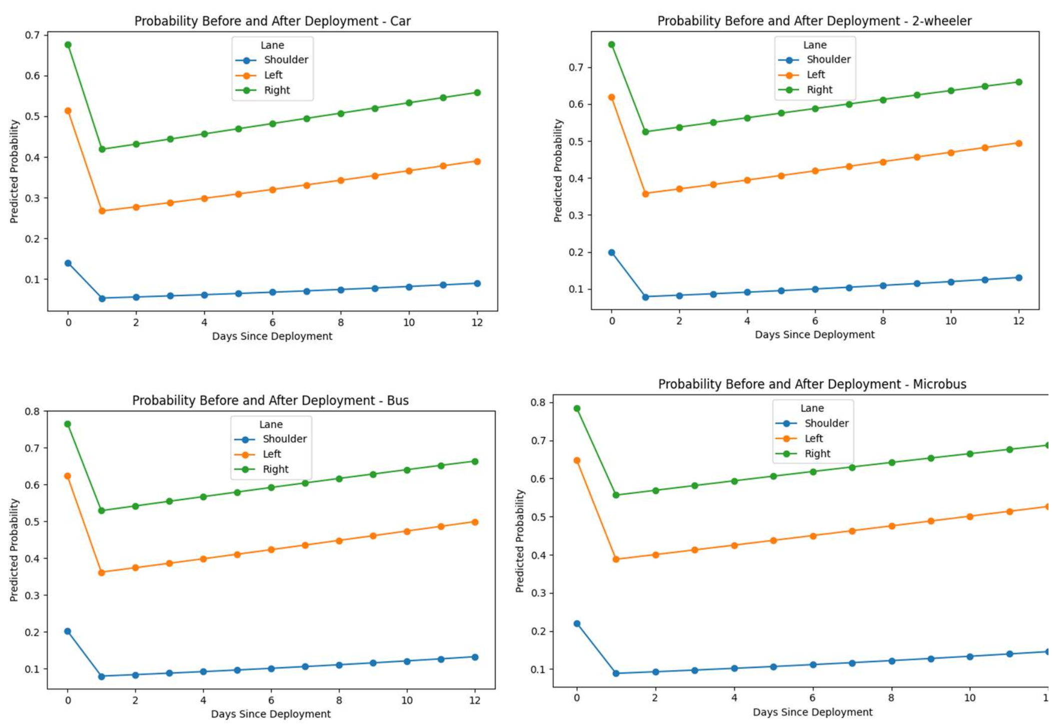

Figure 4.9: Probability Before and After Deployment

4.5. Model Evaluation and Validation

The overall model significance, significance of individual predictors, and goodness-of-fit measures were assessed to examine model adequacy, and predictive performance on the testing dataset was evaluated to determine its generalization capability in classifying speeding behavior.

4.5.1 Model Evaluation

a) Overall Model Significance

The overall performance of the binary logistic regression model was examined by comparing the fitted model (full model) to a baseline (null) model that includes only the intercept. This comparison determines whether the inclusion of predictors significantly improves model fit. A Likelihood Ratio (LR) Chi-Square (χ^2) Test was used to assess whether the full model fitted significantly better than the null model. The LR statistic was calculated as shown in Equation (4.2).

$$\chi^2 = -2(LL_{null} - LL_{full}) \tag{4.2}$$

where LL_{null} = log-likelihood of null model

LL_{full} = log-likelihood of full model

A LR Chi-Square (χ^2) test comparing the full logistic regression model to the intercept-only model was statistically significant, χ^2 (9) = 3031.31, $p < 0.05$, as shown in Table 4.3, indicating that the predictors collectively contributed to improving the model.

Table 4.5: Log Likelihood Chi-Square Test

LL_{null}	LL_{full}	χ^2	p-value	df
-15287.14	-13771.48	3031.31	0.000	9

b) Statistical Test of Individual Predictors

As shown in Table 4.2, the p-values indicate that all variables are statistically significant at the 5% level. The intercept term is also statistically significant ($p < 0.05$), suggesting that the baseline log-odds of speeding are significantly different from zero.

c) Goodness-of-Fit Statistics

The goodness-of-fit of the logistic regression model was evaluated using likelihood-based pseudo R^2 statistics, including Cox & Snell R^2, Nagelkerke R^2, and McFadden R^2, as presented in Table 4.4.

The Cox & Snell R^2 value was 0.1517, indicating that the fitted model provides a meaningful improvement over the null (intercept-only) model. The Nagelkerke R^2, which adjusts the Cox & Snell measure to attain a maximum value of 1, was 0.2022. This suggests that the model achieves approximately 20% explanatory power relative to the null model. In traffic safety and driver behavior studies, values in the range of 0.15 to 0.30 are generally considered acceptable to moderately strong, given the inherent variability in human driving behavior. The McFadden R^2 value was 0.1187. In discrete choice and transportation research, McFadden R^2 values between 0.10 and 0.20 are typically regarded as indicative of a satisfactory model fit. Therefore, the obtained value reflects an adequate level of model performance.

Table 4.6: Goodness of Fit Test

Cox & Snell R^2	Nagelkerke R^2	McFadden R^2
0.1517	0.2022	0.1187

4.5.2 Model Validation

The predictive performance of the model was evaluated using discrimination metrics such as the Receiver Operating Characteristic (ROC) curve and Area Under the Curve (AUC), and classification metrics such as confusion matrix, accuracy, precision, recall, and F1-score.

The Receiver Operating Characteristic (ROC) curve is a graphical tool used to evaluate the performance of a binary classification model. It represents the trade-off between the True Positive Rate (sensitivity) and the False Positive Rate (1 − specificity) across different classification thresholds. The Area Under the Curve (AUC) provides a single scalar value summarizing the model’s ability to discriminate between classes. The AUC ranges from 0 to 1, where values closer to 1 indicate better model performance. The ROC–AUC metric is valuable because it is threshold-independent, evaluating model performance across all classification cut-offs and providing a more robust measure than accuracy, particularly for imbalanced datasets.

The ROC curve for the developed logistic regression model is presented in Figure 4.10, with an AUC value of 0.72 indicating acceptable discriminatory power, meaning the model can correctly distinguish between positive and negative cases about 72% of the time across all possible classification thresholds. Such performance is consistent with previous studies employing logistic regression for driver behavior analysis, where predictive capability is often moderate due to the inherent variability and stochastic nature of human decision-making (Fitzpatrick et al., 2017; Moyo et al., 2025). This observation is further supported by the general principles of classification modeling, which highlight the influence of unobserved factors and data limitations on predictive accuracy (James et al., 2013).

