Science and Engineering Connect, ISSN 3027-7914 (Online)
Vol. 49 No. 1 pp. 3-27 (2026)

Research Article

Development of an Artificial Intelligence Program with CCTV to Detect Red-Light Violations Based on Traffic Light Colors

Jetsada Kumphong*
Faculty of Technical Education, Rajamangala University of Technology Isan
Khon Kaen Campus, Khon Kaen, Thailand
Nathayu Chawapattanayotha
Faculty of Industrial Technology, Nakhonphanom University, Nakhon Phanom, Thailand
**Corresponding author E-mail: Jetsada.ku@rmuti.ac.th*

Received 2 October 2025; Revised 23 January 2026; Accepted 9 March 2026

Abstract

Background and Objectives: Traffic accidents are one of the leading causes of injury and fatality worldwide, and intersections represent particularly high-risk locations. Among various risky driving behaviors, red-light violations significantly contribute to intersection-related crashes, leading to severe injuries and fatalities. Traditional enforcement mechanisms, such as manual monitoring by traffic police or the use of fixed cameras, are often limited in coverage, accuracy, and efficiency. In recent years, the integration of Artificial Intelligence (AI) with closed-circuit television (CCTV) systems has emerged as a promising solution to enhance law enforcement. AI technology, particularly object detection and image recognition, enables real-time monitoring and automatic detection of traffic signal violations. This innovation is not only a tool for surveillance but also an instrument for behavioral change, as the perceived risk of being caught can deter risky driving practices. The present research was designed to address two primary objectives: (1) to develop and evaluate AI technology for detecting traffic light colors in order to identify red-light violation behaviors, and (2) to study the specific phenomenon of “rolling stop” violations, where drivers reduce speed but fail to completely stop at a red light. The study focuses on six major intersections in Khon Kaen, Thailand, where traffic density and violation rates remain high.

Methodology: The study utilized CCTV footage from six significant intersections in Khon Kaen: Si Than, Bangkok Hospital, Ban Kok, Modin Daeng, Pratu Mueang, and Charoen Sri. A dataset of 557 images was compiled to train and evaluate the AI system. The researchers applied YOLO version 4 (You Only Look Once), a state-of-the-art object detection algorithm

capable of identifying objects and classifying them in real time with high accuracy. The model was specifically trained to detect traffic light colors (red, yellow, and green) and correlate them with vehicle behavior at intersections. The performance of the AI system was assessed using a Confusion Matrix, which measures the accuracy of classification by calculating true positives, false positives, true negatives, and false negatives. To analyze red-light violations, a total of 2,041 incidents were documented and coded for statistical analysis. Descriptive statistics provided an overview of violation patterns, while Chi-Square Tests were conducted to examine the relationships between red-light violations and key factors such as vehicle type and time of day. This combination of AI-driven detection and statistical testing ensured both technological reliability and behavioral insights.

Main Result: The results of the study demonstrate the effectiveness of combining AI with CCTV for traffic enforcement. The AI model successfully detected the traffic light color in 94% of the sample images, indicating a high level of accuracy and reliability for law enforcement applications. This accuracy suggests that AI technology can complement or even replace traditional manual monitoring methods, which are often prone to human error and resource limitations. In terms of behavioral patterns, the analysis revealed that vehicle type and time of day were significantly associated with red-light violations (p-value < 0.05). Larger vehicles, such as trucks and buses, showed distinct patterns of non-compliance compared to smaller vehicles. Furthermore, violations were more frequent during peak traffic hours, particularly in the evening, highlighting the role of traffic congestion and driver impatience in risky decision-making. The study also identifies the prevalence of "rolling stop" behavior, where drivers slowed down but failed to come to a complete stop during a red signal. This behavior represents a critical safety concern, as it increases the likelihood of side-impact collisions, especially with pedestrians and motorcyclists who often cross intersections during the red-light phase

Conclusions: The research confirms that AI-powered CCTV systems can substantially enhance the monitoring and enforcement of traffic rules in urban environments. The high detection accuracy of 94% demonstrates the robustness of YOLO v4 as a real-time detection tool for traffic light violations. Moreover, the statistical association between vehicle type, time of day, and violation behavior provides valuable insights for policymakers and urban traffic managers. Importantly, the analysis of rolling stop violations among road users in urban Khon Kaen reveals that vehicle type was statistically significant in its association with rolling stop violations. Stopping at crosswalks was found to have a greater correlation with rolling stop violations for motorcycles than for other vehicles. Public awareness campaigns, strict penalties for repeated offenders, and intersection redesign to improve visibility and compliance should complement AI-based enforcement systems

Practical Application: The practical implications of this study are significant for both local and national road safety strategies. In Khon Kaen, the results can inform municipal authorities and law enforcement agencies in designing targeted interventions. For example, stricter monitoring of larger vehicles and increased enforcement during evening rush hours could reduce the frequency of violations. At the policy level, the study supports the integration of AI technology into Thailand's broader traffic management framework. Government agencies can use such systems to generate evidence-based reports, guiding legislative updates and infrastructure investments. The ability to reliably detect "rolling stop" behavior also opens new avenues for refining traffic laws, which traditionally only account for complete red-light running.

Keywords: Red-light Violations, Road Accidents, Automatic Detection, AI

Introduction

According to a report by the World Health Organization, Thailand ranks 9th in the world for road accident fatalities among all member countries [1]. Khon Kaen province is one of the leading provinces in Thailand, and it has high road accident statistics, primarily caused by speeding and running red lights [2-4]. In response, the Khon Kaen Traffic Accident Prevention Committee and network partners have focused on addressing the severity of accidents caused by traffic signal violations on Mittraphap Road (the main road) in urban Khon Kaen City. Consequently, they proposed a semi-automated CCTV system to monitor traffic light violations to the Safer Roads Foundation in the UK. The project received funding in January 2017, and on September 7, 2017, Khon Kaen Municipality and Khon Kaen Provincial Police signed a collaboration agreement. This project's objective is to ensure safer and more efficient travel through intersections. The municipality has been entrusted with the maintenance of the camera system, while the provincial police use the cameras to enforce traffic laws. [5-6]

The project installed CCTV cameras in two phases. In Phase 1, cameras were installed at three intersections: 1) Pratu Mueang Intersection, 2) Modin Daeng Intersection, and 3)

Charoen Sri Intersection, all located along Mittraphap Road within Khon Kaen Municipality (the system has already been installed and is operational). Phase 2 involved installing cameras at three additional intersections: 1) Ban Kok Intersection on Mittraphap Road, 2) Bangkok Hospital Khon Kaen Intersection, and 3) Si Than Intersection on Maliwan Road, also within Khon Kaen Municipality at shown in Figure 1. [7-22]

Warning signs were also installed to alert drivers that CCTV cameras were monitoring red-light violations 24 hours a day in all directions approaching the intersections. These signs were placed to inform the public and encourage them to slow down before reaching the intersections. An example of the sign is shown in Figure 2.

