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An Evaluation of ANPR Technology for Traffic Violation Detection at Signalized Intersections in Phnom Penh

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Abstract: *Road traffic accidents remain a critical public health and economic issue in Cambodia, with traffic violations at signalized intersections contributing significantly to incidents and congestion. This study examined traffic violations at five intersections in Phnom Penh and assessed the performance of existing ANPR cameras in detecting key violations, including red-light running, motorcycle helmet non-use, car seatbelt non-use, and mobile phone use while driving. Data were collected through manual counts, ANPR-generated reports, and interviews with traffic police. Results show that motorcycles accounted for the majority of violations, with ANPR systems reliably detecting most externally observable violations but underperforming for in-cabin behaviors such as seatbelt and phone use. With an average error rate of 9.3%, the ANPR systems detected 10.2% of total traffic volume as violations, slightly below the 11.3% observed manually. This study indicates that the ANPR system captured over 90% of violations for the included types, demonstrating high reliability and effectiveness for automated traffic monitoring and enforcement. The study demonstrates the potential of ANPR systems to support automated traffic enforcement and data-driven policy for urban road safety improvements.*

Keywords: ANPR; Phnom Penh; Road Safety; Signalized Intersection; Traffic Violation

1. INTRODUCTION

Road traffic accidents are a major concern to public health worldwide. According to the World Health Organization, approximately 1.35 million people die each year due to road traffic accidents, making it the leading cause of death among young people aged 5–29 years. Moreover, road traffic accidents are estimated to cause economic losses of up to 3% of a country's gross domestic product [1]. Based on the 2023 annual report by Phnom Penh Capital Administration (PPCA), there were 957 cases of traffic accidents causing 296 deaths and 1,222 injuries [2]. In 2024, PPCA reported 897 cases of traffic accidents causing 278 deaths and 1,215 injuries [3]. Therefore, it is essential to prioritize measures to reduce the incidence and severity of road traffic accidents.

One of the key contributors to road traffic accidents is traffic rule violations such as over speeding, red-light running, and reckless driving behaviors, which increase the risk of accidents and fatalities on the roads [4]. Drivers are the main subjects of traffic violations, and implementing specific punitive measures can effectively deter such unlawful actions [5]. Beyond contributing to accidents, traffic violations also contribute to traffic congestion which is another major issue in the transportation systems of developing cities. When traffic violation occurs, in many cases, the traffic flow will be interrupted even though there is no accident.

Automatic Number Plate Recognition (ANPR), also known as Automatic License Plate Recognition (ALPR), is an image-processing technology used to capture vehicle images and automatically extract license plate information, converting it into machine-readable formats such as text strings for database storage and analysis. A typical ANPR system consists of camera hardware, a processing unit, a recognition engine, and a license plate database. Although system configurations may vary in terms of components and functionality, the primary objective remains the same: to identify vehicles and record their movement. With rapid urbanization and increasing vehicle ownership, ANPR has become a key source of big data for urban analysts, planners, and transport managers. The integration of ANPR with automated traffic violation detection enables timely

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enforcement actions, improves resource allocation, supports data-driven decision-making, and enhances road traffic management and user safety [6].

In Southeast Asia, ANPR systems are widely deployed for automated traffic enforcement at signalized intersections, particularly for red-light violations. In Thailand, the integration of ANPR into red-light enforcement in Bangkok has been associated with significant reductions in violations, leading the Bangkok Metropolitan Administration and Royal Thai Police to expand AI-enhanced CCTV pilot programs in 2024 to promote "100% Traffic Law Compliance" across 15 districts, including the detection of motorcycle sidewalk use [7, 8]. Indonesia has implemented the Electronic Traffic Law Enforcement (ETLE) system, integrating ANPR with AIoT technologies to automatically detect a broad range of violations—such as red-light running, speeding, lane misuse, helmet and seatbelt non-compliance, and mobile phone use—using locally trained algorithms deployed at high-traffic intersections in Jakarta and South Sumatra [9, 10]. Vietnam has similarly adopted AI-based surveillance capable of detecting approximately 20 violation types on a continuous basis, enabling automated evidence collection and reduced reliance on manual enforcement [11, 12]. Singapore, under its Smart Mobility 2030 vision, has long utilized ANPR and AI-driven systems for automated detection of violations including speeding, red-light running, and illegal parking, with minimal human intervention [13].

In contrast, Cambodia has yet to fully adopt ANPR-based traffic enforcement. Traffic control at urban intersections remains largely dependent on on-site police officers, supported by incentive-based fine collection, an approach that has shown limited effectiveness in reducing violations. Although over 1,000 CCTV cameras have been installed in Phnom Penh, only a small fraction are equipped with ANPR, and these are primarily used for basic license plate recognition rather than automated violation detection. Furthermore, recent academic studies examining traffic violations at signalized intersections and evaluating ANPR system performance in Phnom Penh remain notably absent, highlighting a critical research gap.

This study pursues two primary objectives: (1) to comprehensively examine the characteristics of traffic violations at signalized intersections in Phnom Penh, and (2) to assess the performance of the traffic violation detection function of existing ANPR cameras within the city's public video surveillance system. The findings of this study are intended to address three key research questions namely what are the main characteristics of traffic violations occurring at signalized intersections in Phnom Penh; how reliably the ANPR system can detect such traffic violations at these intersections; and whether the authorities in Phnom Penh should consider expanding the deployment of ANPR cameras for traffic violation detection.

2. METHODOLOGY

2.1. Research Framework

Fig 1 presents the overall research framework, adopted in this study. The framework consists of four key steps: Data Collection, Data Processing, Descriptive Analysis, and Results & Conclusion. The framework illustrates the overall approach of the study and ensures that each stage is systematically aligned with the research objectives.

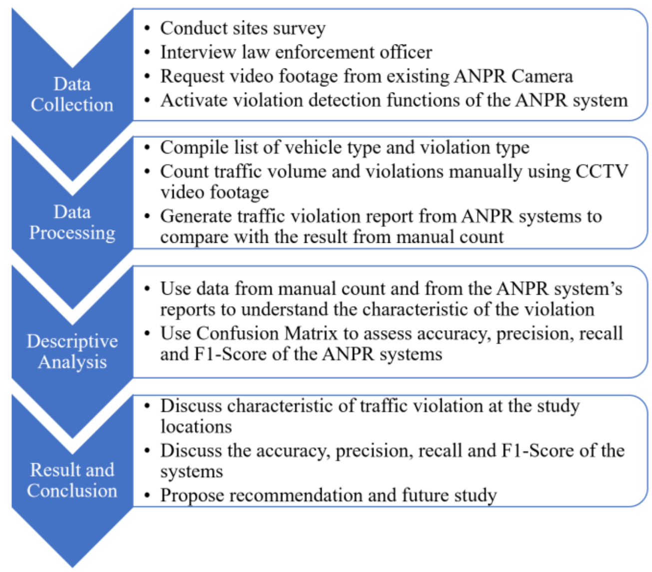

Fig.1. Research Framework

In the data collection step, we first collect needed data from five intersections in Phnom Penh including the 5 Makara (Techno) Overpass, Neak Vorn intersection, the intersection of Street 598 and Street 1800, the intersection of Win-Win Boulevard and a newly constructed road (designated as ANPR-01), and the Camko City intersection (designated as ANPR-02).

