Evaluating the Effectiveness of Artificial Intelligence (AI) Cameras in Detecting Helmet Use

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Abstract

Currently, Thailand has a higher death rate from motorcycle accidents than from other vehicles. Wearing a helmet can reduce the severity of head injuries in accidents, since the head is a crucial part of the human body. The objective of this research was to evaluate the effectiveness of AI camera detection of helmet-wearing behaviours (both drivers and passengers) and to find the relationship between the accuracy of AI cameras in detecting helmet-wearing behaviours and the camera installation points. Data was collected from two AI camera installation points, observing a total of 674 motorcycles. The data was analyzed using descriptive statistics and the Pearson Chi-Square test, as well as a logistic regression analysis. The study found that AI cameras could accurately detect helmet-wearing behaviours, with Point 1 having a detection accuracy of 73.7% and Point 2 having a detection accuracy of 89.5% (Point 1 was a two-lane, one-way roadway featuring a covered pedestrian walkway with high foot traffic; whereas Point 2 was a two-lane, bi-directional roadway flanked by drainage ditches on both sides with no dedicated pedestrian facilities.). Additionally, there was a significant difference in the detection accuracy of the AI cameras between the two installation points (p-value < 0.05), as well as a difference in the detection accuracy based on helmet-wearing behaviours (p-value < 0.05). In addition, analysis revealed that camera location and helmet type had significantly impacted detection accuracy. Specifically, Point 2 outperformed Point 1, and Type 2 helmet detection showed a 23-fold higher accuracy compared to other types (p-value < 0.05)

Keywords: AI, Camera, Helmet-Wearing, Motorcycle, Accidents, Traffic Safety

1. Introduction

1.1 Background

Crashes are a global issue that various countries are trying to address. Crashes often lead to property loss, injuries, disabilities, or deaths, affecting economic growth, society, and tourism. According to the World Health Organization (WHO) in 2023, 1.19 million people die from crashes annually, with higher death rates found in low-income and middle-income countries [1].

Among ASEAN member countries, Malaysia and Vietnam have high helmet-wearing rates, while Thailand has a low rate, similar to Myanmar. The enforcement of helmet-wearing laws in ASEAN countries shows that Indonesia and Singapore have effective enforcement, while Thailand's enforcement is low, which is similar to Myanmar, Cambodia, and the Philippines [2],

The issue of helmet use in countries with high motorcycle usage, particularly in ASEAN countries and Thailand, represents a critical road safety concern at the global level. Reports by the World Health Organization have indicated that motorcyclists are among the most vulnerable road users, accounting for a substantial proportion of road traffic fatalities worldwide, especially in low-income and middle-income countries where motorcycle use is prevalent [1],[2]. Although helmet use has been proven to significantly reduce the risk of death and severe injury, compliance with helmet laws remains inconsistent across different contexts.

In Thailand, studies by Hyder and colleagues have demonstrated a strong correlation between helmet law enforcement, helmet usage rates, and head injuries. [3]. At the urban level, particularly in Chiangrai, Nakhon Ratchasima, Bangkok, and Songkla, research has shown that behavioral factors, risk perception, and roadway characteristics are significantly influencing motorcyclists' decisions to wear helmets [4]. Furthermore, although Thailand has long implemented helmet legislation, its effectiveness largely depends on the level of enforcement and public acceptance [5]. Therefore, examining helmet use within high motorcycle-density urban environments is essential in order to develop effective and sustainable road safety policies.

Khon Kaen Province, located in the Northeastern Thailand, has one of the highest road accident rates in the country, particularly on Mittraphap Road (the main road) passing through Khon Kaen municipality. Despite various traffic enforcement measures, such as speed cameras, traffic light violation cameras, and helmet-wearing detection cameras, crashes leading to death still occur and motorcycles remain the deadliest vehicles on the streets . Khon Kaen Hospital has been seeking ways to reduce motorcycle-related fatalities by addressing and monitoring key risk behaviors, including driving while drunk, using mobile phone while driving, driving under the influence of drugs, and failing to wear helmets during collisions [5].

To address road accident severity on Mittraphap Road, the Khon Kaen Traffic Accident Prevention Committee proposed a project to prevent traffic signal violations and to detect helmet usage with semi-automatic cameras provided by the Safer Roads Foundation of the UK. The project received funding in January 2017, and Khon Kaen Municipality and Khon Kaen Provincial Police signed a cooperation agreement on September 7, 2017. The project began in October 2017. The project has aimed at ensuring safer travel through intersections and supporting public health policies. The locations of the cameras were at the intersection of Moh Din Dang, the City Arch, and Charernsri Road [6–10].

1.2 Literature review

The literature review indicated that research on helmet detection using CCTV and AI has evolved from traditional techniques, such as HAAR features, machine vision, and C++ programming toward advanced deep learning models, including Convolutional Neural Networks (CNN) and YOLO, which provide higher accuracy and real-time object detection capabilities in complex traffic environments [11–19]. Studies conducted in Thailand have demonstrated that CCTV-AI systems can be effectively applied for law enforcement purposes, including detecting red-light violations and identifying motorcyclists, who are not wearing helmets [11–13]. Similarly, international studies have confirmed that deep learning approaches are highly effective in classifying helmet use under real-world urban conditions [14–19]. However, variations in results are often influenced by factors such as camera quality, viewing angles, lighting conditions, traffic density, and occlusion between drivers and passengers, which remain the critical limitations of automated detection systems.