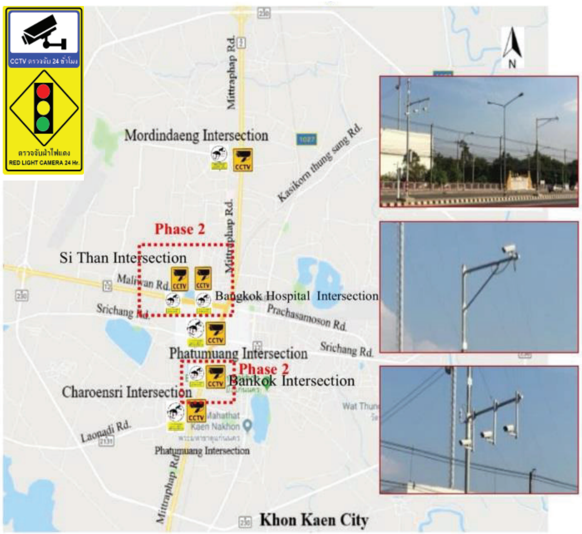

Figure 1 Locations of intersections in the project

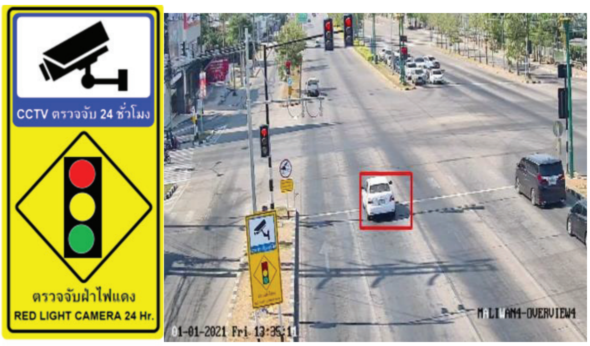

Figure 2 Example of a CCTV-in-use-warning sign used in the project

After the installation of warning signs and CCTV cameras to monitor red-light violations and helmet usage (before police began issuing tickets), a preliminary evaluation over three months showed that the number of red-light violations decreased by approximately 85%. Additionally, helmet usage increased within the first month after the installation of the signs and cameras. However, by the third month, helmet usage began to decline. This decrease, as shown in Figure 3, may be due to road users believing that the warning signs and cameras were only for deterrence and not tied to actual law enforcement through ticketing. Therefore, the enforcement of traffic laws is essential to ensure the long-term success of the project in modifying risky behavior and reducing both the number and severity of traffic accidents [15].

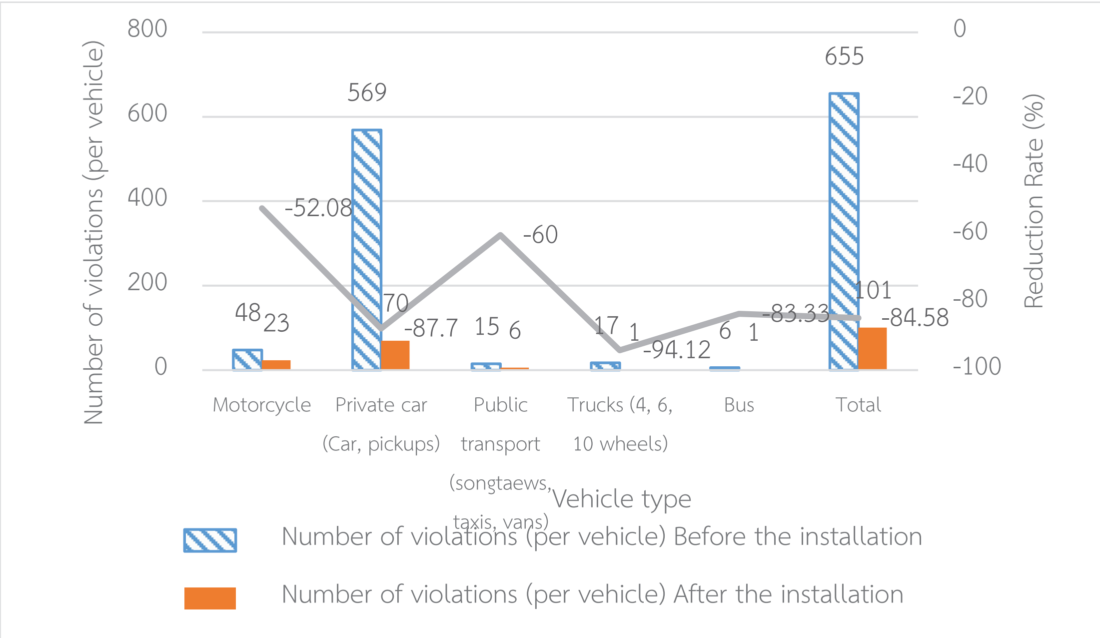

Figure 3 Preliminary evaluation of the number of red-light violations after the installation of warning signs and CCTV cameras

However, in developing countries, inadequate road-level planning and traffic control often result in mixed traffic signals on highways. The primary causes of collisions at these intersections are red-light running by motorcycles and insufficient law enforcement. The objective of this study is to assess the effectiveness of automatic traffic signal control in such scenarios. The study focused on intersections with traffic lights on Mittraphap Road, which passes through Khon Kaen in Thailand, to evaluate changes. We employed a before-and-after observational design with a group comparison. The researchers collected data on traffic light behavior, red-light tickets issued, as well as the frequency of collisions and injuries before and after the implementation of traffic signal control. The results showed a 33.3% reduction in red-light running, a 17.5% decrease in collisions, and a 13.6% drop in injuries. However, longitudinal studies are necessary to evaluate the impact of this type of intervention on fatality rates. These results demonstrate the effectiveness of red-light running (RLR) control for traffic management and accident prevention in the context of developing countries [9].

