Design of Crash Alert System to Prevent Motorcycle-Car Door Collision Using Artificial Intelligence

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***Abstract*—Collisions between motorcycles and opening car doors are common causes of motorcycle-related accidents. To avoid these collisions, this study proposed a new crash alert system embedded in motorcycles to warn motorcyclists of opening car doors ahead, using artificial intelligence and a matching algorithm. The proposed method involved two stages: (1) training a deep learning model to detect car door states and (2) applying a matching process to eliminate incorrect opening door predictions to improve object detection model performance. Experimental results demonstrate that the YOLOv12s object detection model achieved strong performance in predicting car door states, with precision, recall, and mean average precision (mAP) values of 85.5%, 84.0%, and 88.8%, respectively. Validation on the test dataset further confirmed the model's effectiveness, yielding precision and recall values of 86.8% and 83.6%, respectively. Moreover, integrating the matching algorithm improved precision to 92.0%. These findings highlight the high feasibility of the proposed method for real-world applications.**

Keywords-artificial intelligence; crash alert system; matching; motorcycle-related accidents; opening car door; YOLOv12s.

I. INTRODUCTION

Motorcyclist safety is a critical issue because they are highly vulnerable to traffic accidents during operation. Their risk is directly influenced by factors such as motorcycle's advanced brake performance, rider's skill level, traffic infrastructure quality and weather conditions [1]. According to the World Health Organization (WHO), approximately 1.19 million people died in road traffic accidents globally in 2021, with about 30% of these fatalities involving powered two- and three-wheeler riders. The South-East Asia region recorded the highest number of deaths, exceeding 330,000, of which 46% were related to two- and three-wheeler riders) [2]. In Taiwan, 1,886 motorcyclist deaths occurred in 2023. Among common causes of motorcycle accidents, collision between motorcycle and car door contributes a considerable part. This causes 1,171 accidents in Taiwan (2023) [3].

Typically, before opening a car door, drivers or passengers check directly or use the side-view mirror to look for approaching vehicles or pedestrians. However, this method depends entirely on visual judgment and experience, making it difficult to accurately estimate the time for an approaching vehicle to arrive. As a result, many accidents still occur. To reduce collisions between opening car doors and approaching vehicles or pedestrians, several approaches have been proposed that estimate distance, speed, or arrival time to guide safer actions. For example, Zhung et al. [4] designed an anti-collision system using a digital camera and FPGA chip on the side-view mirror to detect oncoming vehicles and issue warnings when speeds exceed 16 km/h. Similarly, Huang et al. [5] developed a fuzzy-logic control model with short-wave radar sensors to assess speed and distance, providing alerts through three hazard levels: danger, caution, and warning. However, these car-centered approaches do not fully prevent the accidents, highlighting the need for a new approach that incorporates motorcyclists' actions.

In recent years, numerous studies have integrated artificial intelligence (AI) techniques such as machine learning, deep learning and reinforcement learning into transportation field [6] to address challenges like urban congestion [7], environmental pollution [8], and road safety [9]. Building on these advancements, the present study introduces a deep-learning model designed to predict opening car doors in front of motorcycles using camera input, thereby reducing the risk of motorcycle–car door collisions.

Collisions between motorcycles and opening car doors often occur when riders lack sufficient time to brake effectively, even with advanced braking systems. This highlights the critical need for early intervention, such as providing timely alerts that allow riders to react appropriately. To address this, we propose a crash-alert system for motorcyclists that leverages a deep-learning-based object detection model.

II. CONCEPT OF PROPOSED CRASH ALERT SYSTEM

The proposed crash alert system is implemented into a motorcycle, with its operation diagram shown in Fig. 1. The system consists of three main components: a camera, an edge AI device, and three LED warning lights. The camera is mounted at the center of the handlebar; the edge AI device is fixed to the motorcycle frame; and the warning lights are installed on the dashboard. When the camera captures frames containing road information ahead of the motorcycle, the image signals are transmitted to the edge AI device, which runs a YOLOv12s object detection model. The device outputs predicted bounding boxes for car shapes and door states. These predictions are then matched to identify correctly opening car doors. Once an opening car door is determined, the system alerts the motorcyclist by activating the corresponding warning lights according to the door opening level. In this study, the green, yellow, and red lights indicate small, medium, and large door opening levels, respectively. The hardware components selected for the system are a Jetson Orin Nano 8 GB Develop Kit (i.e., edge AI device) and a Raspberry Pi AI camera, as in [10].

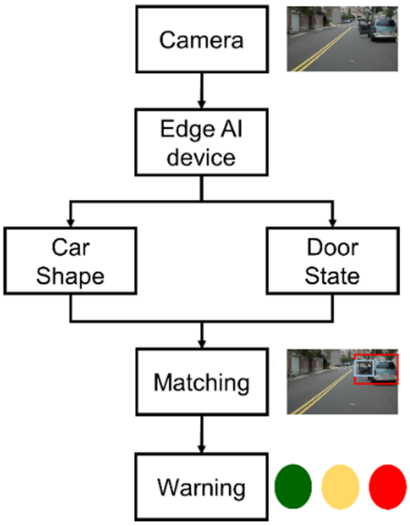

Figure 1. Operation diagram of the proposed method.