Types of vehicles were observed at the 5 intersections via direct visualization. In addition, types of traffic violations were obtained from face-to-face interview surveys with traffic police officers stationed at each of the intersections. To this end, from the on-site surveys and interviews, we obtained the data about vehicle types, traffic violation types and existing measures to mitigate traffic violation issue at those locations. These data were later compiled.

Often the recorded CCTV data (e.g., recorded videos) at public areas such as intersections are not generally available to pubic, and maybe possible to request. Data on traffic violations from ANPR system are even more difficult to get. However, as for this research purpose, we had officially requested for approval from Phnom Penh Capital Administration (PPCA) to retrieve video footage for analysis and to activate the violation detection functions on existing

ANPR system, which were originally intended solely for license plate recognition, at site ANPR-01 and site ANPR-02. The functions enabled the system to perform automatic identification and documentation of traffic violations. The ANPR system that was utilized in this study was originally embedded from manufacturer and comprises platform servers at the backend, network infrastructure, and on-site devices which include a terminal server, capture units (ANPR cameras), and supplement lights. All hardware and software components of the system were developed by HIKVISION, a company specializing in closed-circuit television (CCTV) technologies. Moreover, we also used secondary data from reliable sources, including information from the reports by PPCA.

Upon getting approval from PPCA, violation detection functions were activated on the ANPR system. The ANPR system was capable of generating Excel-based reports for traffic violations for multiple days, which facilitated subsequent data processing. Later, recorded video footage from the ANPR camera system was retrieved; and then, the total traffic volume and the number of traffic violations at site ANPR-01 and ANPR-02 were manually counted at different timing of a day for comparison purposes: from 00:00 to 01h:00, from 07:00 to 09:00, from 11:00 to 13:00, and from 17:00 to 19:00. The manual counts were done for site ANPR-01 on 11-March-2024, and for site ANPR-02 on 02-July-2025.

2.2 Study Sites

Of the five study intersections, only sites ANPR-01 and ANPR-02 were equipped with ANPR systems, with activatable violation detection functions. Although Phnom Penh has 20 ANPR cameras capable of detecting traffic violations, only these two sites were authorized by the PPCA for data retrieval use in this study. The layout of the intersections and camera positions at ANPR-01 and ANPR-02 are illustrated in Fig 2 and Fig 3, respectively. The violations were analyzed for traffic flow of one leg at each studied intersection:

- Site ANPR-01 (Fig 2): the intersection of Win-Win Boulevard and a newly constructed road. This is a 3-leg intersection, located in sub-urban area, with GPS coordinates as 11°39'48.38"N/104°52'30.95"E.
- Site ANPR-02 (Fig 3): the Camko City intersection is a 5-leg intersection, located in urban area, with GPS coordinates as 11°35'27.10"N/104°53'49.51"E.

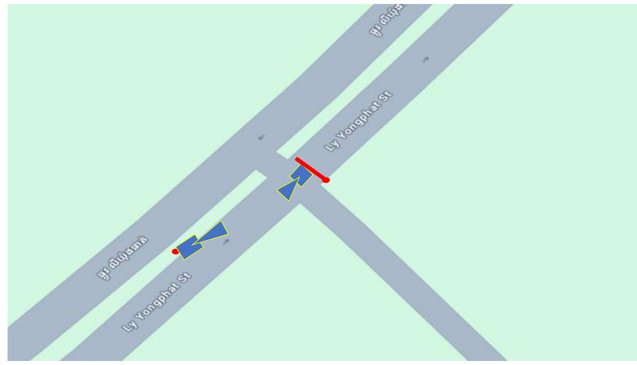

Fig.2. Layout of camera installation at site ANPR-01

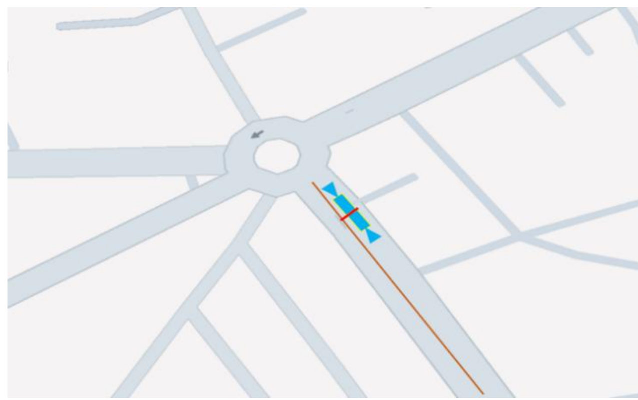

Fig.3. Layout of camera installation at site ANPR-02

- At site ANPR-01, Win-Win Boulevard featured a landscaped median and two traffic lanes in each direction. A “No U-Turn” sign was installed on the median for both traffic directions. Two ANPR cameras were mounted on the arms of separate traffic light poles to capture license plates of vehicles exiting the intersection via Win-Win Boulevard. In contrast, site ANPR-02 was a six-way intersection, where two ANPR cameras were installed on a streetlight pole located on the median of Street 355.
- Prior to this study, the two ANPR cameras at the site ANPR-01 were used solely for license plate recognition and were not configured for violation detection. To enable this functionality, adjustments were made to the cameras’ positions, viewing angles, and software settings, and the violation detection feature was activated. One camera, mounted on the arm of a traffic light pole, captured the front view of approaching vehicles and could detect seatbelt violations and mobile phone use while driving. The second camera, installed on a streetlight pole on the median of Win-Win Boulevard, captured the rear view and could detect red-light running, lane-control violations, and motorcyclists riding without helmets.
- Like site ANPR-01, the two ANPR cameras at site ANPR-02 were initially used only for license plate recognition. Both cameras were mounted on the same streetlight pole but oriented in opposite directions, with one capturing the front

view of approaching vehicles and the other capturing the rear view. While their positions were retained, adjustments were made to the viewing angles and software configurations to enable violation detection. The cameras at site ANPR-02 are now capable of detecting red-light running, motorcycles without helmets, cars without seatbelts, and drivers using mobile phones.