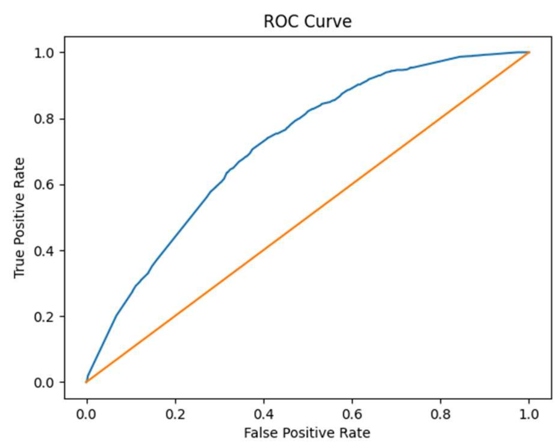

Figure 4.10: ROC-AUC curve

Similarly, the classification performance was evaluated using standard performance metrics, including the confusion matrix, as shown in Table 4.5. The model achieved an overall accuracy of 0.62, indicating that 62% of the observations were correctly classified. The confusion matrix shows that 3666 non-speeders and 1121 speeders were correctly predicted, while 2553 non-speeders were incorrectly classified as speeders and 392 speeders were misclassified as non-speeders. The precision for the speeder class was 0.31, reflecting a relatively high proportion of false positive predictions, whereas the recall was 0.74, indicating that the model successfully identified a substantial proportion of actual speeders. The F1-score for the speeder class was 0.43, suggesting a moderate balance between precision and recall. Overall, the results indicate that the model demonstrates a reasonable capability in identifying speeders; however, this is accompanied by a comparatively higher rate of false positive classifications. In traffic safety applications, models with higher recall are preferred because failing to identify speeding vehicles poses a greater safety risk than incorrectly flagging compliant vehicles, making such models suitable for preventive enforcement and risk-based monitoring systems.

Table 4.7: Confusion Matrix

Actual	Predicted	
	Non-Speeders	Speeders
Non-Speeders	3666	2553
Speeders	392	1121

4.6. Discussion

Speeding remains one of the major contributors to road traffic crashes worldwide, particularly in developing countries like Nepal, where enforcement resources are limited and road user compliance remains inconsistent. In line with the first objective of this study, which aimed to assess driver speeding behavior in the presence and absence of dummy traffic police, the findings demonstrate a clear reduction in speeding during the intervention phase compared to the baseline condition. This confirms that even a symbolic enforcement measure can influence driver behavior. Furthermore, addressing the second objective, a binary logistic regression model was developed to predict drivers' speeding behavior under dummy traffic police deployment, providing a quantitative understanding of the factors influencing such behavior.

The results of the binary logistic regression model indicate that the presence of dummy traffic police significantly influenced driver speeding behavior. These findings are consistent with previous research indicating that visual enforcement cues, such as parked police vehicles, can significantly influence driver behavior (Kaplan et al., 2000; Ravani & Wang, 2018; Shinar & Stiebel, 1986; Simpson, 2019).

Another important finding, aligned with the first objective, is the temporal variation in speeding behavior observed across the study phases. The results indicated that the reduction in speeding was strongest immediately after the deployment of the dummy traffic police and gradually diminished over time. This highlights the presence of a waning effect, suggesting that drivers initially respond to perceived enforcement but gradually adapt to it. Such behavioral adaptation, often referred to as habituation, indicates that prolonged static deployment of dummy enforcement may reduce its effectiveness, emphasizing the importance of strategic placement and periodic variation in deployment.

In addition, the findings of this study are supported by the use of a computer vision (CV)–based speed estimation framework, which enabled continuous and non-intrusive monitoring of vehicle speeds across all study phases. The CV-based approach provided a large and consistent dataset for analysis, capturing real-world driver behavior under varying traffic conditions. The reliability of the extracted speed data, as validated against LiDAR measurements, strengthens the credibility of the observed trends in speeding behavior and the following modeling results. This highlights the potential of CV-based methods as an effective tool for traffic monitoring and behavioral studies, particularly in resource-constrained settings where traditional speed measurement techniques may be limited.

From an operational perspective, this intervention offers practical advantages in addressing enforcement limitations. Given that police agencies cannot deploy personnel across all roadways at all times due to limited manpower and competing responsibilities, dummy traffic police can serve as a supplementary measure to extend perceived enforcement coverage. This aligns with the broader objective of improving traffic enforcement efficiency through low-resource strategies.

Advanced technologies such as Automatic Number Plate Recognition (ANPR) systems can enable automated ticketing of violators; however, they require substantial initial investment, along with significant technical, operational, and maintenance requirements. A cost comparison between dummy traffic police and ANPR systems is presented in Appendix C.

In summary, this study successfully addressed its objectives by both assessing driver speeding behavior under different enforcement conditions and developing a predictive model to understand the influencing factors. The findings highlight that dummy traffic police can serve as a sustainable, cost-effective, and practical intervention for influencing driver behavior and enhancing road safety, particularly in contexts with limited enforcement resources.

CHAPTER 5: CONCLUSION AND RECOMMENDATIONS

5.1. Conclusion

Road traffic crashes are a leading cause of fatalities and non-fatal injuries in Nepal, with over-speeding identified as one of the primary contributing factors. Consequently, speed control has become a priority for government and police agencies. The present study evaluated drivers' speeding behavior under the influence of dummy traffic police using a computer vision-based speed estimation framework and logistic regression modeling. The key conclusions drawn from the study are as follows:

a) The computer vision (CV)–based approach demonstrated reliable performance for traffic speed measurement under local mixed traffic conditions along the Sallaghari–Suryabinayak section of the Araniko Highway. The vehicle detection model achieved strong performance, with a precision of 0.763, recall of 0.795, mAP@0.5 of 0.825, and mAP@0.5:0.95 of 0.594, indicating effective detection and classification of vehicles. Furthermore, speed estimation accuracy was supported by low error metrics, including a mean absolute error (MAE) of 2.50 km/h and a root mean square error (RMSE) of 3.05 km/h, which showed strong agreement with LiDAR-based speed measurements, thereby confirming the suitability of CV-based methods for traffic speed studies.

b) The presence of dummy traffic police significantly reduces speeding behavior, with the logistic regression model indicating a reduction in the odds of speeding by approximately 68% (OR = 0.32, $p < 0.05$) during the intervention phase compared to the baseline condition.

c) The effectiveness of dummy traffic police exhibits a temporal decay**,** as the odds of speeding increases by approximately 5% per day following deployment. This suggests that drivers gradually adapt to the perceived enforcement and resume previous speeding behavior.

d) Vehicle type significantly influences speeding behavior, with 2-wheelers being 1.53 times more likely to speed ($\beta = 0.4273$, $p < 0.05$) compared to cars. Similarly, buses and microbuses exhibit higher odds of speeding, with odds ratios of 1.56 ($\beta = 0.4442$) and 1.74 ($\beta = 0.5542$)**,** respectively. In contrast, trucks and utility vehicles are less likely to exceed the speed threshold, with odds ratios of 0.84 ($\beta = -0.1729$) and 0.77 (β =

−0.2646), respectively ($p < 0.05$), indicating clear variation in speeding tendencies across vehicle categories.

e) The developed logistic regression model demonstrates moderate predictive performance, achieving an accuracy of 62% and an ROC-AUC value of 0.72, indicating acceptable capability in distinguishing between speeders and non-speeders.