A significant research gap lies in the fact that most studies have primarily focused on detecting "drivers" rather than "passengers," and there is limited comparative analysis of AI performance across multiple camera locations in real urban settings [20]. Furthermore, while helmet detection studies in construction safety contexts [21–28] highlight the robustness of YOLO and CNN in complex environments, their direct application to motorcycle behavior in urban traffic requires further adaptation. Therefore, the integration of YOLO with foundational techniques, such as HAAR and C++, is essential in order to develop a system that is both fast and accurate, and is suitable for practical implementation by law enforcement.

Research on evaluating the effectiveness of artificial intelligence (AI) cameras in detecting helmet-wearing behaviours among motorcycle drivers and passengers has been steadily increasing, particularly in the context of traffic law enforcement in many countries. However, a review of the literature reveals several significant gaps in the research. These include the simultaneous detection of multiple types of helmet-wearing behaviours and the analysis of proportional rates for policy formulation purposes. This study is the first to propose an analytical equation for such a modeling approach.

Another important issue concerns the relationship between camera installation points (e.g., mounting height, tilt angle, distance from traffic lanes, and installation at intersections versus straight road segments) and the accuracy of AI systems. Previous studies have primarily focused on software performance rather than focusing on the physical and infrastructural factors of camera placement. As a result, there is a lack of spatial evidence to support planning for optimal camera installation.

This research addresses these gaps by demonstrating environmental variability in model development and by validating the proposed model across different real-world settings.

This research study aimed at evaluating the effectiveness of detecting helmet use by AI for both motorcycle drivers and passengers and examining the comparison between the use of AI cameras to detect the behaviours of people on motorcycles from various locations.

2. Materials and methods

2.1 Development of Helmet-Wearing Detection Program

Khon Kaen Province enforces helmet-wearing using CCTV and computer programs to detect non-helmet wearers automatically. The system works with the Thai Police Ticket Management System (PTM) to issue tickets to motorcycle riders, who violate the law. The enforcement has increased helmet-wearing rates, with program development detailed in **Table 1**.

The table highlights a clear progression in program development—from single-target detection (driver-focused) to more comprehensive systems that include passengers. This evolution is significant in order to improve enforcement effectiveness and to increase overall helmet-wearing rates, since it ensures that all motorcycle occupants are monitored under the law.

Table 1: Program Development

Detection		Reference Documents
Driver	Passenger	
☑	☒	[12–20]
☒	☑	[12–15], [17–20]
☑	☑	[17–18],[20]

Figure 1. demonstrates the study is among the few studies of the helmet-wearing detection program using CCTV. The program detects three things: 1) the type of vehicles and identifies motorcycles; 2) head positions; and 3) whether the riders wear helmets or not [13].

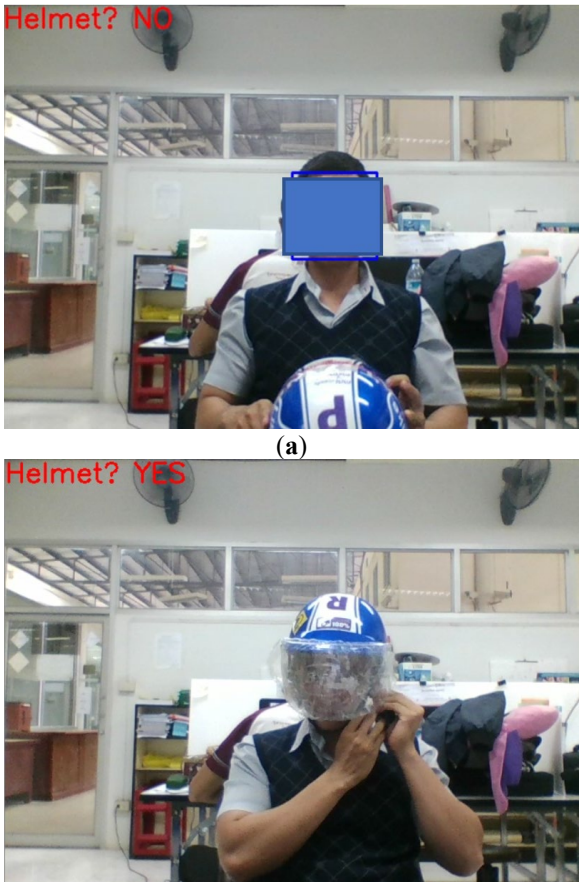


Figure 1. (a) and (b): Version 1 to detect non-helmet wearing riders

Figure 1 demonstrates helmet safety monitoring using a computer-interfaced camera. Subsequently, the helmet-wearing behavior detection program developed by Kumphong [12] utilizes CCTV footage to demonstrate helmet-wearing behaviors. The program performs rapid computations to identify whether riders are wearing helmets. If a rider is detected without a helmet, the system automatically transmits the information to law enforcement to issue a traffic violation ticket. However, current programs are incapable of distinguishing between the driver and the passenger [21–24]. To address this limitation, the proposed program utilizes a rear-view camera angle, enabling law enforcement to clearly display license plate images alongside the issued traffic ticket. In Thailand, motorcycle license plates are strictly positioned at the rear of the vehicle [12].