2.3. About ANPR system

The schematic diagram of the ANPRT system used in this study is illustrated in Fig 4. The ANPR system consists of backend platform servers, network infrastructure, and on-site devices, including a terminal server, capture units (ANPR cameras), and supplementary lighting. The ANPR system operates as follows: when a vehicle enters the camera's detection zone, the camera automatically detects and captures the license plate number using a transitional Optical Character Recognition (OCR) method. This approach combines deep learning–based plate detection with classical character segmentation and format validation, ensuring robust identification under varying lighting and traffic conditions. Simultaneously, CNN-based violation detection algorithms track the vehicle's movement using geometry-based multi-object tracking. When a violation is detected, the ANPR camera triggers the terminal server, which transmits all relevant data to the platform server for processing and report generation.

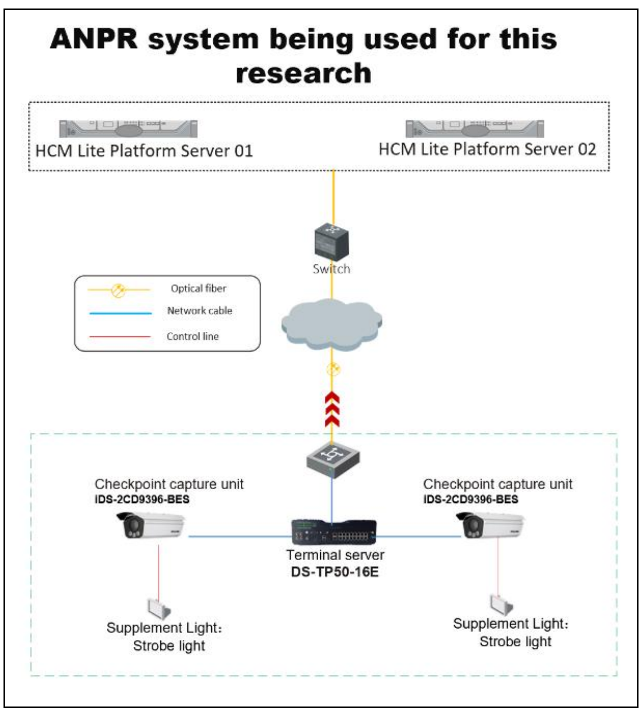

Fig.4. Schematic diagram of the ANPR system

Fig.5. Example of a red-light running violation of a motorcyclist being detected by ANPR system

Fig 5 demonstrates an example of a motorcycle with license plate number 1H0-15XX detected by the ANPR system for red-light running at site ANPR-01. After the motorcycle entered the detection zone, the ANPR camera captured its image and performed license plate recognition while continuously monitoring the traffic signal status and vehicle movements. In this case, the traffic signal had already turned red when the motorcycle proceeded through the intersection, which the system correctly identified as a violation. The camera subsequently captured additional images as evidentiary records and transmitted them, together with the associated violation metadata, to the on-site terminal server. The terminal server stored the data on its internal hard drive and simultaneously forwarded it to the backend platform server for long-term storage and reporting.

It should be noted that, at site ANPR-01, a strobe light assisted the camera in capturing license plates at night (from 17:30 to 07:00) but was insufficient for viewing through windshields of cars, for detecting driver activities such as seatbelt wearing and phone usage. To improve this detection capability, a flash light was added at Site ANPR-02 in June 2025 to better capture in-cabin violation detection.

2.4 Evaluation metrics on the violation detection performance of the ANPR system

Evaluation on the violation detection performance of the ANPR system was based on the metrics that were derived from the confusion matrix, including accuracy, precision, recall and F1-Score. Table 1 presents the general structure of a confusion matrix. In classification tasks, predictions can either be correct or incorrect (errors), resulting in four possible outcomes: True Positive (TP), False Positive (FP), True Negative (TN), and False Negative (FN). A True Positive occurs when both the actual value and the prediction are positive. A False Positive arises when the prediction is positive but the actual value is negative, also referred to as a "Type I error." A True Negative occurs when both the actual value and the prediction are negative. Finally, a False Negative occurs when the prediction is negative, but the actual value is positive, also known as a "Type II error."

In these terms, "True" or "False" indicates whether the prediction is correct, while "Positive" or "Negative" refers to the predicted class.

Table 1. Confusion Matrix

		Actual Values	
		Positive	Negative
Predicted Values	Positive	TP	FP
	Negative	FN	TN

- Following are the evaluation metrics Accuracy, which is the fraction of correct predictions among all predictions or how often a prediction is correct. It is computed as:

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \quad (Eq. 1)$$

- Accuracy is a useful metric when the classes in a dataset are balanced, meaning each class has roughly the same number of instances. However, it has limitations, particularly with imbalanced datasets where one class significantly outnumbers others. In such cases, a model can achieve high overall accuracy by predominantly predicting the majority class, while performing poorly on minority classes. As a result, accuracy can be misleading when the correct prediction of minority classes is critical. Furthermore, in multi-class problems, overall accuracy does not indicate which specific classes are being predicted correctly. In these situations, metrics such as precision provide a more informative evaluation of model performance.
- Precision is the fraction of the correctly predicted positive results. It is computed as:

$$Precision = \frac{TP}{TP + FP} \quad (Eq. 2)$$

- Precision is particularly valuable for evaluating models on imbalanced datasets. A high precision indicates a low rate of false positives, meaning the model's positive predictions are generally accurate. Conversely, a low precision reflects a high number of false positives, suggesting the model frequently misclassifies negative instances as positive. In traffic violation detection, maintaining high precision is crucial to avoid incorrectly flagging non-violations as violations. However, precision does not account for the performance of the model on negative cases and ignores false negatives (Type II errors), where actual positive instances are incorrectly predicted as negative. When minimizing false negatives is important, or when both false positives and false negatives are equally critical, other metrics such as recall or the F1-Score—which balances precision and recall—are more appropriate for evaluating model performance.
- Recall is the proportion of actual positives predicted correctly or how accurately the model predicts positive cases. It is computed as:

$$Recall = \frac{TP}{TP + FN} \quad (Eq. 3)$$

- In traffic violation detection, recall represents the proportion of actual violation cases that the model correctly identifies. A high recall value indicates a low rate of false negatives, meaning the system effectively captures most instances of traffic violations. In other words, a model with a high recall rate successfully detects the majority of actual violations. Conversely, a low recall value suggests a higher number of false negatives, implying that the model is failing to identify many true violation cases.
- The F1-Score, which combines precision and recall, is particularly useful for models where both metrics are equally important. It is calculated as the harmonic mean of precision and recall, taking into account both false positives and false negatives. Unlike a simple average, the harmonic mean gives more weight to lower values, meaning that if either precision or recall is low, the F1-Score will also be low. This makes it especially suitable for datasets with class imbalances, where accuracy alone can be misleading. The F1-Score reaches its maximum when precision and recall are equal, effectively balancing Type I and Type II errors. However, it does not indicate whether a model prioritizes precision or recall, so it is often used alongside other metrics for a more comprehensive evaluation. The closer the F1-Score is to 1, the better the model's overall performance, particularly in cases where both false positives and false negatives carry similar consequences and true negatives are abundant. The F1-Score is computed as:

$$F1 - Score = \frac{2 * Precision * Recall}{Precision + Recall} \quad (Eq. 4)$$

3. ANALYSES AND RESULTS

3.1 Types of Vehicles and Traffic Violations

Based on site observations and interview survey with traffic police officers at the five intersections, different types of vehicular traffic and traffic violations could be classified as in Table 2 and Table 3, respectively. In Table 2, vehicles were classified under different codes, used in this study. Vehicles such as sedans, SUVs, pickups, vans, wagons, buses, trucks, and other similar vehicles are grouped together as "Car", because this group of vehicles would be consistent to that currently recognized by ANPR system. In addition, during the site surveys, only a small number of pedestrians and cyclists were observed, and the ANPR system did not capture violations committed by them. With this regard, pedestrians and cyclists were excluded from the analysis.

Table 2. Types of vehicles observed at 5 intersections

Code	Vehicle Types
MC	Motorcycle
3W	3-Wheeler (Rickshaw)
4W	4-Wheeler (Remork)
Car	Sedan, SUV, Van, Wagon, Pickup, Bus, Truck, and others

Table 3. Types of violations reported by traffic police officers at the 5 intersections

Code	Violation Types
RR-ST	Red-light running (going straight)
YR-ST	Yellow-light running (going straight)
VLC-MC	Violations of lane control signs or marking by motorcycle
VLC-OV	Violations of lane control signs or marking by other vehicles
MWH	Driving/riding MC without a helmet
UPD	Using a phone while driving
DWB	Car driving without a seatbelt.

At the five intersections, a wide range of traffic violations could be observed, including car driving without a seatbelt, using a phone while driving, riding or driving a motorcycle without a helmet, traffic light violations, violations of lane control signs or markings, crosswalk violations (failure to yield to pedestrians), turning from the wrong lane, sudden lane changes, driving in the opposite direction, driving on sidewalks, pedestrian violations (red-light crossing, crossing outside designated crosswalks), and operation of vehicles that were not meeting technical specifications (e.g., overloading). Despite these numerous violations, violations including turning from the wrong lane, sudden lane changes, and insufficient safety distance (tailgating)—in the meantime, were not subject to enforcement despite occurring at the intersections. In addition, technological limitations of the installed ANPR cameras and their associated software constrained the system's ability to automatically detect all violation types. Consequently, this study will analyze the violations that both occurred frequently and were reliably detectable by the ANPR system at sites ANPR-01 and ANPR-02. This focused approach ensured that the evaluation of ANPR performance was based on violation types for which the system was operationally applicable and enforcement-relevant.

The traffic polices reported seven most frequent violations (as seen in Table 3) such as vehicles going straight at the intersection-running on red-light (coded as RR-ST) or running on yellow-light (coded as YR-ST), violations of lane control signs or lane marking by motorcycles (coded as VLC-MC) or by other vehicles (coded as VLC-OV), driving/riding a motorcycle without wearing a helmet (coded as MWH), using a phone while driving (coded as UPD), and driving a car without wearing a seatbelt (coded as DWB).

Under Cambodian traffic law [14], vehicles must stop when the traffic light turns yellow unless the front wheel has already crossed the stop line; proceeding otherwise constitutes a violation subject to police enforcement. However, the current ANPR system used in this study did not diagnose yellow-light running as a violation. Similarly, the systems could not diagnose lane control violations committed by motorcycles. As a result, YR-ST and VLC-MC were not reported by the ANPR system. Yet, these violations were included in the study through manual traffic counts, as on-site observations showed they occurred frequently. In sum, the ANPR system was able to detect five types: RR-ST, VLC-OV, MWH, UPD, and DWB, among the seven types of violations observed via observations at intersections.

3.2 Traffic Volumes

In this study, manual counting was conducted during selected time periods totaling seven hours within a single day. These periods—07:00–09:00, 11:00–13:00, and 17:00–19:00—correspond to peak traffic conditions when traffic volume and violation rates are typically highest. An additional observation period from 00:00–1:00 a.m. was included to assess the system's performance under low-light conditions. The data collected during these intervals were used to establish the evaluation metrics for the ANPR system's violation detection functions.

At site ANPR-01, as seen in Table 4, the traffic was observed for a total of seven hours on March 11, 2024. Motorcycles (MC) were the dominant vehicle type, with 3,922 recorded movements (equivalent to 52.3%), followed by cars (Car) with 3,076 vehicles (41.0%). The total traffic volume peaked during the morning period, as high as 3,854 vehicles, from 07:00 to 09:00, exceeding volumes observed in other time intervals. Three-wheelers (3W) and four-wheelers (4W) were infrequently observed at this location, about 4.4% and 2.3%, respectively.

Table 4. Manual count of traffic volume at site ANPR-01 on 11-March-2024

Vehicle	Volume by time-frame					
Code	00-01	07-09	11-13	17-19	Total	(%)
MC	24	1,961	724	1,213	3,922	(52.3)
Car	64	1,168	803	1,041	3,076	(41.0)
3W	2	134	110	85	331	(4.4)
4W	2	85	50	38	175	(2.3)
Total	92	3,348	1,687	2,377	7,504	(100)

Table 5. Manual count of traffic volume at site ANPR-02 on 02-June-2025

Vehicle Code	Volume by time-frame 00-01	07-09	11-13	17-19	Total	(%)
MC	146	2,542	1,635	2,584	6,907	(60.3)
Car	220	1,069	1,070	1,304	3,663	(32.0)
3W	15	161	379	62	617	(5.4)
4W	8	82	63	115	268	(2.3)
Total	389	3,854	3,147	4,065	11,455	(100)

Table 5 presents the seven-hour manual traffic count at site ANPR-02 on July 2, 2025. Motorcycles (MC) dominated the traffic (6,907 vehicles), followed by cars (3,663). Peak traffic occurred between 17:00 and 19:00. Three-wheelers (3W) and four-wheelers (4W) were minimally observed, with vehicle shares of 60.3% MC, 32.0% Car, 5.4% 3W, and 2.3% 4W.