In developing the program for detecting red-light violations and helmet use through CCTV, which was installed in the initial phase, the goal was to enhance the effectiveness of law enforcement. This would encourage a change in risky behavior among road users, leading to a reduction in both the frequency and severity of traffic accidents. The researchers designed the program to automatically detect red-light violations by analyzing each video frame from wide-angle cameras (Overview). The program works by checking the color of the traffic light. When the light turns red, the program detects vehicles that cross the stop line into the intersection, marking this as a red-light violation. A license plate camera captures the vehicle's plate, and the program records both the event and the plate image in real-time. These images are then stored in a database, along with other necessary information, for future use in issuing fines. The program was written in C++ and utilized the Open CV (Open Source Computer Vision) library for video processing, while MySQL was used as the database management system (DBMS). The program also includes a function to detect helmet usage violations. The performance evaluation revealed that the program could detect 85% of all red-light violations and could accurately detect nearly all types of vehicles, both during the day and night. The accuracy of the program in detecting red-light violations was 96.3%. Additionally, the program can also be applied to detect helmet usage violations. [16]

Currently, artificial intelligence (AI) is playing a bigger role in helping police detect traffic violations more effectively — especially when it comes to running red lights. Modern AI systems can work alongside CCTV cameras and various sensors to monitor how vehicles behave in real-time. Using deep learning, AI analyzes footage to spot cars that go through intersections during a red light. It can automatically log key details like the license plate number, the vehicle's speed, and the exact time of the violation. This not only improves accuracy but also reduces mistakes that can happen with human monitoring. In some cases, the system can even send this information directly to officers or issue electronic tickets (e-Tickets), cutting down on their workload. One of the AI technologies often used for image detection is YOLO v4 — short for "You Only Look Once," version 4. This is a popular model known for being both fast and highly accurate in spotting objects or object detection in real time [23]. This makes the model useful in many fields, including agriculture and environmental science.

In previous research, datasets containing various types of leaf images have been used to train the model. The preprocessing process includes adjustments to lighting, color, and background to improve the model's learning ability. Techniques such as bounding boxes and labeling are used to define the boundaries of each leaf type. GPUs are often used to boost processing efficiency, which requires investment in complex and costly specialized hardware. Currently, YOLO v4 is commonly used in general image classification tasks involving 2–3 categories. In the field of agricultural AI, for instance, it is used to identify plant species or to analyze seed characteristics and leaf health — such as detecting plant diseases. It is also applicable in environmental science and conservation work. However, the quality of the dataset greatly affects the model's accuracy. The complexity and similarity of different leaf types — such as leaves with very similar appearances — can lead to misclassification [23-24].

A commonly detected red-light violation is when a vehicle stops past the stop line during a red light and stops within the intersection area. This behavior is a mix of RLR by Traffic-following (TF) and RLR by Lapse (L). This type of violation tends to be specific to certain areas due to the current driving behaviors or physical conditions that are unsuitable for motorcyclists, as well as the high number of motorcycles on the road. This increases the risk of accidents at intersections.[8, 22]

However, frequent errors occur in detecting red-light violations and storing the data in the police's ticketing system. These errors may result from excessive light affecting the color of the traffic signal or other factors. Therefore, the researchers aim to develop AI technology for detecting traffic light colors in order to identify red-light violation behavior and to study the "rolling stop" red-light violation behavior of road users in urban areas of Khon Kaen.

System Development

Hardware Design and Installation

To ensure the high-speed transmission of data from the CCTV cameras and enable remote control of the cameras, the hardware system was designed and installed as shown in Figure 4. Video signals from the CCTV cameras installed at various intersections are transmitted via fiber optic cables to a server located in a control room for processing. The results from the server are then sent back to control the CCTV system.

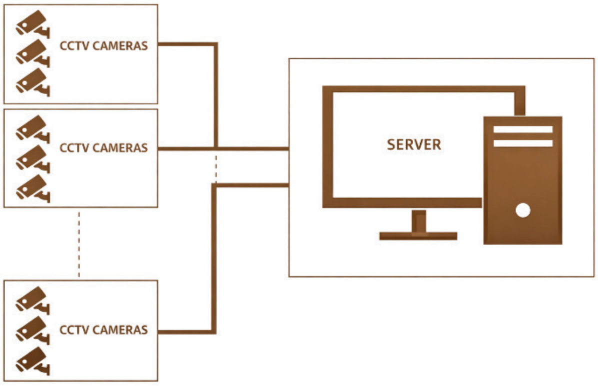

Figure 4 The design and installation of the hardware system

A set of CCTV cameras consists of one high-speed IP camera for capturing wide-angle overview images and additional high-speed IP cameras for capturing license plates, depending on the number of traffic lanes being monitored. For example, if the road has five lanes, but only three straight-through lanes are being monitored, only three license plate cameras would be used. The server is a high-performance computer capable of running 24 hours a day. It features a multi-core processor and a minimum of 16 GB of RAM to efficiently handle parallel processing. The hard drive should have at least 4 TB of storage capacity to ensure that video evidence can be stored for at least two years. Signal transmission is facilitated by fiber optic cables, which connect the CCTV camera system to the server. Additional signal converters and switches may be required for this setup, but the specific details are omitted here.

Program Design and Development

The program is designed to automatically detect red-light violations by analyzing each video frame captured by the wide-angle or overview cameras. The core functionality of the program involves checking the color of the traffic light to determine if it is red which is a part of developing the detection program)[16]. Once the light turns red, the program monitors for any vehicles entering the intersection area beyond the stop line, which is considered a red-light violation. The program will then trigger an alert and mark the violating vehicle with a rectangular box, while also sending a signal to the license plate camera to capture the vehicle's license plate. Both the footage of the incident and the license plate image are recorded and stored in a database along with other necessary details—such as the date, time, and location of the intersection—for use in issuing tickets later.

In developing the program, the researchers coded using C++ because it offers the fastest performance compared to other programming languages, making it ideal for developing real-time systems. The algorithm used by the program is illustrated in Figure 5. For image processing, the program utilizes the OpenCV (Open Source Computer Vision) library, which is a popular open-source library for real-time video processing. MySQL was used as the database management system (DBMS) to handle the storage of data. Additionally, AI was developed to further analyze the color of traffic lights and verify red-light violations to ensure accurate law enforcement.

Developing AI for Traffic Light Color Detection Using YOLO v4

YOLO v4 offers a practical and efficient solution for detecting traffic light colors. It improves accuracy compared to earlier versions while maintaining high processing speed. Importantly, it operates effectively on existing hardware, eliminating the need for additional financial investment. This makes it a suitable choice for projects that prioritize cost-efficiency and system stability. In contrast, YOLO v5 provides enhanced performance with the updated network architecture, making it more effective in recognizing traffic light colors. However, achieving optimal results with YOLO v5 may require hardware modifications to ensure system reliability. For applications that demand maximum accuracy and performance, YOLO v5 is a strong candidate. Still, for most use cases where stability and cost are key considerations, YOLO v4 remains a reliable and competitive option. [23, 25], as shown in Table 1.