5.2. Recommendations

Based on the findings of this study, the following recommendations are proposed:

a) The deployment of dummy traffic police units is recommended as a cost-effective and easily implementable measure for reducing speeding, particularly along highway sections where higher speeds are more prevalent. Traffic police agencies and local authorities may consider using such interventions at high-risk locations as a supplementary enforcement strategy.

b) Dummy-based interventions should be strategically placed in areas with a history of speeding-related incidents, and their positioning may be periodically changed to minimize driver habituation and maintain their effectiveness over time.

c) This approach can be integrated with conventional enforcement methods, such as periodic real police presence or technological systems, to enhance overall compliance and deterrence.

d) Awareness campaigns may be conducted alongside deployment to reinforce the perception of enforcement and improve public acceptance of such measures.

e) Future research should focus on conducting similar studies across different road types, traffic conditions, visibility conditions, and varying sight distances, as well as multi-site implementation, to assess the generalizability of the findings.

f) Further studies should aim to track individual vehicles over multiple points along the roadway, which would allow for the assessment of immediate and sustained behavioral changes before and after exposure to dummy traffic police.

g) Efforts should be made to control for or incorporate environmental and contextual variables such as weather, traffic conditions to improve the robustness of the findings.

h) Finally, future research may also explore the impact of such interventions on additional outcomes, including driver perception, sense of safety, and other risky driving behaviors, to provide a more comprehensive evaluation.

REFERENCES

Abdel-Aty, M., Wang, Z., Zheng, O., & Abdelraouf, A. (2023). Advances and applications of computer vision techniques in vehicle trajectory generation and surrogate traffic safety indicators. *Accident Analysis & Prevention*, *191*, 107191. https://doi.org/10.1016/j.aap.2023.107191

Adhikari, G. P. (2016). Road Traffic Accidents (RTAs) Trends on Kathmandu-Bhaktapur Road after Addition of Lanes. *Open Journal of Civil Engineering*, *06*(03), 388–396. https://doi.org/10.4236/ojce.2016.63033

Aloufi, N., Alnori, A., Thayananthan, V., & Basuhail, A. (2023). Object Detection Performance Evaluation for Autonomous Vehicles in Sandy Weather Environments. *Applied Sciences*, *13*(18), 10249. https://doi.org/10.3390/app131810249

Aryal, S., & Dhakal, S. (2024). Road Traffic Accident Data Visualization: A case study of Bhaktapur. *International Journal on Engineering Technology*, *1*(2), 87–94. https://doi.org/10.3126/injet.v1i2.66715

ATO. (2025). *Nepal Road Safety Profile 2025*. https://asiantransportobservatory.org/analytical-outputs/roadsafetyprofiles/nepal-road-safety-profile-2025/

Doria Usta, D., Hundelshaussen, R., López Martínez, C., Coimbra Leite Costa, J. F., & Machado Marques, D. (2025). Intelligent Traffic Management: Comparative Evaluation of YOLOv3, YOLOv5, and YOLOv8 for Vehicle Detection in Urban Environments in Montería, Colombia. *Future Transportation*, *5*(4), 191. https://doi.org/10.3390/futuretransp5040191

Elvik, R. (2013). A re-parameterisation of the Power Model of the relationship between the speed of traffic and the number of accidents and accident victims. *Accident Analysis & Prevention*, *50*, 854–860. https://doi.org/10.1016/j.aap.2012.07.012

Fitzpatrick, C. D., Rakasi, S., & Knodler, M. A. (2017). An investigation of the speeding-related crash designation through crash narrative reviews sampled via logistic regression. *Accident Analysis & Prevention*, *98*, 57–63. https://doi.org/10.1016/j.aap.2016.09.017

Haglund, M., & Åberg, L. (2000). Speed choice in relation to speed limit and influences from other drivers. *Transportation Research Part F: Traffic Psychology and Behaviour*, *3*(1), 39–51. https://doi.org/10.1016/S1369-8478(00)00014-0

James, G., Witten, D., Hastie, T., & Tibshirani, R. (2013). *An Introduction to Statistical Learning* (Vol. 103). Springer New York. https://doi.org/10.1007/978-1-4614-7138-7

Kaplan, J. L., Wright, M. J., Lazarus, L., Congemi, N., duTreil, K., Arnold, R., Mercante, D., Diaz, J. H., Vrahas, M., & Hunt, J. P. (2000). Use of an Unmanned Police Car to Reduce Traffic Speed: *The Journal of Trauma: Injury, Infection, and Critical Care*, *49*(1), 43–46. https://doi.org/10.1097/00005373-200007000-00006

Krajewski, R., Bock, J., Kloeker, L., & Eckstein, L. (2018). The highD Dataset: A Drone Dataset of Naturalistic Vehicle Trajectories on German Highways for Validation of Highly Automated Driving Systems. *2018 21st International Conference on Intelligent Transportation Systems (ITSC)*, 2118–2125. https://doi.org/10.1109/ITSC.2018.8569552

Moyo, E., Dzinavatonga, K., & Hakunavanhu, Z. L. (2025). Logistic Regression Modelling of Road Traffic Accident Severity: A Study on Driver Characteristics in Zimbabwe.

International Journal of Research and Innovation in Social Science, *9*(11), 3189–3206. https://doi.org/10.47772/IJRISS.2025.91100254

Mu, H., Wang, X., Tian, J., & Yang, Y. (2025). Research on a Real-Time Tunnel Vehicle Speed Detection System Based on YOLOv8 and DeepSORT Algorithms. *Intelligent Infrastructure and Construction*, *1*(3), 10. https://doi.org/10.3390/iic1030010

Nilsson, G. (2004). *Traffic Safety Dimensions and the Power Model to Describe the Effect of Speed on Safety* [Doctoral Thesis (monograph)]. Traffic Engineering.

Ravani, B., & Wang, C. (2018). Speeding in highway work zone: An Evaluation of methods of speed control. *Accident Analysis & Prevention*, *113*, 202–212. https://doi.org/10.1016/j.aap.2018.01.030

Redmon, J., Divvala, S., Girshick, R., & Farhadi, A. (2015). *You Only Look Once: Unified, Real-Time Object Detection* (Version 5). arXiv. https://doi.org/10.48550/ARXIV.1506.02640

Rhodes, N., & Pivik, K. (2011). Age and gender differences in risky driving: The roles of positive affect and risk perception. *Accident Analysis & Prevention*, *43*(3), 923–931. https://doi.org/10.1016/j.aap.2010.11.015

Sangsuwan, K., & Ekpanyapong, M. (2024). Video-Based Vehicle Speed Estimation Using Speed Measurement Metrics. *IEEE Access*, *12*, 4845–4858. https://doi.org/10.1109/ACCESS.2024.3350381

Shinar, D., & Stiebel, J. (1986). The Effectiveness of Stationary versus Moving Police Vehicles on Compliance with Speed Limit. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, *28*(3), 365–371. https://doi.org/10.1177/001872088602800313

Simpson, R. (2019). Police vehicles as symbols of legitimacy. *Journal of Experimental Criminology*, *15*(1), 87–101. https://doi.org/10.1007/s11292-018-9343-5

Simpson, R., McCutcheon, M., & Lal, D. (2020). Reducing speeding via inanimate police presence: An evaluation of a police-directed field study regarding motorist behavior. *Criminology & Public Policy*, *19*(3), 997–1018. https://doi.org/10.1111/1745-9133.12513

Vaa, T. (2014). ADHD and relative risk of accidents in road traffic: A meta-analysis. *Accident Analysis & Prevention*, *62*, 415–425. https://doi.org/10.1016/j.aap.2013.10.003

WHO. (2023). *Global Status Report on Road Safety 2023* (1st ed). World Health Organization.