The ANPR system also generated traffic statistics for the studied time frames. Over the same seven-hour observation period, the system recorded 7,452 vehicles at site ANPR-01 and 11,372 vehicles at site ANPR-02. Although these figures were generally comparable to the manual counts, the ANPR system consistently reported slightly lower traffic volumes (i.e., 52 vehicles or 0.7% for ANPR-01 and 83 vehicles or 0.7% for ANPR-02). Video footage analysis indicates that this small discrepancy, which is approximately 0.7%, is acceptable. As could be explained, this small discrepancy was mainly attributable to mixed-traffic conditions at the study sites. In several cases, smaller vehicles were partially or fully obscured by larger vehicles, limiting the ANPR camera's field of view. While human observers were able to identify and count such vehicles based on visible features, the ANPR system required a clearer and more complete visual capture to register a vehicle successfully.

3.3 Traffic Violations

3.3.1 Violations by Manual Counts

Based on the manual traffic violation counts, the number of violations by different types of vehicles and violations are reported in Table 6 and Table 7 for sites ANPR-01 and ANPR-02, respectively.

In terms of vehicle types, as can been, the majority of traffic violations were committee by motorcycles (MC), up to 57.0% and 84.3% at sites ANPR-01 and ANPR-02, respectively. The share of violations committed by cars (Car) was notably higher at site ANPR-01 (35.2%) than at site ANPR-02 (12.6%), suggesting that a larger proportion of cars violated traffic regulations in the suburban ANPR-01 area compared to the urban ANPR-02 site.

Table 6. Manual count of traffic violations by vehicle types at site ANPR-01 on 11-March-2024

Violation Code	Vehicle types MC	Car	3W	4W	Total	(%)
RR-ST	264	76	9	34	383	(33.2)
YR-ST	42	32	8	3	85	(7.4)
VLC-MC	142	0	0	0	142	(12.3)
VLC-OV	0	142	16	19	177	(15.4)
MWH	209	0	0	0	209	(18.1)
UPD	0	41	0	0	41	(3.6)
DWB	0	115	0	0	115	(10.0)
Total	657	406	33	56	1,152	(100)
(%)	(57.0)	(35.2)	(2.9)	(4.9)	(100)	

Table 7. Manual count of traffic violations by vehicle types at site ANPR-02 on 02-July-2025

Violation Code	Vehicle types MC	Car	3W	4W	Total	(%)
RR-ST	180	53	23	6	262	(21.1)
YR-ST	36	27	9	1	73	(5.9)
MWH	830	0	0	0	830	(66.9)
UPD	0	11	0	0	11	(0.9)
DWB	0	65	0	0	65	(5.2)
Total	1,046	156	32	7	1,241	(100)
(%)	(84.3)	(12.6)	(2.6)	(0.6)	(100)	

In terms of violations types, as can been seen, at site ANPR-01, red-light running (RR-ST) was the most frequent violation, accounting for 32.2% of all recorded violations. Other common violations included motorcycle helmet noncompliance (MWH, 18.1%), vehicle lane crossing-overload (VLC-OV, 15.4%), and vehicle lane crossing-motorcycle (VLC-MC, 12.3%). Notably, VLC-MC, despite its relatively high incidence, was not detected by the ANPR system. At site ANPR-02, MWH was the most frequent violation, representing 66.9% of the total, followed by RR-ST at 21.1%. These results indicate that the prevalence of violation types differed between sites, reflecting variations in traffic conditions and driver behavior.

3.3.2 Violations Detected by ANPR System

Using the records from ANPR system, traffic violations at both sites were examined over a full-day period (00:00–23:59). At site ANPR-01, data for three violation types—RR-ST, VLC-OV, and MWH—were extracted for March 11, 2024. A total of 2,210 violations per day were recorded, comprising 1,039 RR-ST, 415 VLC-OV, and 756 MWH cases. At site ANPR-02, a full-day data for July 2, 2025 showed 620 RR-ST and 2,455 MWH cases, resulting in 3,075 violations per day.

To further examine temporal patterns of traffic violations by time of day and day of the week, ANPR-recorded data were collected continuously over a one-week period (24 hours per day). For this extended timeframe, two violation types— RR-ST and MWH—detected by the ANPR system at site ANPR-02 were extracted and analyzed for the period from July 19 to July 25, 2025. These violations were selected because they represent the two most frequently recorded violation types at both study sites (see Tables 6 and Table 7). Similar information for site ANPR-01 were not available.

Fig 6 shows the variation of the two types of violations (RR-ST and MWH) and their total by time of the day. The hourly variation of different violation types followed broadly similar patterns throughout the day, with one notable exception. Between 17:00 and 18:00, the number of RR-ST began to decline, whereas violations involving MWH continued to increase. In addition, no RR-ST violations were recorded between 22:00 and 04:00, as traffic signals were not operational during this period.

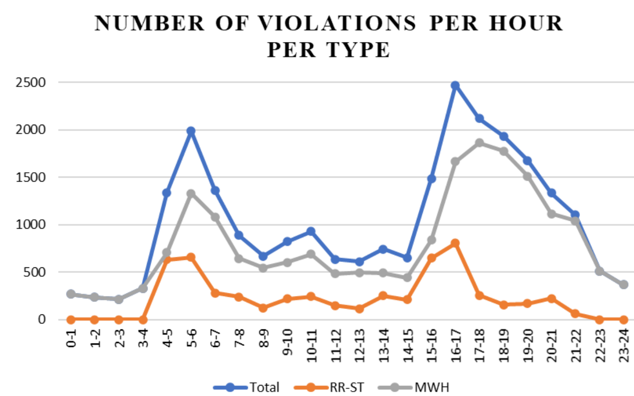

Fig.6. Hourly variations of different types of violations at site ANPR-02, from 19-July-2025 to 25-July-2025

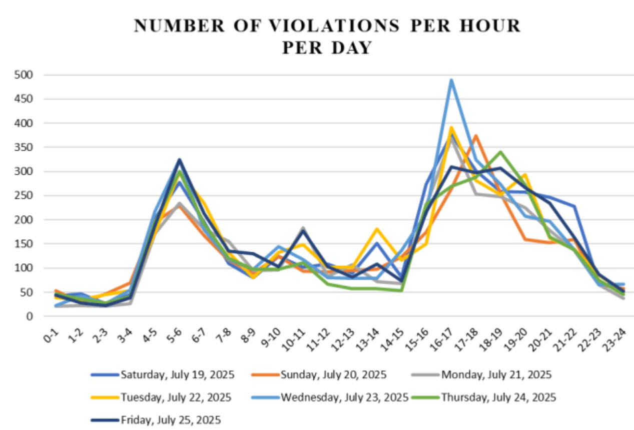

Fig.7. Hourly variations in number of violations by different days at site ANPR-02, from 19-July-2025 to 25-July-2025