2.2 Research Design and Setting

The program was designed to detect people not wearing helmets using CCTV cameras. This is a useful technology for law enforcement to increase the efficiency of law enforcement and to increase the rate of helmets wearing in the province. However, to collect data on helmet wearing rates among motorcycle riders, data on helmet wearing must distinguish between drivers and passengers for more accuracy and clarity. During this phase of program testing, the researcher developed the accuracy to 95% and the program was able to determine 7 types of behaviours in relation to helmet wearing by Kumphong and Chawapattanayotha [20].

To delineate the research framework more comprehensively, the investigation is organized into a 5 steps sequence [20]:

2.2.1 Literature Review

The initial phase of the study establishes a solid theoretical foundation by conducting an exhaustive review of existing literature pertaining to automated helmet detection, computer vision models, and urban traffic safety. This step involves synthesizing current advancements in deep learning frameworks used for object detection, evaluating the efficacy of intelligent transportation systems (ITS) in reducing traffic-related fatalities, and identifying existing research gaps—such as the limitations of standard surveillance cameras in distinguishing between drivers and passengers. The insights gained from this review guide the formulation of the research hypotheses and the selection of appropriate technological architectures.

2.2.2 Site Selection and Data Collection

Following the theoretical grounding, the operational phase focuses on identifying strategic urban locations characterized by high motorcycle traffic volumes and frequent traffic violations. Data collection is systematically executed using high-resolution AI-powered cameras deployed at designated checkpoints. These cameras are positioned at optimal angles—specifically utilizing rear-view perspectives—to capture clear imagery of both riders and vehicle license plates without obstructing regular traffic flow. Environmental variables such as lighting conditions and weather are accounted for to ensure the robustness and generalizability of the collected dataset.

2.2.3 Motorcycle Data

This quantitative phase aggregates and categorizes the empirical data captured during the field deployment. The dataset comprises a comprehensive sample size of 674 motorcycles, yielding detailed behavioral records for 674 drivers and 113 passengers. Each record is meticulously cataloged to document compliance metrics, including helmet-wearing status, positioning on the vehicle, and associated timestamp data. This rigorous data compilation forms the empirical backbone required for subsequent computational analysis and validation of the detection models.

2.2.4 Data Distribution and AI Model

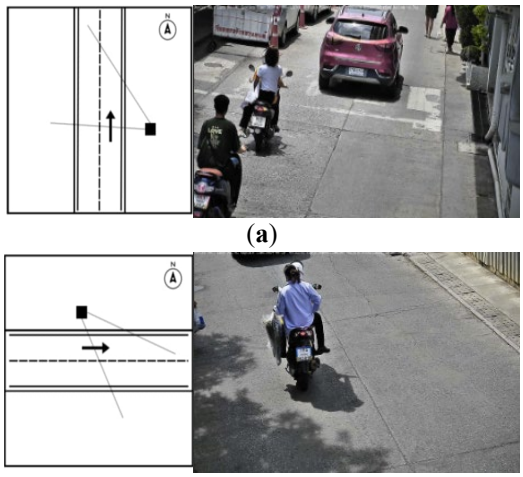
To evaluate performance across different urban settings, the compiled dataset is strategically distributed between two distinct observational nodes: Point 1, comprising 437 motorcycles, and Point 2, comprising 237 motorcycles. Rather than relying on generic third-party software, this study implements a custom-developed artificial intelligence model tailored specifically to process and analyze the captured imagery. The model leverages advanced computer vision algorithms to automate the detection

of helmet compliance, isolating individual riders and extracting precise license plate details for enforcement integration. The details of each point are as follows:

Point 1 consisted of a two-lane, one-way roadway with a clearly designated pedestrian zone. The sidewalk was equipped with a continuous covered walkway (canopy), resulting in high pedestrian volumes. This environment naturally encourages drivers to reduce speed and to exercise increased caution. From a technical perspective, the canopy structure may have introduced lighting and shadowing complexities in the camera feed, leading to image processing challenges, such as occlusion and inconsistent lighting contrast. Consequently, cameras at this location are typically installed at an oblique lateral angle to ensure comprehensive coverage of both lanes of traffic and the pedestrian area.

Point 2 is also a two-lane roadway but supports bi-directional traffic. Unlike Point 1, this section lacks dedicated sidewalks and is flanked by drainage ditches on both sides. The open-space characteristic allows for higher traffic flow and potentially higher average vehicle speeds. While the absence of lateral obstructions minimizes occlusion—making object detection more straightforward for AI—the open environment is susceptible to variabilities in high ambient light. Factors, such as intense direct sunlight or irregular shadows from trees, may affect the system's overall accuracy.