Yamamoto, Y., Nakahara, M., Sumiyoshi, R., Jiang, W., Kamiya, D., & Imai, R. (2025). *A Study on the Development of a Traffic Volume Counting Method by Vehicle Type and Direction Using Deep Learning*.

APPENDIX A: Summary of Data

1. Sample Data on CV-Speed Calibration using LiDAR Gun

Vehicle No.	Veh Type	Radar Speed (km/h)	CV Speed (km/h)	Error (CV - Radar)	Absolute Error	Squared Error	Percentage Error (%)
1	Motorcycle	52	51.4	-0.6	0.6	0.36	-1.15
2	Motorcycle	57	58.3	1.3	1.3	1.69	2.28
3	Motorcycle	44	39.2	-4.8	4.8	23.04	-10.91
4	Motorcycle	59	58.3	-0.7	0.7	0.49	-1.19
5	Motorcycle	55	49	-6	6	36	-10.91
6	Motorcycle	40	36.6	-3.4	3.4	11.56	-8.50
7	Motorcycle	45	43.2	-1.8	1.8	3.24	-4.00
8	Motorcycle	50	55.5	5.5	5.5	30.25	11.00
9	Car	51	55.5	4.5	4.5	20.25	8.82
10	Truck	52	55.5	3.5	3.5	12.25	6.73
11	Car	42	43.2	1.2	1.2	1.44	2.86
12	Car	37	40.5	3.5	3.5	12.25	9.46
13	Bus	60	60.7	0.7	0.7	0.49	1.17
14	Motorcycle	89	84.4	-4.6	4.6	21.16	-5.17
15	Car	50	51.1	1.1	1.1	1.21	2.20
16	Bus	51	51.1	0.1	0.1	0.01	0.20
17	Car	45	48.6	3.6	3.6	12.96	8.00
18	Motorcycle	55	53.9	-1.1	1.1	1.21	-2.00
19	Car	56	57.1	1.1	1.1	1.21	1.96
20	Utility	51	49.8	-1.2	1.2	1.44	-2.35
21	Bus	46	46.2	0.2	0.2	0.04	0.43
22	Bus	40	42.2	2.2	2.2	4.84	5.50
23	Motorcycle	42	43.2	1.2	1.2	1.44	2.86
24	Motorcycle	40	43.2	3.2	3.2	10.24	8.00
25	Motorcycle	57	55.5	-1.5	1.5	2.25	-2.63
26	Bus	47	51.1	4.1	4.1	16.81	8.72
27	Truck	60	67	7	7	49	11.67
28	Car	51	55.5	4.5	4.5	20.25	8.82
29	Bus	46	49.8	3.8	3.8	14.44	8.26
30	Motorcycle	56	60.7	4.7	4.7	22.09	8.39
31	Motorcycle	44	45.2	1.2	1.2	1.44	2.73
32	Motorcycle	54	57.1	3.1	3.1	9.61	5.74
33	Car	38	41.3	3.3	3.3	10.89	8.68
34	Utility	54	58.9	4.9	4.9	24.01	9.07
35	Motorcycle	59	62.6	3.6	3.6	12.96	6.10

2. Sample data output from CV-based system

Vehicle ID	Vehicle Type	Lane	Speed (km/h)	Vehicle ID	Vehicle Type	Lane	Speed (km/h)
295	Truck	Right	61.5	445	Motorcycle	Left	40.0
313	Motorcycle	Right	47.6	453	Utility	Right	46.1
312	Motorcycle	Left	52.1	451	Motorcycle	Left	40.6
314	Motorcycle	Shoulder	44.5	456	Motorcycle	Shoulder	37.3
317	Utility	Right	64.5	466	Car	Right	64.7
318	Motorcycle	Shoulder	42.7	460	Motorcycle	Left	52.5
326	Motorcycle	Right	59.7	474	Bus	Left	60.0
328	Utility	Right	66.1	487	Motorcycle	Right	53.4
329	Motorcycle	Left	53.7	488	Car	Left	52.3
330	Motorcycle	Right	51.5	486	Bus	Shoulder	35.8
333	Motorcycle	Left	48.1	489	Utility	Right	43.9
336	Motorcycle	Left	55.7	492	Car	Right	31.5
343	Micro	Left	48.2	493	Motorcycle	Left	45.3
344	Truck	Right	59.0	501	Bus	Left	67.1
368	Car	Right	58.6	507	Motorcycle	Shoulder	49.0
381	Motorcycle	Left	47.1	509	Bus	Left	53.8
369	Car	Right	59.3	513	Motorcycle	Right	65.1
376	Car	Left	48.7	520	Motorcycle	Right	49.7
383	Motorcycle	Left	61.9	522	Motorcycle	Shoulder	40.6
382	Car	Right	58.0	525	Motorcycle	Left	38.7
378	Motorcycle	Shoulder	44.4	527	Motorcycle	Right	52.7
393	Car	Right	60.4	529	Motorcycle	Right	77.8
392	Car	Left	50.2	531	Motorcycle	Left	47.3
396	Motorcycle	Shoulder	45.4	541	Motorcycle	Right	52.5
406	Motorcycle	Left	46.5	535	Car	Right	42.6
410	Motorcycle	Left	42.4	538	Motorcycle	Right	53.9
416	Truck	Right	53.2	526	Truck	Left	21.2