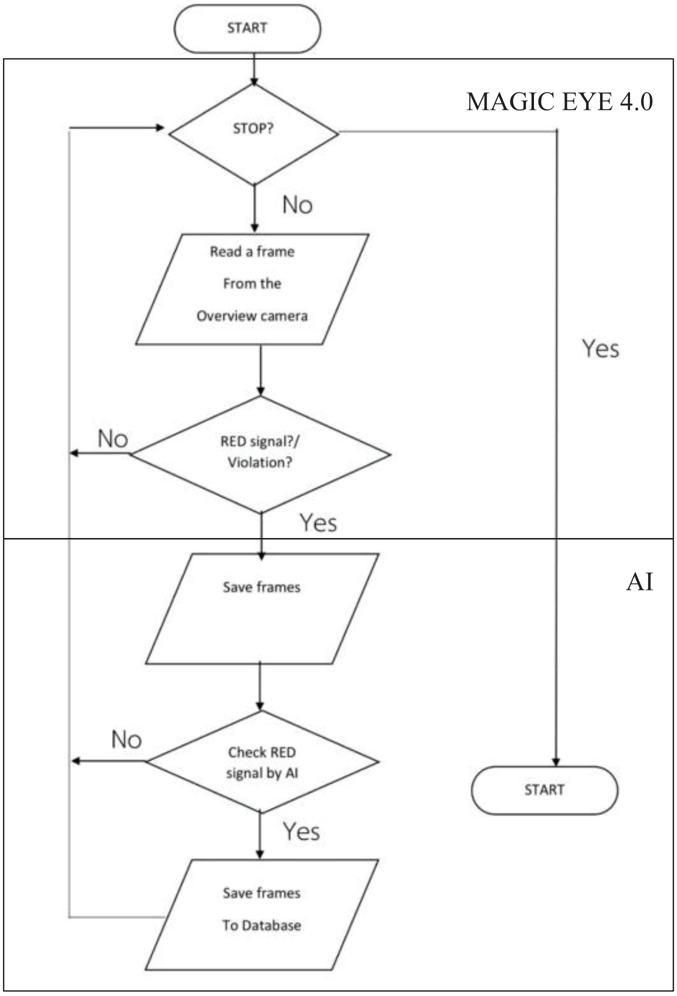

Figure 5 Flow Chart illustrating the program's operational algorithm

AI Development and Accuracy Verification

To assess the effectiveness of the developed program, the researchers integrated AI with the CCTV system. We used 43 images of traffic lights from various intersections, including the Si Than intersection at Khon Kaen University, the Bangkok Hospital intersection, and the Ban Kok intersection, to train the machine learning model using Yolo V.4. The training process involved 1,000 iterations. After training, data was collected to evaluate the accuracy of the program, with images captured from four directions at the Modin Daeng, Pratu Mueang, and Charoen Sri intersections between March and June 2023. A total of 557 images of traffic lights were used as shown in Figure 6.

Table 1 Comparison of YOLO Versions

Criteria	YOLO v3	YOLO v4	YOLO v5
Release Year	2018	2020	2021
Accuracy (mAP)	Moderate	Higher (uses CSPDarknet53)	Higher
Speed (FPS)	Fast	Faster	Faster
Network Architecture	Darknet-53	CSPDarknet53	PyTorch-based
Hardware Performance	Requires GPU	Optimized for lower resource consumption	Lighter and more efficient
Primary Use	General object detection	General detection with improved accuracy	Easier to use and implement

The accuracy of the program was tested using a Confusion Matrix. According to previous studies [26], a Confusion Matrix is a square table with the number of rows equal to the number of classes. For example, in Table 2, there are two classes (yes and no), resulting in a 2x2 Confusion Matrix, as shown in Table 2. The columns represent the actual data classes (actual data), while the rows represent the predicted classes (model output).

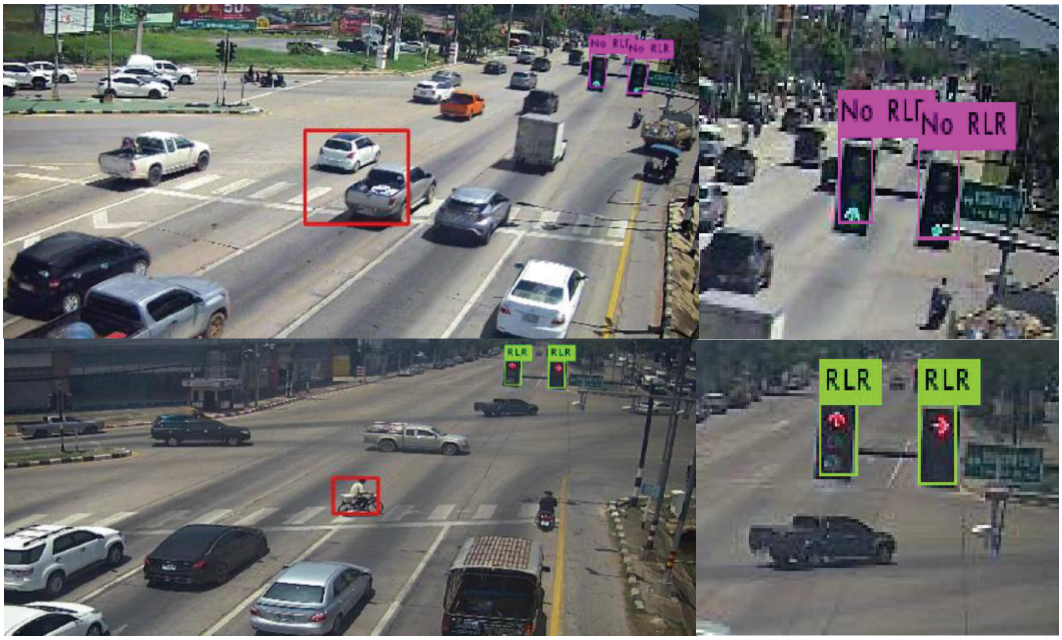

Figure 6 Example of the images of traffic lights

Table 2 Confusion Matrix Table

Predicted/ Actual	Yes	No
Yes	TP	FN
No	FP	TN

From Table 2, the values in the different cells represent the following:

- True Positive (TP): The number of instances correctly predicted as the class of interest.
- True Negative (TN): The number of instances correctly predicted as a class that is not of interest.
- False Positive (FP): The number of instances incorrectly predicted as the class of interest.
- False Negative (FN): The number of instances incorrectly predicted as not being the class of interest.