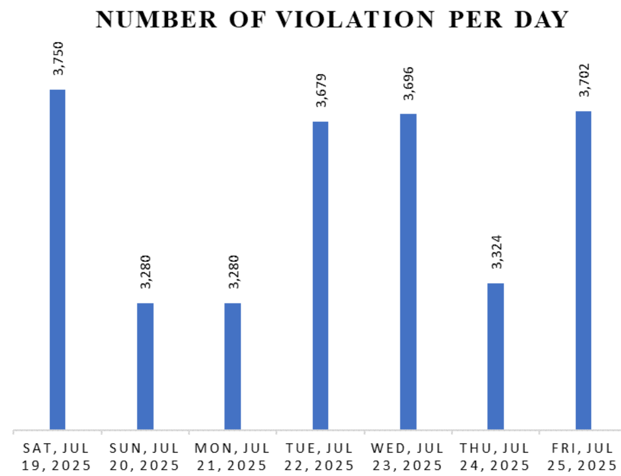

Fig.8. Daily variation in Number of violations at site ANPR-02, from 19-July-2025 to 25-July-2025

Fig 7 illustrates the hourly variation of traffic violations at site ANPR-02 for different days of the week. The daily pattern indicates that violations increased between 04:00 and 06:00, declined after 06:00, and then rose sharply again around 15:00. Violations reached their highest levels between 16:00 and 19:00, before gradually decreasing later in the evening. The highest hourly count—490 violations—was observed on Wednesday, July 23, 2025, between 16:00 and 17:00. And Fig 8 presents the daily distribution of traffic violations from July 19 to July 25, 2025. During this period, daily violations ranged from a minimum of 3,280 cases on Sunday, July 20, to a maximum of 3,750 cases on Saturday, July 19, with an average of approximately 3,530 violations per day.

3.4. Evaluating the performance of the ANPR system in violation detection

The numbers of traffic violations recorded by the ANPR system and identified through manual counts within the same time period at sites ANPR-01 and ANPR-02 are reported in Tables 8 and 9, respectively, for comparative analysis. Overall, for the included types of violations, the ANPR system detected fewer cases than those identified through manual counts. At site ANPR-01, a total of 925 violations were manually recorded out of 7,504 vehicles observed during the study period, indicating that approximately 12.3% (=925 / 7504) of vehicles committed traffic violations; while ANPR system detected a lower violation counts with the total 791 violations, equivalent to 10.5% (=791 / 7504) of vehicles committed violations. At site ANPR-02, there were 1,168 violations manually counted out of the total traffic volume of 11,455 vehicles, corresponding to a violation rate of 10.2% (=1168 / 11455). ANRP system detected 1,121 violations, equivalent to 9.8% (=1121 / 11455). Noted that YR-ST and VLC-MC were not included in this comparison tables, as the ANPR system could not identify them—thus, allow use assess the ANPR system performance explicitly for the included violation types. On average for the two sites, ANPR system detected 10.2% (= (10.5% + 9.8%) / 2), lower than the violation rate by manual counts of 11.3% (= (12.3% + 10.2%) / 2). In other words, the ANPR system could detect the included violations approximately 1.1% (=11.3% - 10.2%) lower than the actual counted violations, which is highly acceptable for the included violation types.

As human error in the manual traffic counting is generally minimal, typically less than 1% [15], the manual counts were used as a benchmark to assess an error rate of the ANPR system. The error rate is assessed by Error rate (%) = (Manual Count – ANPR System) / Manual Count. For example, for RR-ST at site ANPR-01 in Table 9, the error rate is calculated by Error rate (%) = (383 - 353) / 383 = 31/383 = 8.1%. For RR-ST at site ANPR-02 in Table 10, the error rate (%) = (262 - 249) / 262 = 13/262 = 5.0%. This indicates that the error rate of ANPR system to detect RR-ST violation is 8.1% at site ANPR-01 and is 5.0% at site ANPR-02. The average error rate for these two sites is 6.6% (= (8.1% + 5.0%)/2), meaning that the ANPR system could detect RR-ST violations within 6.6% errors (in this case, ANPR system generated a lower count of RR-ST violations than the manual counts approximately 6.6%). With the included violations, the average error rate for both sites is 9.3% (= (14.5% + 4.0%) / 2); indicating that the current ANPR system could detect violations up to 90% or more (=100% - 9.3%), compared to the number of violations counted manually.

Table 8. Comparing traffic violations between manual count and ANPR system at site ANPR-01 for 7-hour period on 11-March-2024

Violation Code	Manual Count	ANPR System	Difference	Error rate (%)
RR-ST	383	352	31	(8.1)
VLC-OV	177	166	11	(6.2)
MWH	209	208	1	(0.5)
UPD	41	10	31	(75.6)
DWB	115	55	60	(52.2)
Total	925	791	134	(14.5)

Table 9. Comparing result from manual count and ANPR system report of traffic violation at site ANPR-02 for 7-hour period on 02-July-2025

Violation Code	Manual Count	ANPR System	Difference	Error rate (%)
RR-ST	262	249	13	(5.0)
MWH	830	825	5	(0.6)
UPD	11	5	6	(54.5)
DWB	65	42	23	(35.4)
Total	1,168	1,121	47	(4.0)

The ANPR system seems to be able to perform the automatic detection much better for violations such as MWH, VLC-OV, and RR-ST (with Error rate < 10%). This is plausible because the activities involving these violations could be explicitly captured by the ANPR system. For instance, when someone was driving/riding a motorcycle without a helmet (MWH), it is easy for ANPR system to detect that she/she was not wearing a helmet. In other words, the image that someone without a helmet on a motorcycle can be easily detected with naked eyes or a camera. Similarly, it might be easier for ANPR system to detect a driver changed the traffic lane while driving (VLC-OV) and red-light running when traffic light turned to red and when other drivers in the same traffic streams started to stop their vehicles. In contrast, it may not be easy for detecting some violation behavior—e.g., it is often unclear to see a car driver wearing seatbelt or using a mobile phone or not, when he/she is observed from outside of his/her car. In particular, the ANPR system appears to inaccurately classify the small number of non-violations as violations (i.e., UPD, DWB), as these violations show high errors (Error rate > 50%). The ANPR may have failed to detect instances of a driver without a seatbelt or with a phone, at the moment he/she was passing the detection zones of ANPR system. This suggests that the system exhibited an extremely low number of false positives (FP) across all violation types, while the number of false negatives (FN) for UPD and DWB was comparatively high. It should be noted that the ANPR system did not generate records for certain violation types, such as yellow-light running (YR-ST) and motorcycle violations of lane control signs or markings (VLC-MC), as these behaviors are not defined as violations within the system. Consequently, the corresponding error rates could not be calculated.