3. Sample Dataset

Dummy Traffic Police Presence	Time since dummy deployment	Time after dummy removal	2-Wheelers	Bus	Truck	Utility	Microbus	Left lane	Right lane	Speeding
0	0	0	1	0	0	0	0	0	1	1
1	5	0	0	0	0	1	0	1	0	0
0	0	0	1	0	0	0	0	1	0	1
1	2	0	1	0	0	0	0	0	1	1
1	8	0	1	0	0	0	0	0	0	0
1	11	0	1	0	0	0	0	1	0	0
0	0	1	1	0	0	0	0	1	0	0
0	0	0	1	0	0	0	0	1	0	0
0	0	0	1	0	0	0	0	1	0	0
0	0	1	1	0	0	0	0	0	1	0
1	10	0	0	0	0	0	0	0	1	0
0	0	0	1	0	0	0	0	1	0	0
0	0	0	1	0	0	0	0	1	0	0
0	0	0	1	0	0	0	0	0	0	0
0	0	2	0	0	0	1	0	0	0	0
0	0	0	1	0	0	0	0	1	0	1
1	10	0	1	0	0	0	0	1	0	0
1	7	0	1	0	0	0	0	0	1	0
0	0	0	1	0	0	0	0	1	0	1
1	1	0	1	0	0	0	0	1	0	0
0	0	2	0	0	0	0	0	0	1	1
1	6	0	1	0	0	0	0	1	0	0
1	11	0	1	0	0	0	0	1	0	0
0	0	0	1	0	0	0	0	0	0	0
1	2	0	0	0	0	0	0	0	1	0
1	8	0	0	1	0	0	0	0	1	1
1	1	0	0	0	0	0	0	1	0	0
1	2	0	1	0	0	0	0	1	0	1
1	4	0	1	0	0	0	0	1	0	0
0	0	0	0	0	0	0	0	0	1	0
0	0	2	0	0	0	0	0	1	0	0
1	12	0	0	1	0	0	0	1	0	0
1	8	0	1	0	0	0	0	0	1	0
1	4	0	1	0	0	0	0	1	0	0
0	0	0	0	0	1	0	0	1	0	1
1	5	0	1	0	0	0	0	1	0	0
1	10	0	1	0	0	0	0	1	0	0

Dummy Traffic Police Presence	Time since dummy deployment	Time after dummy removal	2-Wheelers	Bus	Truck	Utility	Microbus	Left lane	Right lane	Speeding
1	11	0	0	0	0	0	0	0	1	0
1	4	0	0	1	0	0	0	1	0	0
0	0	0	0	0	0	1	0	1	0	0
1	3	0	1	0	0	0	0	1	0	0
1	1	0	0	0	0	0	0	0	1	0
1	2	0	1	0	0	0	0	1	0	1
1	3	0	0	0	1	0	0	0	1	1
0	0	0	1	0	0	0	0	0	1	0
0	0	3	1	0	0	0	0	0	0	0
1	12	0	1	0	0	0	0	1	0	1
0	0	1	1	0	0	0	0	0	0	0
1	11	0	1	0	0	0	0	0	0	0
0	0	0	0	0	1	0	0	0	0	0
0	0	1	1	0	0	0	0	1	0	0
0	0	0	1	0	0	0	0	0	0	0
1	2	0	1	0	0	0	0	1	0	0
1	5	0	0	0	0	0	0	0	1	0
0	0	3	1	0	0	0	0	1	0	1
0	0	0	1	0	0	0	0	0	0	0
1	1	0	1	0	0	0	0	1	0	0
1	8	0	0	0	1	0	0	1	0	0
1	12	0	1	0	0	0	0	1	0	0
1	3	0	1	0	0	0	0	0	1	0
0	0	0	1	0	0	0	0	1	0	1
1	11	0	0	1	0	0	0	0	1	0
0	0	0	1	0	0	0	0	1	0	0
1	6	0	0	0	0	0	0	0	1	0
0	0	0	1	0	0	0	0	0	0	0
0	0	1	1	0	0	0	0	0	1	0
1	5	0	0	0	0	0	0	0	1	0
0	0	0	1	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	1	0
0	0	0	1	0	0	0	0	0	1	0
1	9	0	0	0	0	1	0	1	0	0
1	9	0	0	0	0	0	0	0	1	1
0	0	0	1	0	0	0	0	1	0	1
1	1	0	1	0	0	0	0	1	0	0
1	8	0	1	0	0	0	0	1	0	0

Dummy Traffic Police Presence	Time since dummy deployment	Time after dummy removal	2-Wheelers	Bus	Truck	Utility	Microbus	Left lane	Right lane	Speeding
0	0	3	1	0	0	0	0	1	0	1
0	0	0	1	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	1	0	0
1	1	0	0	0	0	0	0	0	1	0
1	3	0	0	0	0	0	0	1	0	0
1	10	0	1	0	0	0	0	0	0	0
1	5	0	0	0	0	0	0	1	0	0
0	0	2	1	0	0	0	0	1	0	1
1	12	0	1	0	0	0	0	0	1	1
0	0	0	1	0	0	0	0	0	0	0
1	2	0	0	0	0	0	0	1	0	0
1	5	0	1	0	0	0	0	1	0	0
0	0	1	1	0	0	0	0	1	0	0
1	1	0	1	0	0	0	0	1	0	0
1	8	0	0	1	0	0	0	1	0	0
0	0	3	0	0	0	1	0	0	1	0
0	0	0	1	0	0	0	0	0	1	1
1	10	0	1	0	0	0	0	0	1	0
0	0	0	1	0	0	0	0	1	0	0
0	0	0	1	0	0	0	0	1	0	0
0	0	2	1	0	0	0	0	1	0	0
0	0	0	0	0	0	0	0	0	1	0
1	12	0	0	0	0	0	0	0	1	0
1	10	0	1	0	0	0	0	1	0	0
1	8	0	1	0	0	0	0	1	0	0
0	0	0	0	1	0	0	0	0	1	0
1	4	0	1	0	0	0	0	0	0	0
1	1	0	1	0	0	0	0	1	0	0
0	0	0	0	1	0	0	0	0	0	0
1	9	0	1	0	0	0	0	0	0	0
1	1	0	1	0	0	0	0	1	0	1
1	2	0	0	0	0	0	0	1	0	0
1	5	0	1	0	0	0	0	0	0	0
1	9	0	1	0	0	0	0	0	1	0
1	4	0	1	0	0	0	0	0	1	0
1	1	0	0	0	0	0	0	0	1	1
0	0	0	1	0	0	0	0	0	1	1
1	12	0	0	1	0	0	0	0	1	1

Dummy Traffic Police Presence	Time since dummy deployment	Time after dummy removal	2-Wheelers	Bus	Truck	Utility	Microbus	Left lane	Right lane	Speeding
0	0	1	1	0	0	0	0	1	0	0
0	0	3	0	0	0	1	0	1	0	0
0	0	3	1	0	0	0	0	1	0	0
0	0	1	1	0	0	0	0	0	0	0
0	0	0	1	0	0	0	0	0	0	0
0	0	0	0	0	0	1	0	0	1	0
0	0	2	1	0	0	0	0	1	0	0
1	12	0	1	0	0	0	0	1	0	0
1	3	0	0	0	0	0	1	1	0	0
0	0	2	1	0	0	0	0	0	0	0
0	0	0	1	0	0	0	0	1	0	0
1	6	0	0	0	0	0	0	0	1	0
1	9	0	1	0	0	0	0	1	0	0
0	0	0	0	1	0	0	0	1	0	0
1	11	0	1	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	1	0
1	1	0	0	0	0	0	0	1	0	0
1	1	0	1	0	0	0	0	0	0	0
1	6	0	0	0	0	0	0	0	1	0
1	6	0	1	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	1	0	0
1	1	0	0	0	0	0	0	0	1	0
1	2	0	1	0	0	0	0	0	1	0
0	0	2	0	0	0	0	0	1	0	1
1	4	0	1	0	0	0	0	0	0	0
0	0	0	1	0	0	0	0	1	0	0
0	0	0	0	0	0	0	1	1	0	1
0	0	1	1	0	0	0	0	1	0	0
1	6	0	1	0	0	0	0	0	0	0
1	7	0	1	0	0	0	0	0	0	0
1	9	0	0	0	0	0	0	0	1	0
1	10	0	0	0	0	0	0	1	0	0
0	0	0	0	0	0	0	0	1	0	1
1	3	0	1	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	1	0
0	0	0	1	0	0	0	0	0	1	1
1	9	0	1	0	0	0	0	1	0	0
1	7	0	1	0	0	0	0	0	0	0