The study used a helmet-wearing detection program with AI cameras in various environments, focusing on Sri Chan Road near Khon Kaen Hospital (Gate 1) and Soi Sri Chan 10/1 (Gate 5) in **Figure 2**.



(**a**)

(**b**)

Figure 2. The installation points and angles of the AI cameras (**a**) Point 1 (**b**) Point 2

2.2.5 Study Results, Interpretation, and Conclusion

The final phase centers on the systematic analysis, synthesis, and contextualization of the model's outputs. Quantitative results derived from Points 1 and 2 are evaluated to measure helmet adherence rates and model accuracy. The findings are then interpreted within the broader context of public policy, road safety regulations, and automated law enforcement mechanisms. Finally, the study draws definitive conclusions regarding the feasibility and effectiveness of implementing rear-view AI camera systems for targeted traffic violation ticketing.

2.3 AI in Behavioral Analysis

Recent advancements in closed-circuit television (CCTV) systems have enabled the effective integration of artificial intelligence (AI) to support automated image analysis. These systems collect visual data which can be processed through machine learning (ML) algorithms in order to develop automated detection capabilities. AI systems can now identify various visual features, such as objects, faces, or human behaviors. For example, in the field of traffic enforcement, agencies have developed helmet detection systems by collecting large datasets of images showing riders with and without helmets. Researchers use these datasets to train AI [29].

Models via machine learning enable the system to learn and memorize the features associated with helmet usage and to automatically, detect such behaviors during real-time monitoring [20],[25–26].

One widely adopted AI approach for image classification is the *You Only Look Once* (YOLO) algorithm, particularly its more recent versions. YOLO is known for its speed and high accuracy in real-time object detection and classification tasks [20], [27]. In previous research, datasets of motorcycle riders were used to train such models. Preprocessing techniques, such as adjusting lighting, color balance, and background segmentation, were applied to enhance the model's ability to learn. Additionally, bounding box and labeling techniques were used to define the areas of interest for each behavior or object type. These models were trained using GPU-based systems to maximize processing efficiency. YOLO-based models have become increasingly common in behavior detection systems involving vehicles and drivers. However, the quality of the training dataset and the complexity of the behaviours being classified can significantly impact the model's accuracy [20],[28].

In this study, we adopted the AI-based motorcycle helmet detection approach previously developed by Kumphong and Chawapattanayotha [20]. The original system was developed by integrating artificial intelligence with existing CCTV cameras to identify motorcycle riders and passengers according to their helmet-wearing characteristics. The development procedure consisted of data collection, image preparation and categorization, artificial neural network training, and subsequent evaluation of the detection accuracy.

The dataset used for developing the original model comprised approximately 1,119 images obtained from CCTV cameras under both daytime and nighttime conditions. Of these, 1,019 images were used for model development and training, while an additional 100 images were independently selected for accuracy

verification. The verification images were separated from the training dataset so that they were not previously encountered by the learning program during model development [20].

The original study employed the YOLO V.4 library for the development of the detection program. Prior to training, CCTV video data were converted into image files and categorized according to predefined characteristics of motorcycle riders and passengers. The classification scheme included seven helmet-use configurations: 1) driver without a helmet, 2) driver wearing a helmet, 3) helmeted driver with an unhelmeted passenger, 4) unhelmeted driver with a helmeted passenger, 5) both driver and passenger without helmets, 6) both driver and passenger wearing helmets, and 7) other configurations.

Artificial neural network training was then performed to improve detection performance. According to the original study, the learning process was conducted for 4,500 training cycles, after which the program achieved a reported training accuracy of 95%. The model was specifically trained to identify motorcycle riders and passengers with respect to helmet use, thereby focusing the learning process on the primary target required for automated helmet-law enforcement.

For independent verification, the original researchers randomly selected 100 photographs that were different from those used for training and that had not previously been encountered by the model. The automated detection results were compared with observations made by the researchers to evaluate the ability of the program to identify helmet-wearing and non-helmet-wearing motorcycle users. The original study reported an overall detection accuracy of 95% and demonstrated that the trained algorithm could distinguish between riders wearing helmets and those not wearing helmets.

Therefore, the present study utilized this previously developed AI model as the underlying detection approach rather than developing a new model from the beginning. Its adoption was based on its demonstrated capability to process CCTV-derived images and identify helmet-wearing characteristics of motorcycle riders and passengers under the conditions evaluated in the original study [20].

2.4 Data and Data Analysis

The data was collected with 437 motorcycles passing Point 1 and 237 passing Point 2, totaling 674 motorcycles. Then the data was sorted from 759 photos. To evaluate the effectiveness of AI cameras in detecting helmet-wearing behavior, the data was analyzed and categorized into seven types (**Table A1**). In order to find the relationship between camera accuracy and the installation points the Pearson Chi-Square test with a 95% confidence level was used. This research was approved by the Human Research Ethics Committee of Rajamangala University of Technology Isan (Ethics number HEC-02-67-018).