The accuracy of classifying data for the "Yes" (Positive) class can be calculated using Equation 1:

$$True\ Positive\ Rate\ (TPR) = \frac{TP}{TP+FN} \tag{1}$$

The accuracy of classifying data for the "No" (Negative) class can be calculated using Equation 2:

$$True\ NegativeRate\ (TNR) = \frac{TN}{FP+TN} \tag{2}$$

Precision measures the accuracy of the model for each class individually. It can be calculated using Equation 3:

$$Precision\ \ = \frac{TP}{TP+FP} \tag{3}$$

Recall, also known as sensitivity or True Positive Rate, measures the correctness of the model for each class individually. It can be calculated using Equation 4:

$$Recall\ \ = \frac{TP}{TP+FN} \tag{4}$$

The F-measure, also known as the F1 score, combines both Precision and Recall to provide a balanced measure of the model's accuracy. It is calculated using Equation 5:

$$F - measure = \frac{2 \times Precision \times Recall}{Precision + Recall} \quad (5)$$

Accuracy measures the overall correctness of the model by considering all classes. It is calculated using Equation 6:

$$Accuray = \frac{TP+TN}{TP+FN+FP+TN} \quad (6)$$

Study of Factors Influencing Red-Light Violation Behavior

1. Sampling Method and Data Collection

Data on "rolling stop" red-light violations was gathered to evaluate the program's accuracy. The study focused on violations at three intersections: Modin Daeng, Pratu Mueang, and Charoen Sri. Data was collected over three months, with random samples taken on two weekdays. The data was captured using wide-angle or overview cameras and processed using the MAGIC EYE 4.0 system.

Figure 7 Example of the MAGIC EYE 4.0 program

2. Sample Size

This research aims to compare red-light violation behavior between motorcycles and other vehicles. Based on the preliminary data collected, a purposive sampling method was used to determine the sample size. The study included 1,514 samples of motorcycles and 527 samples of other vehicles (such as private cars, public transport vehicles, vans, and pickup trucks).

3. Sampling Process and Variable Control

The researchers employed a random sampling technique to select images, ensuring that the dataset represented a broad range of real-world conditions. This included capturing footage during both peak and non-peak traffic hours, as well as under various weather conditions. To control key variables, the researchers standardized image quality by using CCTV cameras of the same model or with similar resolution. This helped minimize inconsistencies caused by hardware differences. They also carefully positioned the cameras to ensure consistent viewing angles across all intersections, reducing the impact of perspective variation on the AI model's learning process.

4. Statistical Analysis

4.1 Descriptive Statistics

The researchers analyzed various variables, such as red-light violations, time of day, vehicle type, and stopping at the pedestrian crossing. These variables were presented in terms of frequency and percentage.

4.2 Chi-Square Analysis

The Chi-Square test was used to test the hypothesis that the function of consistency equals zero. If the Chi-Square value is high, it indicates that the function differs significantly from zero, meaning the model does not fit the data. Conversely, if the Chi-Square value is low and close to zero, it indicates that the model aligns well with the data. The Chi-Square test was used to identify relationships between the dependent and independent variables (predictor variables) at a significance level of 0.05, as shown in Table 3. [27]

4.3 Logistic Regression Analysis

The researchers conducted a logistic regression analysis to examine the relationship between variables. The analysis included two types of variables: the dependent variable (Y) and the independent variables (X). In this study, the dependent variable (Y) was red-light running (RLR). The independent variables were: vehicle type (X1), time of day (X2), and whether the vehicle stopped near a pedestrian crossing (X3). The analysis was conducted at a significance level of 0.05, as shown in Table 3. [27]

Table 3 Variables Used to Analyze "Rolling Stop" Violation Behavior

Dependent Variable	Code/Meaning
RLR (Y)	1 = Rolling stop violation 0 = Other
Independent Variables	**Code/Meaning**
Vehicle Type (X1)	1 = Motorcycle 0 = Other vehicles
Time (X2)	1 = Rush hour (07:30-08:30) 0 = Non-rush hour (09:30-10:30)
Stopping at Crosswalk (X3)	1 = Stopped 0 = Not stopped

Results and Discussion

AI Program Accuracy

The researchers evaluated the accuracy of the developed AI program using a Confusion Matrix analysis on 557 traffic light images. The analysis revealed the following performance metrics:

- True Positive Rate (TPR): 0.96
- True Negative Rate (TNR): 0.93
- Precision: 0.93
- Recall: 0.96
- F-measure: 0.94
- Accuracy: 0.94

The detailed results are shown in Table 4.

However, when analyzing the program's accuracy through a graph that compares the number of images tested with the program's accuracy, we observed the following results:

Table 4 Confusion matrix of results

Predicted/ Actual	Red	Green
Red	263	12
Green	19	263

At the beginning of the test, near 100 images, the program's accuracy was 0.96. When testing 376 to 557 images, the accuracy stabilized at 0.94. The overall accuracy of the program remained high throughout the tests. The detailed Confusion Matrix analysis results are shown in Table 4.

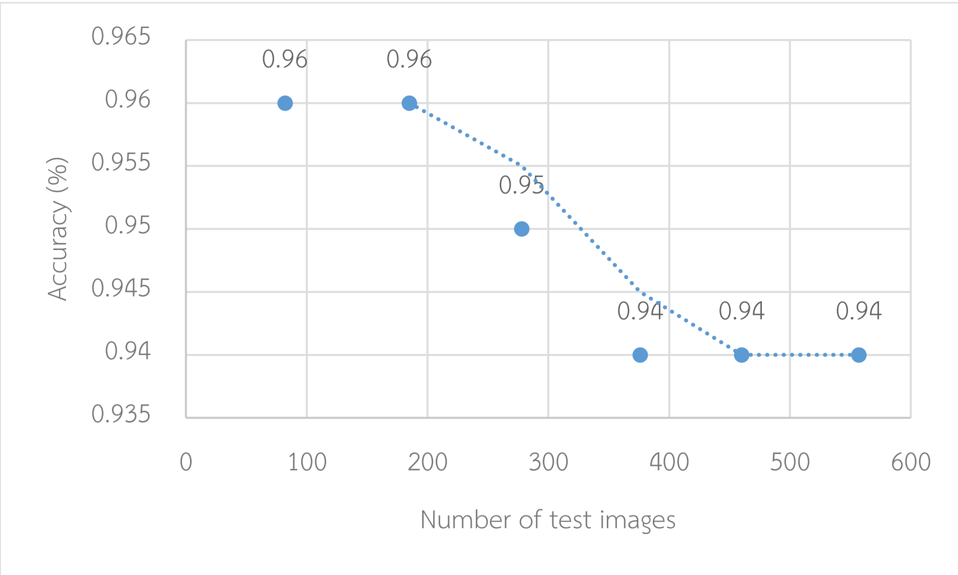

Figure 8 Relationship between the number of images tested and the program's accuracy