APPENDIX B: Python Code

1. CV-based speed estimation python code

```
# pip install ultralytics pandas openpyxl deep-sort-realtime torch
torchvision torchaudio --index-url
https://download.pytorch.org/whl/cu121

import cv2
import pandas as pd
import os
import datetime
import numpy as np
import torch
from ultralytics import YOLO
from deep_sort_realtime.deepsort_tracker import DeepSort

# --------------------------
# GPU DETECTION & SETUP
# --------------------------

device = "cuda" if torch.cuda.is_available() else "cpu"
print("=" * 60)
print(f"Using device: {device}")
if device == "cuda":
    print("GPU Name:", torch.cuda.get_device_name(0))
    x = torch.rand(1000, 1000).to(device)
    torch.matmul(x, x)
    print("GPU is working.")
else:
    print("No GPU detected. CPU will be used.")
print("=" * 60)

# --------------------------
# CONFIGURATION
# --------------------------
# NOTE:
# All spatial references (lines, lanes, perspective points)
# are defined in ORIGINAL video resolution.
# Frame resizing is used only for YOLO inference.

model = YOLO("bestofbest.pt").to(device)
class_list = list(model.names.values())

#class_list = ['Micro', 'Truck', 'Utility', 'bus', 'car',
'motorcycle']
tracker = DeepSort(
    max_age=15,
    n_init=5,
    max_iou_distance=0.5,
    max_cosine_distance=0.3
)

CONF_THRESH = 0.35

config = {
    "blue_line_y": 357,     # example ORIGINAL pixel
    "red_line_y": 633,      # example ORIGINAL pixel
    "line_start_x": 628,
    "line_end_x": 1326,
    "actual_distance": 20,
    "frame_skip": 1,
}
```

```
SHOW = True   # True = debug mode, False = fast batch mode
SAVE_VIDEO = True


# -------------------------
# PERSPECTIVE TRANSFORM
# -------------------------

src_pts = np.float32([
    [835, 357],   # top-left blue line
    [1149, 357],  # top-right blue line
    [628, 633],   # bottom-left red line
    [1326, 633]   # bottom-right red line
])


dst_width, dst_height = 370, 200
dst_pts = np.float32([
    [0, 0],
    [dst_width, 0],
    [0, dst_height],
    [dst_width, dst_height]
])

M = cv2.getPerspectiveTransform(src_pts, dst_pts)
M32 = M.astype(np.float32)

def warp_point(x, y, M):
    pt = np.array([[[x, y]]], dtype=np.float32)
    wp = cv2.perspectiveTransform(pt, M)
    return int(wp[0][0][0]), int(wp[0][0][1])

# -------------------------
# LANE CONFIG
# -------------------------

lane_config = {
    "blue_line_down": [835, 954, 1045, 1149],
    "red_line_down":  [628, 894, 1093, 1326],
}


def get_lane_three_category(cx, points):
    p = sorted(points)
    if cx < p[1]:
        return "Right"
    elif cx < p[2]:
        return "Left"
    else:
        return "Shoulder"

def get_down_lane_position_at_blue_line(cx):
    return get_lane_three_category(cx,
lane_config["blue_line_down"])

def get_down_lane_position_at_red_line(cx):
    return get_lane_three_category(cx,
lane_config["red_line_down"])

# -------------------------
```

```
def count_down_vehicles_between_lines(tracks, blue_y, red_y,
down_frames):
    c = 0
    for tr in tracks:
        if not tr.is_confirmed():
            continue
        obj_id = tr.track_id
        _, _, _, y2 = tr.to_tlbr()
        cy = int(y2)
        if ((blue_y <= cy <= red_y) or (red_y <= cy <= blue_y))
and obj_id in down_frames:
            c += 1
    return c

# -------------------------
# INITIALIZATION
# -------------------------

cap = cv2.VideoCapture("part1.mp4")
fps = cap.get(cv2.CAP_PROP_FPS) or 30
print(f"FPS detected: {fps}")
ORIG_W = int(cap.get(cv2.CAP_PROP_FRAME_WIDTH))
ORIG_H = int(cap.get(cv2.CAP_PROP_FRAME_HEIGHT))

RES_W, RES_H = 1020, 500
scale_x = ORIG_W / RES_W
scale_y = ORIG_H / RES_H

print("Original size:", ORIG_W, ORIG_H)
print("YOLO size:", RES_W, RES_H)
down_frames = {}
counter_down = []
vehicle_data = []
vehicle_blue_line_lanes_down = {}
vehicle_red_line_lanes_down = {}
vehicle_density_down = {}
vehicle_class_history = {}
vehicle_speed_down = {}
prev_cy = {}
# ---------- SMOOTHING VARIABLES ----------
smoothed_centers = {}
speed_history = {}
SMOOTHING_ALPHA = 0.7

frame_count = 0
count = 0

# folders for frame saving
os.makedirs("detected_frames/red_line", exist_ok=True)

out = cv2.VideoWriter(
    "output.avi",
    cv2.VideoWriter_fourcc(*"XVID"),
    30,
    (ORIG_W, ORIG_H)
)


# -------------------------
# MAIN LOOP
# -------------------------
```

```
while True:
    ret, frame_orig = cap.read()
    if not ret:
        break

    count += 1
    frame_count += 1
    if count % config["frame_skip"] != 0:
        continue


    frame_yolo = cv2.resize(frame_orig, (RES_W, RES_H))


    for i in range(4):
        if SHOW:
            cv2.line(frame_orig,
                  (lane_config["blue_line_down"][i],
config["blue_line_y"]),
                  (lane_config["red_line_down"][i],
config["red_line_y"]),
                  (0, 255, 255), 1)

    results = model.predict(frame_yolo, conf=CONF_THRESH, iou=0.5,
                            imgsz=640, verbose=False,
device=device)

    detections = []
    for row in results[0].boxes.data.detach().cpu().numpy():
        x1, y1, x2, y2, conf, cls = row
        x1 *= scale_x
        y1 *= scale_y
        x2 *= scale_x
        y2 *= scale_y

        detections.append([[x1, y1, x2 - x1, y2 - y1], conf,
int(cls)])


    tracks = tracker.update_tracks(detections, frame=frame_orig)

    current_between = count_down_vehicles_between_lines(
        tracks, config["blue_line_y"], config["red_line_y"],
down_frames
    )

    for tr in tracks:
        if not tr.is_confirmed():
            continue
        if tr.time_since_update > 1:
            continue

        x1, y1, x2, y2 = tr.to_tlbr()
         # ADD THIS
        if y2 > frame_orig.shape[0] * 0.95:
            continue
        obj_id = tr.track_id
        cls_id = tr.get_det_class()

        vehicle_class_history.setdefault(obj_id, []).append(
```

```
            class_list[cls_id] if cls_id < len(class_list) else
"unknown"
        )
        vehicle_type = max(set(vehicle_class_history[obj_id]),