Table A1 presents a structured classification framework for analyzing helmet-wearing behaviours among motorcycle drivers and passengers using CCTV-AI data. The table, which categorizes observations into six behavioral types based on helmet use, distinguishes between compliant and non-compliant conditions for both drivers and passengers. Types 1 and 2 focus on driver-only scenarios, while Types 3 and 4 capture mixed compliance between drivers and passengers. Types 5 and 6 represent complete non-compliance and full compliance, respectively, serving as key indicators for evaluating road safety outcomes. Type 7 was excluded due to atypical conditions (>3 riders). This framework supports data labeling, AI validation, and behavioral analysis.

$$\text{The percentage of drivers wearing helmets} = \frac{B+C+I}{A+B+C+D+E+F+G+H+I+J} \times 100 \quad (1)$$

$$\text{The percentage of drivers not wearing helmets} = \frac{A+E+G}{A+B+C+D+E+F+G+H+I+J} \times 100 \quad (2)$$

$$\text{The percentage of passengers wearing helmets} = \frac{F+J}{A+B+C+D+E+F+G+H+I+J} \times 100 \quad (3)$$

$$\text{The percentage of passengers not wearing helmets} = \frac{D+H}{A+B+C+D+E+F+G+H+I+J} \times 100 \quad (4)$$

$$\text{The overall helmet wearing percentage} = \frac{B+C+F+I+J}{A+B+C+D+E+F+G+H+I+J} \times 100 \quad (5)$$

$$\text{The overall non-helmet wearing percentage} = \frac{A+D+E+G+H}{A+B+C+D+E+F+G+H+I+J} \times 100 \quad (6)$$

Based on **Table A1**, variables A–J represent the frequency of observed behaviors across helmet-wearing categories (Types 1–6). These variables were used to compute key helmet-use indicators through Eqs (1)–(6). The denominator in all equations was the total number of observations (A + B + C + D + E + F + G + H + I + J), which included both drivers and passengers in all valid cases (excluding Type 7).

For example, assume A = 50, B = 200, C = 150, D = 80, E = 40, F = 120, G = 30, H = 60, I = 180, and J = 140. (Total observations = 1,050)

1) The percentage of drivers wearing helmets = ((200 + 150 + 180) / 1,050) × 100 = 50.48%
2) The percentage of drivers not wearing helmets = ((50 + 40 + 30) / 1,050) × 100 = 11.43%
3) The percentage of passengers wearing helmets = ((120 + 140) / 1,050) × 100 = 24.76%
4) The percentage of passengers not wearing helmets = ((80 + 60) / 1,050) × 100 = 13.33%
5) Overall helmet-wearing percentage = ((200 + 150 + 120 + 180 + 140) / 1,050) × 100 = 75.24%
6) Overall non-helmet-wearing percentage = ((50 + 80 + 40 + 30 + 60) / 1,050) × 100 = 24.76%

2.5 Logistic Regression Analysis

This research utilized logistic regression analysis and Cramér's V analysis at a statistical significance level of 0.05. The dependent variable was detection (1 = Correct, 0 = Incorrect), and the independent variable was

the camera installation location (1 = Point 1, 0 = Point 2), as detailed in **Table** 2, which defined all variable indicators used in this study.

Table 2. Variable Descriptions

Nos.	Variables	Descriptions
1	Y	Detection (1 = Correct, 0 = Incorrect)
2	X1	Camera installation location (1 = Point 1, 0 = Point 2)
3	X2	1 = Type 1 was correctly detected. 0 = Other
4	X3	1 = Type 2 was correctly detected. 0 = Other
5	X4	1 = Type 3 was correctly detected. 0 = Other
6	X5	1 = Type 4 was correctly detected. 0 = Other
7	X6	1 = Type 5 was correctly detected. 0 = Other
8	X7	1 = Type 6 was correctly detected. 0 = Other
9	X8	1 = Type 7 was correctly detected.; 0 = Other

3. Results and discussion

From the analysis of the collected image data (after excluding the irrelevant information) the data used for analysis consisted of 674 drivers and 113 passengers, making a total of 787 individuals from 674 motorcycles. It was found that the most common helmet-wearing behaviour was Type 2, involving 494 motorcycles.

Conversely, Types 4 and 7 helmet-wearing behaviours were the least common, with only 1 motorcycle each. Additionally, the data was classified by camera installation points, as detailed in **Table A2**.

Table A3 presents the results of helmet-wearing behavior data collection using artificial intelligence (AI), categorizing observations into six types and comparing two distinct subsets (labelled as Point 1 and Point 2). A total of 809 individuals were recorded, consisting of 674 drivers and 135 passengers. Type 2 was the most frequently observed, with 429 drivers and no passengers, followed by Type 1 with 111 drivers. Type 3 and Type 5 were the only configurations involving both drivers and passengers, contributing 41 and 41 observations, respectively. Type 6, the least frequent, had 26 individuals (13 drivers and 13 passengers), while Type 4 was entirely absent.