Results of the Study on Red-Light Violation Behavior of Drivers in Urban Khon Kaen

The study analyzed the behavior of road users committing red-light violations, focusing on patterns and factors contributing to these violations within the urban areas of Khon Kaen. The study analyzed the "rolling stop" red-light violation behavior of road users in urban Khon Kaen using a Chi-Square analysis. The dependent variable was the rolling stop violation, and the independent variables were vehicle type (X1), time of day (X2), and stopping at the pedestrian crossing (X3). Out of the 2,041 samples used in the analysis, 527 were other vehicles, and 1,514 were motorcycles. The data were categorized based on the three independent variables: vehicle type, time of day, and whether there were pedestrians in the crosswalk. The dependent variable was the occurrence of a rolling stop violation.

The results of the analysis revealed a significant relationship between vehicle type and red-light violation behavior. Motorcycles were found to have a rolling stop violation rate of 6.0%, compared to 1.4% for other vehicles. The Chi-Square test results were Chi-Square = 3.897 (p-value < 0.05), which is less than the significance level of 0.05. This indicates that there is a statistically significant relationship between vehicle type and red-light violation behavior at the 0.05 significance level, as shown in Table 5.

From Table 5, the analysis of the sample data for vehicles other than motorcycles (527 samples) revealed that the time of day was categorized into two groups: rush hour and non-rush hour. When comparing the two categories, the rolling stop violation rate during rush hour was 4.6%, while during the non-rush hour, it was 0.9% of the total sample.

The results of the Chi-Square test showed a value of Chi-Square = 40.162 (p-Value < 0.05), which is less than the significance level of 0.05. This indicates a statistically significant relationship between the stopping at crosswalk and red-light violation behavior for motorcycles than other vehicles at the 0.05 significance level.

Based on Table 6. , the results of the logistic regression analysis for variables related to rolling-stop red-light violations revealed that two variables — vehicle type and stopping at crosswalk— was significantly associated with this behavior at the 0.05 significance level. The analysis indicated that motorcycle riders were less likely to commit rolling-stop violations compared to drivers of other vehicle types, and this difference was statistically significant.

Literature on the development of the AI program for detecting traffic light violations showed an accuracy rate of 95%. This system builds upon the MAGIC EYE 4.0 program, which was used to analyze red-light violations. The primary method used is Image Processing, where the system identifies the color of traffic lights and marks the stop line area of traffic lanes. It detects objects (vehicles) passing through a designated position when the traffic light turns red, and stores the captured images in a database [19].

After the system had been operational for some time, monitoring red-light violations and issuing tickets, an issue arose with false detections. Specifically, the system sometimes incorrectly identified vehicles passing through the intersection while the traffic light was still green, highlighting a potential flaw in the detection process.

This study contributes to improving the efficiency of filtering data before online tickets are issued by the police, reducing errors in enforcement, and introducing a practical innovation for real-world application. Accurate enforcement is crucial when issuing violations, and this system helps minimize errors. Beyond the current issues with automatic red-light detection, errors in speed camera systems—where incorrect speeding violations are recorded—have also been observed in other studies [28-29].

Implementing advanced technology to verify the accuracy of detection systems can lead to more reliable data, improve the image of law enforcement agencies, and increase public trust. The study of red-light violation behavior found a significant relationship between vehicle type and the occurrence of "rolling stop" violations. The rolling stop violation rate was 7.4%, which is consistent with previous research conducted in Khon Kaen Province [8] However, unclear traffic signals and ambiguous road markings were also significantly associated with traffic violations, which may encourage risky behaviors [15-16].

The study by P. Jantosut et al. (2021) then looked at the conduct and contributing variables of red-light breaches by drivers of private vehicles in Khon Kaen. Their study's goal was to identify the variables affecting motorcycle riders' opportunistic red-light running behaviour. Video cameras were utilised in their investigation to record more than 1,000 motorcycle riders' behaviour at eight junctions in the province. In line with the current study's examination of red-light violation rates, the variables involved, and the behaviour seen during rush and non-rush hours, the results indicated that 61% of red-light runners engaged in opportunistic behaviour. In order to examine averages and determine the causes or incentives driving red-light infractions, data was gathered.

Table 5 Summary of variable proportions and Chi-Square test results for rolling stop violations

Variables		All No RLR (%)	All RLR (%)	Pearson Chi-Square	Motorcycle No RLR (%)	Motorcycle RLR (%)	Pearson Chi-Square	Other vehicles No RLR (%)	Other vehicles RLR (%)	Pearson Chi-Square
Vehicle Type					-	-		-	-	-
	Motorcycle	1391 (68.2%)	123 (6.0%)	3.897*						-
	Other vehicles	498 (24.4%)	29 (1.4%)							
Time										
	Rush hour	1071 (52.5%)	92 (4.5%)	0.842	794 (52.4%)	68 (4.5%)	0.149	277 (52.6%)	24 (4.6%)	8.239*
	Non-rush hour	818 (40.1%)	60 (2.9%)		597 (39.4%)	55 (3.6%)		221 (41.9%)	5 (0.9%)	
Stopping at Crosswalk										
	Stopped	373 (18.3%)	1 (0.0%)	34.248**	376 (24.2%)	1 (0.1%)	40.162**	6 (1.1%)	0 (0%)	.0353
	Not stopped	1516 (74.3%)	226 (7.4%)		1024 (67.6%)	122 (8.1%)		492 (93.4%)	29 (5.5%)	
Total		1889 (92.6%)	152 (7.4%)		1391 (91.9%)	123 (8.1%)		498 (94.5%)	29 (5.5%)	

Note * p-value < 0.05 / ** p-value <0.001

Table 6 Logistic Regression Model for Rolling-Stop Red-Light Violations (N = 2,041)