key=vehicle_class_history[obj_id].count)

        cx = int((x1 + x2) // 2)
        raw_cy = int(0.8 * y2 + 0.2 * y1)

        if obj_id not in smoothed_centers:
            smoothed_centers[obj_id] = raw_cy
        else:
            smoothed_centers[obj_id] = int(
                SMOOTHING_ALPHA * smoothed_centers[obj_id]
                 + (1 - SMOOTHING_ALPHA) * raw_cy
             )

        cy = smoothed_centers[obj_id]
        prev_y = prev_cy.get(obj_id, cy)
        prev_cy[obj_id] = cy

        if SHOW:
            cv2.rectangle(frame_orig, (int(x1), int(y1)),
(int(x2), int(y2)), (0, 255, 0), 2)
            cv2.circle(frame_orig, (cx, cy), 3, (0, 0, 255), -1)
            cv2.putText(frame_orig, f"{obj_id}:{vehicle_type}",
                        (int(x1), int(y1) - 10),
                        cv2.FONT_HERSHEY_SIMPLEX, 0.5, (255, 255,
255), 1)

        # continuous speed display
        if obj_id in vehicle_speed_down and obj_id in
smoothed_centers:
            if SHOW:
                cv2.putText(frame_orig,
f"{vehicle_speed_down[obj_id]:.1f} km/h",
                            (int(x2), int(y2)),
                            cv2.FONT_HERSHEY_SIMPLEX, 0.7, (0, 255,
255), 2)

        # -------- BLUE LINE CROSS (WARPED SPACE) --------
        # --- FAST WARP (only near lines) ---
        if abs(cy - config["blue_line_y"]) < 40 or abs(cy -
config["red_line_y"]) < 40:
            p1 = np.array([cx, prev_y, 1], dtype=np.float32)
            w1 = M32 @ p1
            wy_prev = w1[1] / w1[2]

            p2 = np.array([cx, cy, 1], dtype=np.float32)
            w2 = M32 @ p2
            wy_now = w2[1] / w2[2]
        else:
            continue


        blue_crossed = wy_prev < 0 and wy_now >= 0

        if blue_crossed and obj_id not in down_frames:

            dy = wy_now - wy_prev
```

```
            if abs(dy) > 1e-6:   # safety check

                alpha = (0 - wy_prev) / dy
                alpha = max(0.0, min(1.0, alpha))  # clamp

                blue_cross_time = ((frame_count - 1) + alpha) /
fps

                down_frames[obj_id] = {"time": blue_cross_time}
                vehicle_blue_line_lanes_down[obj_id] =
get_down_lane_position_at_blue_line(cx)
                vehicle_density_down[obj_id] = current_between




        # -------- RED LINE CROSS (WARPED SPACE) --------
        red_crossed = wy_prev < dst_height and wy_now >=
dst_height

        if obj_id in down_frames and red_crossed:

            if obj_id not in counter_down:
                counter_down.append(obj_id)
                if obj_id in vehicle_speed_down:
                    continue

                raw_speed = None
                dy = wy_now - wy_prev

                if abs(dy) > 1e-6:
                    alpha = (dst_height - wy_prev) / dy
                    alpha = max(0.0, min(1.0, alpha))
                    red_cross_time = ((frame_count - 1) + alpha) /
fps
                    time_s = red_cross_time -
down_frames[obj_id]["time"]

                    if time_s > 0:
                        raw_speed = (config["actual_distance"] /
time_s) * 3.6

                if raw_speed is None:
                    continue



                if obj_id not in speed_history:
                    speed_history[obj_id] = raw_speed
                else:
                    speed_history[obj_id] = (
                    0.7 * speed_history[obj_id] +
                    0.3 * raw_speed
                    )

                vehicle_speed_down[obj_id] = speed_history[obj_id]


                vehicle_data.append({
                    "Vehicle ID": obj_id,
                    "Vehicle Type": vehicle_type,
```

```
                    "Direction": "Down",
                    "Lane":
vehicle_blue_line_lanes_down.get(obj_id, "unknown"),
                    "Blue Line Lane":
vehicle_blue_line_lanes_down.get(obj_id, "unknown"),
                    "Red Line Lane":
get_down_lane_position_at_red_line(cx),
                    "DOWN Vehicle Density":
vehicle_density_down.get(obj_id, 0),
                     "Speed Raw (km/h)": raw_speed,
                     "Speed Smoothed (km/h)":
vehicle_speed_down[obj_id],
                    "Time (seconds)": time_s,

                })

                frame_copy = frame_orig.copy()

                # Vehicle ID + type (for cross verification)
                cv2.putText(
                    frame_copy,
                    f"ID:{obj_id} | {vehicle_type}",
                    (int(x1), int(y1) - 10),
                    cv2.FONT_HERSHEY_SIMPLEX,
                    0.8,
                    (0, 255, 0),
                    2
                )

                # speed
                cv2.putText(frame_copy,
f"{vehicle_speed_down[obj_id]:.1f} km/h",
                        (int(x2), int(y2)),
                        cv2.FONT_HERSHEY_SIMPLEX, 0.8, (0, 255,
255), 2)


                cv2.imwrite(

f"detected_frames/red_line/veh_{obj_id}_speed_{raw_speed:.1f}.jpg"
,
                    frame_copy
                )

    if SHOW:
        cv2.putText(frame_orig, f"Vehicles Between Lines:
{current_between}",
                (10, 450), cv2.FONT_HERSHEY_SIMPLEX, 0.6, (255,
255, 255), 2)

    if SHOW:
        cv2.line(frame_orig, (config["line_start_x"],
config["blue_line_y"]),
              (config["line_end_x"], config["blue_line_y"]), (255,
0, 0), 2)
    if SHOW:
        cv2.line(frame_orig, (config["line_start_x"],
config["red_line_y"]),
              (config["line_end_x"], config["red_line_y"]), (0, 0,
255), 2)
```

```
    if SHOW or SAVE_VIDEO:
        out.write(frame_orig)

    if SHOW:
        cv2.imshow("Speed Detection", frame_orig)


    if SHOW and cv2.waitKey(1) & 0xFF == ord("q"):
        break


cap.release()
out.release()
cv2.destroyAllWindows()

# -------------------------
# SAVE REPORT
# -------------------------

if vehicle_data:
    df = pd.DataFrame(vehicle_data)
    ts = datetime.datetime.now().strftime("%Y%m%d_%H%M%S")
    df.to_excel(f"vehicle_speed_report_{ts}.xlsx", index=False)

print("Program finished.")
```