Table A4 presents a comparative analysis of helmet-wearing behaviours, contrasting detections made by AI cameras with manual observations conducted by a researcher. The findings revealed significant discrepancies between the two methods. Among drivers, the AI cameras recorded a helmet-wearing rate of 64.52%, while the manual count indicated a higher rate of 72.81%, reflecting an under-reporting of 8.29% by the AI cameras. For passengers, the AI cameras identified a helmet-wearing rate of 1.61%, whereas the manual observations showed 4.96%, resulting in a discrepancy of 3.35%. When considering the overall percentage of helmet-wearing and non-helmet-wearing behaviours, the analysis revealed an 11.59% difference between the data recorded by AI cameras and the manual count.

These results underscored the limitations of AI-based detection systems in accurately identifying helmet-wearing behavior, highlighting the need for further refinement to enhance detection accuracy, particularly for passengers.

Table A5 presents the relationship between the accuracy of AI cameras in detecting the helmet-wearing behaviours of both drivers and passengers and the camera installation points. It was found that Point 1 had an accuracy rate of 73.7%, while Point 2 had an accuracy rate of 89.5%.

Additionally, the results of the Pearson chi-squared test analysis indicated that the accuracy of the AI camera predictions depends on the installation points. This implied that the two installation points had significantly different proportions of AI camera detection accuracy at the 0.05 significance level.

Table A6 presents the relationship between the accuracy of AI cameras in predicting helmet-wearing behavior types and the camera installation points. After analysis, it was found that at both Point 1 and Point 2, the AI cameras had accurately predicted the Type 6 helmet-wearing behaviour at 100%. However, for Types 4 and 7, there was only one motorcycle passing through the cameras at each point, and the AI cameras had predicted these types accurately. Additionally, the results of the Pearson chi-squared test analysis indicated that the accuracy of AI camera predictions had depended on the helmet-wearing behavior types. This meant that the proportions of AI camera detection accuracy had varied significantly across the different helmet-wearing behavior types at a 0.05 significance level.

Table 3. The analysis of the relationship between detection accuracy using Cramér's V indicated that detection accuracy is significantly associated with the camera installation location variable (X1) and the detection of helmet use for Types 1, 2, and 3 at a statistically significant level. (**Table A7**) Furthermore, the multiple logistic regression results (representing the best-fit model) showed that the camera installation location (X1) and Type 2 helmet detection (X3) had been significant factors, with Nagelkerke R Square = 0.44, Cox & Snell R Square = 0.28, -2 Log likelihood = 469.537, and $p < 0.05$. Consistently, the results demonstrated that the detection accuracy at Point 2 had been greater than at Point 1. Additionally, the accuracy for Type 2 helmet detection was 23 times higher than that of other categories at a statistical significance level of 0.05.

Table 3. The Logistic Regression Model

		B	df	Sig.	Exp(B)
	X1	-1.177*	1	0.000	0.308
	X3	3.150*	1	0.000	23.336
	Constant	0.840*	1	0.000	2.315

Note: *Significant at 95% confidence level.

From the results of the study evaluating the effectiveness of AI cameras in detecting helmet-wearing behaviours (both drivers and passengers) and the relationship between the accuracy of AI cameras in detecting helmet-wearing behaviours and the camera installation points, the researcher found the following:

The helmet-wearing detection program was applied in two study areas. It was found that Point 2 had demonstrated greater accuracy than Point 1 when comparing the percentage accuracy of prediction or detection, with a correctness rate of 89.5%. This trend indicated the potential of using a program trained in different environments but achieving similar accuracy. When comparing the two points, it was found that the roadside environment affects the accuracy. For instance, at Point 1, parked cars and pedestrians had constantly interfered with the AI cameras, reducing detection efficiency. Past research attempted to avoid environmental interference with the camera's view [12–15]. This study demonstrated a method for determining the helmet-wearing rate of drivers and passengers, differing from past research that captured side views of motorcycles [17],[18]. However, this research tested the perspective of AI cameras to determine which heights or viewing angles provided the highest quality and benefit. For surveillance camera data collection, achieving accurate identification of helmet-wearing for drivers or passengers requires using two cameras to capture both the rear and side views, complicating system design and increasing data collection costs [13]. This research showed that by reducing costs and choosing to collect data only from the rear view, it is possible to support legal prosecution and to monitor helmet-wearing rates among drivers and passengers. This approach can be applied to other areas with similar camera angles [12],[13],[20],[30].

Regarding the issue of the relationship between the accuracy of AI cameras in detecting helmet-wearing behavior (for drivers and passengers) and the camera installation points, this research found that the accuracy of the AI camera's predictions had varied significantly (at the 0.05 level) depending on the camera installation point. Additionally, the accuracy of the AI camera's predictions for helmet-wearing behaviours had also varied significantly (at the 0.05 level). Previous research has used helmet-wearing behavior images without distinguishing them into multiple types, and no theory was definitively established on how to categorize helmet-wearing behavior types for higher accuracy. Some studies defined just one type [12–15],[20],[31], while others defined two types [12–15],[20].