Table 10. Performance metrics of the ANPR system

Violation Code	Accuracy	Precision	Recall	F1-Score
At site ANPR-01				
RR-ST	0.9951	0.9915	0.9112	0.9497
VLC-OV	0.9980	0.9880	0.9266	0.9563
MWH	0.9993	0.9904	0.9856	0.9880
UPD	0.9955	0.8182	0.2195	0.3462
DWB	0.9915	0.9636	0.4609	0.6235
At site ANPR-02				
RR-ST	0.9985	0.9920	0.9427	0.9667
MWH	0.9989	0.9952	0.9892	0.9921
UPD	0.9993	0.8000	0.3636	0.5000
DWB	0.9976	0.9524	0.6154	0.7477
Average values for sites ANPR-01 and ANPR-02				
RR-ST	0.9968	0.9917	0.9270	0.9582
VLC-OV	0.9980	0.9880	0.9266	0.9563
MWH	0.9991	0.9928	0.9874	0.9901
UPD	0.9974	0.8091	0.2916	0.4231
DWB	0.9946	0.9580	0.5381	0.6856

The performance metrics derived from the confusion matrix are summarized in Table 10, which presents the accuracy, precision, recall, and F1-Score for each type of violation detected by the ANPR system at sites ANPR-01 and ANPR-02. The traffic survey was conducted over 7-hour period, covering peak hour traffic volumes, for each site—this results in a very large number of True Negatives (TN) for each violation type. Consequently, the dataset was highly imbalanced, making accuracy a potentially misleading indicator of system performance. Although the accuracy values were exceptionally high across all violation types, this was largely due to the relatively small number of violations compared to the overall traffic volume. As a result, the system could still achieve high accuracy despite producing a substantial number of incorrect detections. Given this imbalance, precision, recall, and F1-Score might be considered as more reliable performance indicators. High precision reflects the system's ability to avoid misclassifying non-violations as violations, while high recall indicates effective detection of actual violations. As shown in Table 10, at site ANPR-01, the precision, recall, and F1-Scores for RR-ST, VLC-OV, and MWH were consistently high, all exceeding 0.91. These results demonstrate that the system detected these violation types effectively and with minimal false alarms. In contrast, although the precision values for UPD (using a phone while driving) and DWB (driving without a seatbelt) remained high, both recall and F1-Score were notably low. This indicates that the system failed to identify a substantial proportion of these violations, highlighting the need for further system improvements.

At site ANPR-02, no VLC-OV were present; therefore, lane-related violations were not evaluated. The precision, recall, and F1-Scores for RR-ST and MWH were exceptionally high, exceeding 0.94, indicating high detection performance with minimal misclassification. Yet, the recall and F1-Score values for UP and DWB remain substantially low.

The mean values of the evaluation metrics across both sites were also reported in Table 10. For RR-ST, VLC-OV, and MWH, the mean precision, recall, and F1-Scores all exceeded 0.92, indicating reliable and consistent detection performance. Currently, no official guidelines define minimum accuracy, recall, or precision for ANPR systems in traffic violation detection. The closest benchmark, issued by the International Association of Chiefs of Police (IACP) in 2007 [17] for red-light cameras, requires capturing at least 90% of events—effectively a minimum recall of 0.9. Using this standard, an ANPR system is considered acceptable if accuracy, precision, recall, and F1-Score each meet or exceed 0.9. By this criterion, the system in this study reliably detects RR-ST, VLC-OV, and MWH violations at Phnom Penh intersections. Nevertheless, human validation remains essential to correct misclassifications and prevent false citations. However, DWB detection, despite a high mean precision of 0.9580, exhibited a relatively low recall of 0.5381 and an F1-Score of 0.6856. UPD detection performed weakest overall, with a mean precision of 0.8091, recall of 0.2916, and F1-Score of 0.4231, emphasizing the ongoing challenges associated with detecting in-cabin violations under varying roadway and lighting conditions.

4. DISCUSSIONS

4.1 Improving Detection Capability of ANPR System

The low detection rates for UPD and DWB at both sites should be improved by possible means. As such, further analysis of the video footage and manual traffic counts revealed that UPD and DWB violations occurred more frequently during nighttime conditions. As discussed previously, the ANPR system at site ANPR-01 was not equipped with a supplementary flash light, which limited the camera's ability to clearly capture vehicle interiors through the front windshields of a car. This constraint significantly reduced detection performance for in-cabin violations, explaining the low recall observed for UPD and DWB. To address this limitation, an infrared (IR) flash light was installed at site ANPR-02 alongside the front-facing ANPR camera. Because IR illumination is invisible to drivers, it does not cause distraction while substantially enhancing the camera's ability to detect in-cabin violations such as UPD and DWB. With the addition of IR illumination at site ANPR-02, the camera was able to capture clearer views through vehicle windshields, leading to significantly improved precision, recall, and F1-Scores for UPD and DWB compared with those obtained at site ANPR-01.

However, the effectiveness of the IR flash light was constrained by roadway geometry. A single flash light was capable of illuminating only one traffic lane, while the roadway at site ANPR-02 consisted of multiple lanes. As a result, vehicles traveling outside the illuminated lane were not captured clearly enough for reliable in-cabin violation detection. This finding suggests that one IR flash light per lane is required to ensure adequate illumination across the entire roadway. In addition to illumination, camera positioning also influenced detection performance. According to the manufacturer's recommendations, effective detection of UPD and DWB requires mounting the camera on a long arm to achieve an optimal viewing angle of approaching vehicles. At site ANPR-02, the camera was mounted on a 1.5 m arm attached to a streetlight pole on the median, which restricted its viewing angle and further limited detection performance for these violation types.

4.2 Traffic Violations in Cambodia

The Cambodia Road Traffic Law defines a broad spectrum of traffic violations, encompassing unsafe and unlawful behaviors such as failure to use seatbelts or helmets, mobile phone use while driving, red-light running, lane and signal violations, unsafe maneuvers, sidewalk encroachment, pedestrian-related offenses, drunk driving, illegal parking, and various administrative and technical infractions [14]. The law aims to ensure road traffic safety and order, protect human and animal life and health, safeguard property, and preserve the environment. Its objectives include raising public awareness of road safety, regulating traffic behavior, maintaining traffic order, and deterring violations by road users [14]. The legislation clearly specifies categories of traffic violations and corresponding penalties, which were substantially strengthened in the 2020 revision through higher fines and stricter enforcement measures [16]. Minor offenses are often addressed through educational warnings, whereas serious or repeat violations result in monetary fines and potential imprisonment.