III. OBJECT DETECTION MODEL AND MATCHING ALGORITHM

This section explains the object detection model and the matching algorithm, including data collection and labeling, model selection, descriptions of augmentation methods, analysis of the matching algorithm, and method verification.

A. Building AI-Based Object Detection Model

1) Dataset

In real traffic scenarios, a widely opened car door presents a considerable hazard to approaching vehicles. By contrast, a slightly opened door may not pose an immediate threat, though it can become dangerous if it continues to open. Early detection of a slightly opened door allows riders to adjust their maneuvering and reduce the risk of collisions. To achieve this, car door states are labeled as small, medium, and large, corresponding to three opening angles: less than 10°, between 10° and 40°, and greater than 40°, respectively. These angle thresholds were analyzed and adopted from [10]. A full car is also labeled as an object to be matched with the opening car door to reduce false detections.

A total of 1,485 images were collected for training and 32 images for testing, comprising car shapes with doors in small, medium, and large opening states. The dataset was built using two approaches: (1) extracting images that display car door states from road-recording videos captured by vehicle-mounted cameras, and (2) photographing vehicles with opened doors parked along roads or displayed at exhibition centers. These images span diverse settings in Taiwan (e.g., urban, suburban, and rural areas), various commercial car segments, and different times of day across several months. Figure 2 present an example of labeled full car and opening door objects.

Figure 2. An example of labeled medium opening car door.

2) YOLOv12 Architecture

Object detection is a fundamental task in computer vision with applications spanning education, agriculture, industry, health care, and transportation. The YOLO (You Only Look Once) family of models has consistently demonstrated strong performance in real-time detection tasks [11]. The YOLOv12 framework incorporates advanced modules including the Residual Efficient Layer Aggregation Network (R-ELAN), a FlashAttention-based area attention mechanism, optimized loss functions, bounding box regression, streamlined multiscale detection pathways, and data augmentation within its backbone, neck, and head. These enhancements yield faster prediction speeds and higher mean average precision compared with earlier versions [12]. YOLOv12s was selected for car-door opening detection in this study because it provides efficient processing in real time [13], which is required for timely alerts.

3) Augmentation Methods

During training, several augmentation techniques were employed to enhancing model's robustness, including scaling, translation, hue-saturation-value (HSV) adjustment, mixup, cutmix, and mosaic. Specifically, scaling improves the detection of opened doors at varying distances and sizes, while HSV adjustment strengthens performance under diverse lighting and weather conditions. Translation, mixup, cutmix, and mosaic augmentations increase the model's ability to detect doors that are partially occluded [10]. In this study, beyond the default setting, scale and translation values were set to 1.0 and 0.2, respectively. Figure 3 describes augmentation techniques.

Figure 3. Several examples of augmentation techniques: (a) original, (b) translate, (c) scale, and (d) cutmix images.

4) Metrics for Evaluating

The performance of the proposed method is assessed using precision, recall, and mean average precision (mAP). Precision, defined in (1), represents the ratio of true positive (TP) predictions to the total number of predicted positives (i.e., TP + false positives (FP)). Recall, as shown in (2), is the ratio of true positive predictions to the total number of actual positives (i.e., TP + false negatives (FN)). Average precision (AP), defined in (3), is computed as the area under the precision–recall curve, representing the model's precision and recall performance. Finally, mAP is obtained by averaging the AP values across all object classes, as presented in (4).

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \tag{1}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \tag{2}$$

$$\text{AP} = \sum_{i=1}^{K}(R_i - R_{i-1})P_i \tag{3}$$

$$\text{mAP} = \frac{\sum \text{AP}}{\text{Num(class)}} \tag{4}$$

B. Matching Algorithm

Figure 4 presents the matching algorithm. Once the YOLOv12s model detects both the full car shape and the opening door state objects, their bounding boxes are matched. The process begins by computing the intersection over union (IoU) between the car and door bounding boxes to determine whether the detected door belongs to the car. If the IoU equals zero (i.e., the door's bounding box does not overlap with the car's), the opening door is considered a false positive prediction by the YOLOv12s model and is eliminated by the proposed method. If the IoU is greater than zero (i.e., the door's bounding box overlaps with the car's), the door is considered associated with the car, and the algorithm proceeds to the next step. This step evaluates the relative positions of the bottom edges of the bounding boxes. Since the bottom edge of a door is always higher than that of the full car shape in reality, any detected door with a lower bottom edge than the car's bounding box is deemed incorrect and eliminated. Otherwise, the detection is confirmed as a valid car opening door.

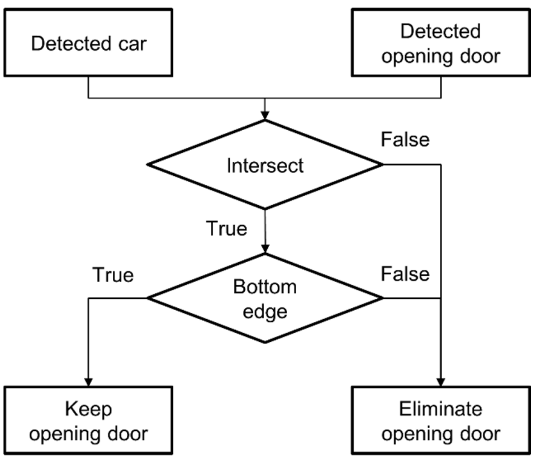

Figure 4. Matching algorithm.