Moreover, the use of detection programs to determine helmet-wearing behaviours, whether for cases in which the driver does not wear a helmet or for cases in which the driver wears a helmet, but the passenger does not, will be considered a legal violation. This program was developed for law enforcement in Thailand and can also be used to monitor helmet-wearing rates, thereby providing clear data about drivers and passengers**.**

4. Conclusions

The objectives of this research were to evaluate the effectiveness of AI cameras in detecting helmet-wearing behaviors (for both drivers and passengers) and to find the relationship between the accuracy of AI cameras in detecting helmet-wearing behaviours and the camera installation points. The researcher found that the detection accuracy for helmet-wearing behaviours at installation point 2 had been 89.5% compared to counts by the researcher. Additionally, it was found that the accuracy of the AI camera's predictions had varied depending on the installation point of the camera and the types of helmet-wearing behaviours. Both camera installation points had been able to accurately detect helmet-wearing behavior in Type 6 with 100% accuracy, which is the behavior in which both the driver and passenger are wearing helmets. Additionally, detection accuracy was significantly associated with camera location (X1) and all helmet types. The best-fit logistic regression model (Nagelkerke R Square= 0.44, $p < 0.05$) highlighted that Point 2 had yielded a higher accuracy than Point 1, and that Type 2 helmet detection had been 23 times more accurate than other categories.

The key findings from this research were:

1) Focusing on collecting data on all helmet-wearing types allows the program to effectively target detection purposes, resulting in higher efficiency.
2) Developing a detection program for helmet-wearing behaviors under various environmental conditions or disturbances reduces errors in the program.
3) Direct detection of the desired behavior reduces the need for extensive analysis, which saves time and funds.
4) Regarding helmet-wearing Types 4 and 7, further studies are needed. Additionally, the number of observation points should be increased (≥ 4–6 locations), and variations according to the time of day should be included (e.g., rush hour vs. normal time, day vs. night).
5) This study's results suggested that there is the potential for the future development of helmet-wearing behavior detection tools that are machine-based.

This article contributes to the development of an AI-based system that can be utilized to detect various types of helmet-wearing behaviors. The innovation was designed to support law enforcement by enhancing operational efficiency for police officers. Furthermore, to streamline the enforcement process, the system can be integrated with Thailand's Police Ticket Management (PTM) system.

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7. APPENDIX

7.1 Appendix A – Classification of Helmet-Wearing Behaviours

This Appendix presents the classification framework used to categorize helmet-wearing behaviours in the study. **Table A1** defines the behavioural types according to helmet use by drivers and passengers, while **Figure A1** visually illustrates these categories. This information is necessary to ensure consistent interpretation of the behavioural classifications used for both researcher observations and AI-based detection throughout the study.

Table A1 Analysis of Helmet-Wearing Behaviours

Types	Numbers of Drivers	Numbers of Passengers	Notes
1	☒ (A)	-	The driver is not wearing a helmet
2	☑ (B)	-	The driver is wearing a helmet
3	☑ (C)	☒ (D)	The driver is wearing a helmet, but the passenger is not.
4	☒ (E)	☑ (F)	The driver is not wearing a helmet, but the passenger is.
5	☒ (G)	☒ (H)	Neither the driver nor the passenger is wearing a helmet.
6	☑ (I)	☑ (J)	Both the driver and the passenger are wearing helmets.
7	>3 people would be excluded		

Note: Various types of illustrations are shown in **Figure A1**



Type 1 Type 2 Type 3 Type 4

Type 5 Type 6 Type 7

Figure A1. Type of Helmet-Wearing Behaviours

7.2 Appendix B – Helmet-Wearing Behaviours Observed by Researchers

This Appendix presents the helmet-wearing behaviour data manually identified by the researchers at the two observation points. **Table A2** provides the numbers of drivers and passengers classified according to each behavioural type. These data serve as the reference observations for evaluating and comparing the performance of the AI-based detection system.

Table A2 Analysis of Helmet-Wearing Behaviours by Researcher

	All			Point 1			Point 2		
Types	Numbers of Drivers	Numbers of Passengers	Totals	Numbers of Drivers (1)	Numbers of Passengers (1)	Totals (1)	Numbers of Drivers (2)	Numbers of Passengers (2)	Totals (2)
1	67	-	67	44	-	44	23	-	23
2	494	-	494	322	-	322	172	-	172
3	41	41	82	27	27	54	14	14	28
4	1	1	2	1	1	2	0	0	0
5	33	33	66	17	17	34	16	16	32
6	38	38	76	26	26	52	12	12	24
Total	674	113	787	437	71	508	237	42	279

7.3 Appendix C – Helmet-Wearing Behaviours Detected by AI

This Appendix presents the helmet-wearing behaviour data identified by the AI-based detection system at the two observation points. **Table A3** summarizes the numbers of drivers and passengers detected within each behavioural category. These results are necessary for assessing the AI system's ability to identify helmet-wearing behaviours and for comparison with the researcher-observed data.