Penalties vary by vehicle type. Typical fines include approximately 15USD for helmet non-use, 30USD-60USD for driving without a license or license plate, 19USD-38USD for seatbelt non-use, 75USD-160USD for speeding (depending on the degree of excess speed), and about $38 for red-light violations. Sanctions for illegal overtaking or turning vary and are often preceded by educational measures. More severe penalties apply to high-risk behaviors: driving under the influence of alcohol (blood alcohol concentration > 0.50 g/L or breath alcohol content > 0.25 mg/L) is punishable by fines of 100USD-1,000USD and up to six months' imprisonment, while dangerous driving that endangers others may result in imprisonment of up to one year and substantial fines.

However, many of the violations do not typically occur at signalized intersections (e.g., licensing issues, illegal parking, or over speeding). As this study focuses on evaluating ANPR performance at urban intersections, the analysis is therefore limited to the most frequently observed intersection-related violations, as identified through field observations and reports from on-site traffic police. In this study, from the interview survey with traffic polices at 5 urban intersections, there were seven major types of traffic violations; that is, RR-ST, YR-ST, VLC-MC, VLC-OV, MWH, UPD, and DWB. A rough estimation of the top two violations (i.e., RR-ST and MWH), generated by ANPR system, for both studied sites in Table 8 and Table 9, recorded 4,870 cases in a single day (1,795 at site ANPR-01 + 3,075 at site ANPR-02). This record of these two violations alone is equivalent to almost 1.8 million cases per year, indicating a high frequency of traffic violations at urban intersection. In contrast, the Phnom Penh Capital Administration reported only 40,438 traffic violations citywide in 2023 [2] and 64,657 in 2024 [3]. Given the number of intersections in the capital and the limited enforcement hours (7:00–11:00 and 13:00–17:00), with not all intersections monitored daily, a substantial proportion of traffic violations is likely to go unrecorded. Nevertheless, the data generated by ANPR system at site ANPR-02 between July 19 and 25, 2025, showed that the high number of violations occurred on Friday, Saturday, Tuesday, and Wednesday (Fig 8). Within a day, the high number of violations occurred in the morning between 04:00 and 06:00, and in the evening between 16:00 and 17:00 (Fig 6 & Fig 7). This finding suggests that the standard enforcement hours (7:00–11:00 and 13:00–17:00) would not be sufficient, as the top two violations (RR-ST and MWH) have been largely committed outside the traffic police's working hours. Additional schedule for urban traffic enforcement—e.g., additional nighttime and/or weekend enforcement at random streets/intersections—would essentially help minimizing overall traffic violations in urban areas.

4.3 Strategies to Detect and Reduce Traffic Violations

Traffic violations can be detected through a combination of automated and manual enforcement strategies. Automated technologies such as ANPR (as discussed in this study), speed cameras, red-light cameras, and CCTV enable continuous and objective monitoring of traffic behavior, improving detection efficiency and coverage, particularly for speeding, red-light running, and illegal parking. Manual enforcement by traffic police, including patrols and roadside checkpoints, remains essential for identifying violations that are difficult to capture automatically, such as drunk driving, mobile phone use while driving, and seatbelt or helmet non-use. Integrating violation data with vehicle registration and driver licensing systems, together with community report mechanism, further enhances enforcement effectiveness.

Minimizing traffic violations requires a comprehensive approach that combines education, enforcement, engineering, and policy measures. Public awareness campaigns and driver training programs promote understanding of traffic laws and safer driving behavior, while consistent enforcement and meaningful penalties increase deterrence, particularly for high-risk offenses. Infrastructure improvements—such as clearer signage, improved road markings, traffic calming measures, and optimized signal control—help reduce opportunities for violations. In addition, institutional coordination and the use of intelligent transport systems, including real-time driver feedback and warning devices, support sustained compliance and long-term improvements in road safety.

5. CONCLUSIONS

This study investigated the characteristics of traffic violations at signalized intersections in Phnom Penh and evaluated the performance of existing ANPR systems in detecting such violations. Based on field observations, interviews with traffic police, manual traffic counts, and ANPR-generated records, the results show that traffic violations at urban intersections are both frequent and diverse, with motorcycles accounting for the majority of violations. Red-light running and motorcycle helmet noncompliance were consistently identified as the most prevalent violations across study sites (ANPR-01 and ANPR-02), reflecting persistent safety challenges in Phnom Penh's urban traffic environment.

The performance evaluation demonstrates that the ANPR system is generally effective and acceptable in detecting externally observable violations, particularly red-light running, motorcycle helmet non-use, and lane-control violations by other vehicles. For these violation types, the system achieved high precision, recall, and F1-Scores, indicating reliable detection with minimal false alarms. Overall, the ANPR system detected 10.2% of total traffic volume as violations, slightly below the 11.3% observed manually, with an average error rate of 9.3%. This study indicates that the system captured over 90% of violations for the included types, demonstrating high reliability and effectiveness for automated traffic monitoring and enforcement. This level of accuracy is considered acceptable for automated enforcement. However, the system showed limited capability in detecting in-cabin violations, such as mobile phone use while driving and seatbelt non-use, primarily due to insufficient illumination, suboptimal camera placement, and roadway geometry constraints. These limitations resulted in high false-negative rates, highlighting the need for technical enhancements.

The findings suggest that expanding the deployment of ANPR-based traffic enforcement in Phnom Penh could substantially improve violation detection, particularly when combined with system upgrades such as infrared illumination, optimized camera mounting, and lane-specific coverage. Moreover, the temporal analysis indicates that a significant proportion of violations occur outside standard traffic police working hours, underscoring the importance of continuous, automated enforcement. To effectively reduce traffic violations and improve road safety, ANPR deployment should be integrated with broader strategies, including targeted enforcement scheduling, infrastructure improvements, public education, and stronger institutional coordination. Together, these measures can support data-driven traffic management and contribute to sustained reductions in traffic violations and road traffic accidents in Cambodia.

Future research should expand ANPR studies to more intersections and diverse urban areas, improve detection of in-cabin violations like seatbelt and phone use, and incorporate currently undetectable violations such as yellow-light running. Long-term, multi-temporal analyses could reveal patterns across times and locations, while spatial studies identify high-risk hotspots. Evaluating the impact of ANPR enforcement on accidents, compliance, and cost-effectiveness is recommended, alongside exploring enhanced technologies, multi-lane coverage, and integration with broader traffic management systems. Combining automated detection with public awareness and predictive analytics could further optimize urban traffic safety and support evidence-based policy decisions.

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