Variables	Category /Unit	Coef.	*p*-value	Odd ratio	95% C.I.for EXP(B) Lower	95% C.I.for EXP(B) Upper
X1	Other vehicles					
	Motorcycle	0.707	<0.05*	2.028	1.334	3.084
X2	Non-rush hour					
	Rush hour	0.192	0.273	1.212	0.861	1.705
X3	Not Stopped					
	Stopped	-3.794	<0.001**	0.023	0.003	0.162
Constant		-2.946	<0.001**			
ρ^2		0.080				
-2LL		1013.575				

Note * p-value < 0.05 / ** p-value <0.001

In the long term, integrating AI into the screening process for detecting traffic violations is expected to influence driver behavior by increasing awareness and compliance with traffic laws. This is due to AI's accuracy and consistency in enforcement, which reduces errors in issuing tickets and improves detection efficiency. As a result, road accidents are likely to decrease. Additionally, AI can help instill disciplined driving habits, enhance road safety, and reduce corruption in law enforcement. However, complementary measures may be necessary to ensure that the public understands and accepts the use of AI to its fullest potential. Furthermore, the AI model developed in this study can be applied to other areas with similar traffic conditions and infrastructure. This includes areas characterized by mixed traffic and main arterial roads. [30] Notably, this study focused on vertically oriented traffic lights, while in some areas, horizontally oriented traffic lights have also been installed [25] (as shown in Figure 9).

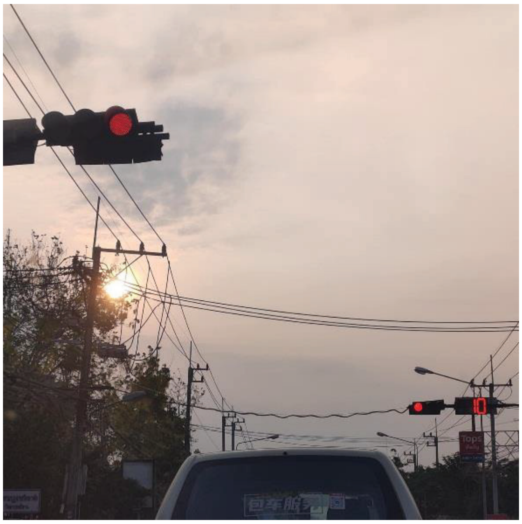

Figure 9 Example of Horizontally Oriented Traffic Light Installation

Collecting data through both surveys and CCTV footage to identify the factors influencing red-light violations is crucial in developing strategies to address this issue. Therefore, more strict enforcement measures should be introduced for red-light violators to reduce the risk of accidents at intersections [8, 21].

Conclusion

This study focused on developing an AI program using CCTV to detect red-light violations, with two main objectives: 1) to develop an AI system for detecting traffic light colors via CCTV and 2) to analyze red-light violation behavior among road users in urban Khon Kaen. The results showed that the AI program achieved a 94% accuracy rate in detecting the color of traffic lights. Additionally, the program was able to significantly improve upon the existing system, effectively reducing errors caused by environmental factors such as sunlight intensity, the direction of sunlight, malfunctioning or non-operational traffic signals, dim traffic lights due to aged bulbs, and irregularities in the physical structure of traffic light poles (e.g., poles that had fallen or were misaligned due to collisions). The system allows law enforcement officers to review the recorded video footage of incidents stored in the database to further verify the accuracy of the program. This ensures that sufficient clarity is achieved before issuing traffic tickets, enhancing the reliability and fairness of law enforcement actions.

Additionally, the analysis of red-light violation behavior (rolling stop) among road users in urban Khon Kaen found that vehicle type was significantly associated with rolling stop violations at a statistically significant level. Stopping at crosswalk was also significantly associated with rolling stop violations for motorcycles than other vehicles. The researchers aim to develop this program to help law enforcement effectively utilize technology in enforcing traffic laws, deterring violations, issuing tickets, and reducing confrontations between police officers and the public. The ultimate goal is to reduce both the number and severity of traffic accidents.

Suggestions for Future Research

1. There should be an analysis of detection performance (Precision and Recall) for vehicle detection specifically under red-light conditions.

2. The training parameters of the model—such as batch size, learning rate, optimizer, augmentation techniques, hyper parameters, GPU specifications, etc.—should be reported to enable reproducibility of the study.

3. There should be an analysis of data-related issues or limitations to support model adjustments that can reduce false negatives (FN) and erroneous predictions (EP).

4. The data classes should be divided into frames corresponding to red, green, and yellow traffic-light phases.

5. More than 1,000 samples should be used, and the dataset should reflect real-world conditions with diversity in lighting, weather, and environmental factors.

Acknowledgments

This research article is part of the project titled "Creation of an AI Program Using CCTV Cameras to Identify Risky Behavior in Driving" (HEC-02-66-006). This article is dedicated to Mr. Vutidach Kumphong, who tragically passed away in a motorcycle accident.

References

1. World Health Organization (WHO). 2023. Global Status Report on Road Safety 2023 [Online]. Available: https://www.who.int/teams/social-determinants-of-health/safety-and-mobility/global-status-report-on-road-safety-2023 [15 September 2025]
2. Klungboonkrong, P. and Woolley, J.E. 2003. Modelling the environmental adaptation of a collector road in a area of high pedestrian activity in the city of Khon Kaen. *Transport Engineering in Australia*, 9, 25-34.
3. Kumphong, J., Satiennam, T., Satiennam, W. and Tirapat, S. 2019. Change of motorcycle speedunder speed enforcement camera on urban arterial in Khon Kaen city, Thailand. *GEOMATE Journal*, 16, 159-164.
4. Prabnasak, J. and Yue, W.L. 2006. Using aaSIDRA and PARAMICS in evaluation of a traffic signal coordination development in Khon Kaen City, Thailand. *ATRF06: 29th Australasian Transport Research Forum* [Online]. Available: http://www.scopus.com/inward/record.url?eid=2-s2.0-84866294465&partnerID= MN8TOARS [15 September 2025]
5. Safer Roads Foundation. 2024. Khon Kaen location two | Red-Light-Running-&-Non-Helmet-Wearing-Recognition-Cameras [Online]. Available: https://www.saferroadsfoundation.org/casestudy/detail/thailand.html [15 September 2025]
6. Safer Roads Foundation. 2024. Khon Kaen location one | Speed-enforcement-camera-system [Online]. Available: https://www.saferroadsfoundation.org/ casestudy/detail/khon-kaen.html [15 September 2025]