Table A3 The Results of the Data Collection of Helmet-Wearing Behaviours by AI

	All			Point 1			Point 2		
Types	Numbers of Drivers	Numbers of Passengers	Totals	Numbers of Drivers (1)	Numbers of Passengers (1)	Totals (1)	Numbers of Drivers (2)	Numbers of Passengers (2)	Totals (2)
1	111	-	111	87	-	87	24	-	24
2	429	-	429	264	-	264	164	-	164
3	81	81	162	61	61	122	20	20	40
4	0	0	0	0	0	0	0	0	0
5	41	41	82	22	22	44	19	19	38
6	13	13	26	3	3	6	10	10	20
Total	674	135	809	437	86	523	237	49	286

7.4 Appendix D – Comparison between AI and Researcher Observations

This Appendix provides a comparative analysis of helmet-wearing behaviours identified by the AI system and the researchers. **Table A4** presents the percentages of helmet use and non-use among drivers and passengers at each observation point, together with the differences between the two assessment approaches. This comparison is necessary to demonstrate the level of agreement and identify differences between AI-based and researcher-based observations.

Table A4 Comparative Analysis of the Results of the Helmet-Wearing Behaviors among Riders

Types	AI			Researcher			Δ		
	Point 1	Point 2	Totals	Point 1	Point 2	Totals	Point 1	Point 2	Totals
Percentages of drivers wearing helmets	62.72	67.83	64.52	73.82	70.97	72.81	11.10	3.14	8.29
Percentages of drivers not wearing helmets	20.84	15.03	18.79	12.20	13.98	12.83	-8.64	-1.06	-5.96
Percentages of passengers wearing helmets	0.57	3.50	1.61	5.31	4.30	4.96	4.74	0.80	3.35
Percentages of passengers not wearing helmets	15.84	13.64	15.08	8.66	10.75	9.40	-7.21	-2.88	-5.68
Totals	100	100	100	100	100	100	-	-	-
The overall percentages of wearing helmets	63.29	71.33	66.13	79.13	75.27	77.76	15.78	3.94	11.59
Totals	100	100	100	100	100	100	-	-	-

7.5 Appendix E – Detection Accuracy by Camera Installation Point

This Appendix examines whether AI detection accuracy differs between camera installation points. **Table A5** presents the proportions of correct and incorrect detections and the results of the Pearson Chi-Squared test. This analysis is necessary to determine whether camera location is significantly associated with the detection performance of the AI system.

Table A5 The Proportion of the Detection accuracy and Camera Installation Points Analyzed Using the Pearson Chi-Squared Test

Installation Points	Detection accuracy (%)				
	Yes	No	N	%	*p*-value
Point No. 1	73.7	26.3	437	64.8	<0.000*
Point No. 2	89.5	10.5	237	35.2	
Totals	79.2	20.8	674	100	

Note: *Significant at 95% confidence level.

7.6 Appendix F – Detection Accuracy by Helmet-Wearing Behaviour Type

This Appendix examines AI detection accuracy across different helmet-wearing behaviour types at the two camera installation points. **Table A6** presents detection accuracy for each behavioural category and the corresponding Pearson Chi-Squared test results. This information is necessary to identify behavioural categories for which AI detection performance varies and to provide a more detailed assessment of the system's operational performance.

Table A6. The Proportion of the Detection accuracy and the Types of Helmet-wearing Behaviours Analyzed Using the Pearson Chi-Squared Test (N=674 motorcycles)

Behavioral Types	Installation Point 1				*p*-value	Installation Point 2				*p*-values
	Detection accuracy (%)		Totals			Detection accuracy (%)		Totals		
	Yes	No	N	%		Yes	No	N	%	
1	39.1	60.9	87	19.9		70.8	29.2	24	10.1	
2	94.3	5.7	264	60.5		98.2	1.8	164	69.2	
3	34.4	65.6	61	13.9	<0.000*	50.0	50.0	20	8.4	<0.000*
4	N/A	N/A	N/A	N/A		N/A	N/A	N/A	N/A	
5	63.4	36.6	22	5.0		73.7	26.3	19	8.1	
6	100.0	0	3	0.7		100.0	0	10	4.2	
7	N/A	N/A	N/A	N/A		N/A	N/A	N/A	N/A	
Totals			437					237		

Note: *Significant at 95% confidence level. Both Types 4 and 7 had one motorcycle pass through the cameras, and the AI cameras did not correctly predict these types.

7.7 Appendix G – Strength of Association with AI Detection Accuracy

This Appendix evaluates the strength of the associations between AI detection accuracy, camera installation points, and helmet-wearing behaviour types. **Table A7** presents the Cramér's V statistics and significance levels for the investigated variables. This analysis complements the Chi-Squared tests by quantifying the strength of statistically significant associations and provides additional evidence regarding factors related to AI detection performance.

Table A7. The Proportion of the Detection accuracy (Y), Camera Installation Points (X1) and the Types of Helmet-wearing Behaviours (X2-X8), Analyzed Using the Cramér's V Test.

Variables	Value	Sig.
X1	0.187*	0.000
X2	0.362*	0.000
X3	0.542*	0.000
X4	0.371*	0.000
X5	N/A	N/A
X6	0.068	0.079
X7	0.072	0.061
X8	N/A	N/A

Note: *Significant at 95% confidence level.