Figure 5 illustrates an example of the matching algorithm. In this case, by the YOLOv12s model detects the bounding boxes of two cars (A and B) and four opening doors (I, II, III, and IV). In reality, doors I, II, and III are false positive predictions, likely mistaken as parts of the road or roadside objects, while door IV and car A and B are correctly predicted. Specifically, after matching, bounding boxes II and III do not belong to either car A or car B (i.e., their IoU values are zero), and are therefore discarded. Although bounding box I overlaps with car A, its bottom edge lies lower than that of car A, indicating an incorrect prediction for opening door I; thus, box I is also eliminated. Finally, the matching algorithm confirms a valid association between car B and opening door IV.

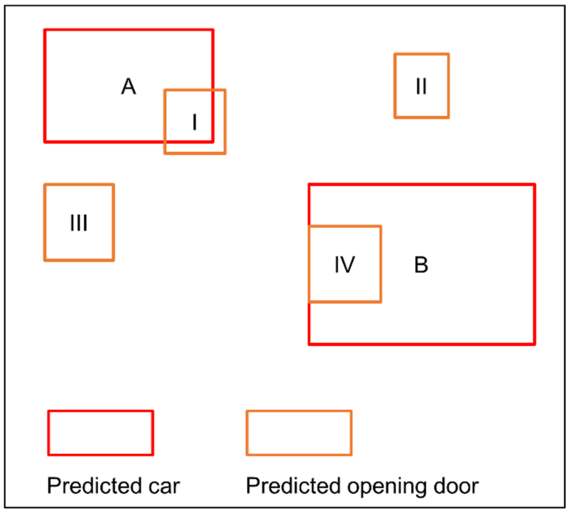

Figure 5. An example of matching algorithm.

C. Verification of Proposed Method

1) Performance Evaluation

Table I presents the mean values of three performance metrics: precision, recall, and mAP@0.5 for the YOLOv12s model across four classes ("car", "doormin", "doormid", and "doormax"), evaluated with and without augmentation techniques. The results show that applying augmentation consistently improves performance compared to the baseline. In particular, precision, recall, and mAP@0.5 increase by 4.52%, 24.26%, and 16.54%, respectively. Figure 6 illustrates the overall training performance of YOLOv12s with augmentation. The model was trained for 300 epochs, achieving strong detection accuracy, with mAP@50 and mAP@50–95 values of 88.8% and 65.4%, respectively.

TABLE I. PERFORMANCE OF TRAINING MODEL

Model	**Precision**	**Recall**	**mAP@0.5**
YOLOv12s without augmentation	0.818	0.676	0.762
YOLOv12s with augmentation	0.855	0.840	0.888

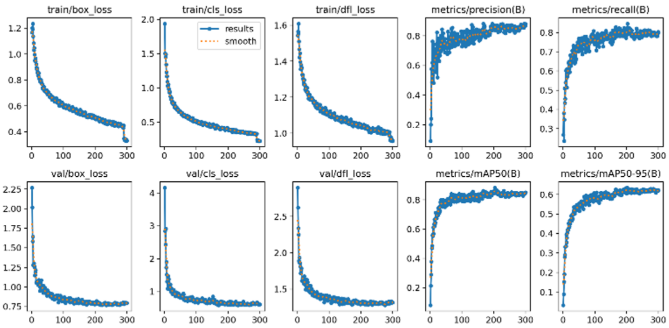

Figure 6. The average values of training performance metrics of YOLOv12s model for all four classes.

2) Prediction Results

A total of 32 unseen images were employed to evaluate the trained YOLOv12s model with and without matching algorithm. The test dataset covered all door states: 8 images of small openings, 8 images of medium openings, 8 images of large openings, and 8 images of closed doors (i.e., cars with non-opening doors). Table II compares the test results of the YOLOv12s model with and without the matching algorithm. The findings indicate that incorporating the matching algorithm yields superior performance, achieving a 5.2% increase in precision compared to the model without matching. Several examples of prediction results are shown in Fig. 7.

TABLE II. PERFORMANCE OF TRAINED MODEL AND MATCHING

Model	TP	FP	TN	FN	Precision	Recall
Trained YOLOv12s without matching	46	7	6	9	0.868	0.836
Trained YOLOv12s with matching	46	4	6	9	0.920	0.836

Figure 7. Prediction results.

IV. CONCLUSION

This study developed successfully a crash alert system incorporating a deep-learning-based object detection model and matching algorithm. The YOLOv12s model exhibited high performance in the detection of car door states across the performance metrics, which were improved significantly with matching algorithm. The study demonstrates that the proposed method is highly feasible to be applied in the real world to prevent motorcycle-car door collisions. However, further experimental research is warranted to confirm the method's effectiveness, especially in more complex and diverse real-world conditions.

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