7. Satiennam, T., Kumphong, J., Satiennam, W., Klungboonkrong, P., Jaensirisak, S. and Ratanavaraha, V. 2020. Change in helmet use behavior enforced by CCTV cameras with automatic helmet use detection system on an urban arterial road. *Traffic Injury Prevention*, 21, 494-499.
8. Jantosut, P., Satiennam, W., Satiennam, T. and Jaensirisak, S. 2021. Factors associated with the red-light running behavior characteristics of motorcyclists. *IATSS research*, 45, 251-257.
9. Satiennam, T., Satiennam, W., Klungboonkrong, P., Kumphong, J., Rasri, N., Jantosut, P., Ung-arunyawee, R., Leelapatra, W., Sittivichai, S., Polkert, N. and Daengpruan, N. 2023. Effectiveness of automated red-light running control using closed-circuit television cameras in Thailand. *Asia-Pacific Journal of Science and Technology*, 28, 1-9.
10. Kumphong, J., Jantosut, P., Kaewkluengklom, R., Tankasem, P., Kaewhanam, N. and Promraksa, T. 2024. Red light running behavior of motorcyclists on urban roads: Psychological factors and risk perception. *Engineering Access*, 10, 114-123.
11. Daowadueng, P. and Kumphong, J. 2022. Capital investment analysis for the product of a startup company case study: Detection program for traffic light violations. *Journal of Management Science Chiangrai Rajabhat University*, 17, 163–186.
12. Tankasem, P., Chaipanha, W., Kaewwichian, P., Kumphong, J., Promraksa, T. and Sateinnam, T. 2021. Effects of drivers' speed during the yellow-light signal and satisfaction of drivers at the intersections with the red-light cameras. *Engineering and Applied Science Research*, 49, 353–362.
13. Kumphong, J., Satiennam, T., Satiennam, W. and Tirapat, S. 2019. Change of motorcycle speedunder speed enforcement camera on urban arterial in Khon Kaen City, Thailand. *GEOMATE Journal*, 16, 159-1649.
14. Kumphong, J., Satiennam, T. and Satiennam, W. 2016. A correlation of traffic accident fatalities, speed enforcement and the gross national income of Thailand and its cross-border countries. *International Journal of Technology*, 7, 1141-1146.
15. Kumphong, J., Satiennam, T. and Satiennam, W. 2018. PW 2344 Preliminary evaluation of helmet law enforcement by cctv camera: case of phatumuang intersection, Khon Kaen City, Thailand, *Injury Prevention*, 24, A85.

16. Wonghabut, P., Ung-arunyawee, R., Satiennam, T., Leelapatra, W., Jantosut, P. and Kumphong, J. 2019. Development of program for red light running violation and helmet wearing using Cctv camera. *KKU Research Journal (Graduate Studies)*, 19, 41-52.
17. Tankasem, P., Satiennam, T., Satiennam, W. and Klungboonkrong, P. 2019. Automated speed control on urban arterial road: An experience from Khon Kaen City, Thailand. *Transportation Research Interdisciplinary Perspectives*, 1, 100032.
18. Tankasem, P., Satiennam, T., Satiennam, W., Jaensirisak, S. and Rujopakarn, W. 2022. Effects of automated speed control on speeding intention and behavior on mixed-traffic urban arterial roads. *IATSS Research*, 46, 492-498.
19. Wonghabut, P., Kumphong, J., Ung-arunyawee, R., Leelapatra, W. and Satiennam, T. *2018.* Traffic light color identification for automatic traffic light violation detection system. *2018 International Conference on Engineering, Applied Sciences, and Technology (ICEAST)*, Phuket, Thailand, 1-4.
20. Satiennam, W., Satiennam, T., Triyabutra, T. and Rujopakarn, W. 2018. Red light running by young motorcyclists: Factors and beliefs influencing intentions and behavior. *Transportation Research Part F*: *Traffic Psychology and Behaviour*, 55, 234-245.
21. Jantosut, P., Satiennam, W., Satiennam, T. and Jaensirisak, S. 2021. Behavioral characteristics and factors associated to red light running of passenger car drivers in Khon Kaen City. *KKU Research Journal (Graduate Studies)*, 21, 26-37.
22. Tippayanate, N., Impool, T., Sujayanont, P., Muttitanon, W., Chemin, Y.H. and Som-Ard, J. 2024. Temporal analysis of road traffic accidents at major intersections in Khon Kaen Province, Thailand: A time series investigation from 2012 to 2021. *International Journal of Geoinformatics*, 20, 43-58.
23. Dhinnabutra, B., Kumphong, J., Dhinnabutra, P. and Phurimsak, C. 2025. Hi-Tech plant leaf classification using artificial intelligence (AI). *Science Essence Journal*, 41, 12–23.
24. Aldakheel, E.A., Zakariah, M. and Alabdalall, A.H. 2024. Detection and identification of plant leaf diseases using YOLOv4. *Frontiers in Plant Science*, 15, 1355941.
25. Song, J., Hu, T., Gong, Z., Zhang, Y. and Cui, M. 2024. TLDM: An enhanced traffic light detection model based on YOLOv5. *Electronics*, 13, 3080.

26. Promboonruang, S., Boonrod, T. and Ratchatawetchakul, Y. 2024. Efficient waste detection and classification based on YOLOv5 models. *Engineering Access*, 10, 51–58.
27. Hair, J.F., Black, W.C., Babin, B.J. and Anderson, R.E. 2010. Multivariate Data: Analysis a Global Perspective. Pearson Education, New Jersey.
28. Llorca, D.F., Salinas, C., Jimenez, M., Parra, I., Morcillo, A.G., Izquierdo, R., Lorenzo, J. and Sotelo, M.A. 2016. Two-camera based accurate vehicle speed measurement using average speed at a fixed point. *IEEE 19th International Conference on Intelligent Transportation Systems (ITSC)*, Rio de Janeiro, Brazil, 2533-2538.
29. Liu, Y., Ge, Z., Yuan, Y., Su, X., Guo, X., Suo, T. and Yu, Q. 2021. Study of the error caused by camera movement for the stereo-vision system. *Applied Sciences*, 11, 9384.
30. Tankasem, P., Kumphong, J., Chawapattanayotha, N., Jantarakot, S. and Daengpruan, N. 2025. A study of road crashes by applying a space syntax model on collector roads in Khon Kaen, Thailand. *Journal of Road Safety*, 36, 4, 79-92.