2. **Logistic Regression Model Analysis code**

```
# =========================================
# 1. IMPORT LIBRARIES
# =========================================
import pandas as pd
import numpy as np
import statsmodels.api as sm
import matplotlib.pyplot as plt
from sklearn.metrics import (
    accuracy_score,
    confusion_matrix,
    classification_report,
    roc_auc_score,
    roc_curve,
    precision_recall_curve,
    average_precision_score
)

# =========================================
# 2. LOAD TRAINING DATA
# =========================================
df_train = pd.read_excel("Train_Test_Split.xlsx",
sheet_name="Training_Data")

y_train = df_train['Speeding']
X_train = df_train[[
    "Dummy Traffic Police Presence",
    "Time since dummy deployment",
    "Time after dummy removal",
    "2-Wheelers",
```

```
    "Bus",
    "Truck",
    "Utility",
    "Microbus",
    "Left lane",
    "Right lane"

]]

X_train = sm.add_constant(X_train)

# =========================================
# 3. COMPUTE CLASS WEIGHTS (INVERSE FREQUENCY)
# =========================================
n_total = len(y_train)
n_pos = sum(y_train == 1)
n_neg = sum(y_train == 0)

weight_pos = n_total / (2 * n_pos)
weight_neg = n_total / (2 * n_neg)

weights = np.where(y_train == 1, weight_pos, weight_neg)

print("\nClass Distribution (Training):")
print(y_train.value_counts())
print("\nClass Weights:")
print("Weight for Speeding (1):", weight_pos)
print("Weight for No Speeding (0):", weight_neg)

# =========================================
# 4. TRAIN WEIGHTED LOGISTIC MODEL
# =========================================
model = sm.GLM(
    y_train,
    X_train,
    family=sm.families.Binomial(),
    freq_weights=weights
)

result = model.fit()

print("\nModel trained with inverse-frequency class weights\n")
print(result.summary())

# =========================================
# 5. LOAD TEST DATA
# =========================================
df_test = pd.read_excel("Train_Test_Split.xlsx",
sheet_name="Testing_Data")

y_test = df_test['Speeding']
X_test = df_test[[
    "Dummy Traffic Police Presence",
    "Time since dummy deployment",
    "Time after dummy removal",
    "2-Wheelers",
    "Bus",
    "Truck",
    "Utility",
    "Microbus",
    "Left lane",
```

```
    "Right lane"
]]

X_test = sm.add_constant(X_test)

# ==========================================
# 6. PREDICT PROBABILITIES
# ==========================================
y_pred_prob = result.predict(X_test)

# ==========================================
# 7. DEFAULT THRESHOLD (0.5)
# ==========================================
y_pred_05 = (y_pred_prob >= 0.5).astype(int)

# ==========================================
# 8. OPTIMAL THRESHOLD (Youden's J)
# ==========================================
fpr, tpr, thresholds = roc_curve(y_test, y_pred_prob)

optimal_idx = np.argmax(tpr - fpr)
optimal_threshold = thresholds[optimal_idx]

print("\nOptimal Threshold (Youden's J):", optimal_threshold)

y_pred_opt = (y_pred_prob >= optimal_threshold).astype(int)

# ==========================================
# 9. EVALUATION (THRESHOLD = 0.5)
# ==========================================
print("\n===== PERFORMANCE (Threshold = 0.5) =====")

print("Accuracy:", accuracy_score(y_test, y_pred_05))
print("ROC-AUC:", roc_auc_score(y_test, y_pred_prob))
print("Average Precision (PR-AUC):",
average_precision_score(y_test, y_pred_prob))

print("\nConfusion Matrix:\n", confusion_matrix(y_test,
y_pred_05))

print("\nClassification Report:\n")
print(classification_report(y_test, y_pred_05))

# ==========================================
# 10. EVALUATION (OPTIMAL THRESHOLD)
# ==========================================
print("\n===== PERFORMANCE (Optimal Threshold) =====")

print("Accuracy:", accuracy_score(y_test, y_pred_opt))
print("ROC-AUC:", roc_auc_score(y_test, y_pred_prob))
print("Average Precision (PR-AUC):",
average_precision_score(y_test, y_pred_prob))

print("\nConfusion Matrix:\n", confusion_matrix(y_test,
y_pred_opt))

print("\nClassification Report:\n")
print(classification_report(y_test, y_pred_opt))

# ==========================================
```

```
# 11. ROC CURVE
# ==========================================
plt.figure()
plt.plot(fpr, tpr)
plt.plot([0, 1], [0, 1])
plt.title("ROC Curve")
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.show()

# ==========================================
# 12. PRECISION-RECALL CURVE
# ==========================================
precision, recall, _ = precision_recall_curve(y_test, y_pred_prob)

plt.figure()
plt.plot(recall, precision)
plt.title("Precision-Recall Curve")
plt.xlabel("Recall")
plt.ylabel("Precision")
plt.show()

# ==========================================
# 13. CONFUSION MATRIX (OPTIMAL)
# ==========================================
cm = confusion_matrix(y_test, y_pred_opt)

plt.figure()
plt.imshow(cm, cmap='Blues')
plt.title("Confusion Matrix (Optimal Threshold)")
plt.colorbar()

plt.xticks([0, 1], ["No Speeding", "Speeding"])
plt.yticks([0, 1], ["No Speeding", "Speeding"])

for i in range(2):
    for j in range(2):
        plt.text(j, i, cm[i, j], ha="center", va="center")

plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()

# ==========================================
# 14. SAVE RESULTS
# ==========================================
output = X_test.copy()
output['Actual'] = y_test
output['Predicted_Prob'] = y_pred_prob
output['Predicted_0.5'] = y_pred_05
output['Predicted_Optimal'] = y_pred_opt

output.to_excel("Final_Test_Results.xlsx", index=False)

print("\nResults saved to 'Final_Test_Results.xlsx'")
```

APPENDIX C: Cost Comparison

Cost Comparison between Dummy Traffic Police and ANPR System

S.N.	Cost Component	Dummy Traffic Police (NPR)	ANPR with Speed Detection System (NPR)
1	Equipment cost	10,000 (mannequin, traffic uniform)	2,50,000 – 8,00,000 per camera (high-resolution ANPR cameras, sensors, storage units)
2	Initial Setup cost	Nil	8,00,000 – 25,00,000 per site (camera system, software, server, installation)
3	Installation cost	Nil	1,50,000 – 5,00,000 per site (civil works, poles, network setup)
4	Operational cost (Annual)	Nil	3,00,000 – 12,00,000 per site ((electricity, data processing, monitoring staff))
5	Maintenance cost (Annual)	120,000 (Assuming replacement every month)	2,00,000 – 8,00,000 per site (maintenance, calibration, software updates)

Note: The cost figures are indicative estimates derived from international ANPR system pricing literature and vendor-reported ranges, adjusted to reflect Nepalese implementation conditions. Actual costs may vary depending on system configuration, vendor selection, and site-specific requirements.