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ICT Express 7 (2021) 104–109
www.elsevier.com/locate/icte

# Real-time license plate detection for non-helmeted motorcyclist using YOLO

Yonten Jamtsho[a,*], Panomkhawn Riyamongkol[b], Rattapoom Waranusast[b]

[a] Gyalpozhing College of Information Technology, Gyalpozhing 43002, Bhutan
[b] Naresuan University, Phitsanulok 65000, Thailand

Received 29 November 2019; received in revised form 3 June 2020; accepted 31 July 2020
Available online 22 August 2020

**Abstract**

Nowadays, detection of license plate (LP) for non-helmeted motorcyclist has become mandatory to ensure the safety of the motorcyclists. This paper presents the real-time detection of LP for non-helmeted motorcyclist using the real-time object detector YOLO (You Only Look Once). In this proposed approach, a single convolutional neural network was deployed to automatically detect the LP of a non-helmeted motorcyclist from the video stream. The centroid tracking method with a horizontal reference line was used to eliminate the false positive generated by the helmeted motorcyclist as they leave the video frames. The overall LP detection rate was 98.52%.


*Keywords:* YOLO; Helmet detection; LP detection; Centroid tracking

## 1. Introduction

Nowadays two-wheelers are the most popular modes of transport since all level of people can afford it. When the number of motorcyclist increases, there has been an increasing number of motorbike accidents due to reckless riding [1]. The carelessness of motorcyclists not wearing a helmet is a predominant factor, and it commonly contributes to the biker's head injury. To solve this issue, most countries have laws which mandate the use of helmets for two-wheeler riders. In some countries, the government have installed a specialized sensor to check the presence of the helmet, but it is economically not reliable to buy sensors for every bike [2]. Without a proper system, the traffic police personnel are deployed to check whether the motorcyclists are wearing the helmet or not. Automatic detection of LP for non-helmeted motorcyclist will help to reduce the burden faced by the traffic police, and it also need fewer human resources. As a result, the number of motorcyclists not wearing a helmet will get reduced. The main objective of this study is to develop a real-time application for detection of LP for non-helmeted motorcyclist using the single convolutional neural networks. A centroid tracking method with a reference line is also proposed to eliminate the number of false positives generated by the helmeted bikers when they leave the video frames.

The rest of the paper is organized as follows: The related work is explored in Section 2, followed by the methodology in Section 3. Section 4 discusses the experimental results and the conclusion in Section 5.

## 2. Related work

### 2.1. License plate detection

In recent years, many researchers have solved the problem of LP detection for vehicles. LP detection is one of the crucial steps in the Automatic Number Plate Recognition (ANPR) since the accurate detection of LP hampers the accuracy of segmentation and the recognition stages. One of the distinguishing features used in LP detection is its geometric shape with the known aspect ratio. In [3] and [4], a vertical Sobel operator was applied to detect the vertical edges followed by plate verification using width to height aspect ratio. The boundary-based approach is more sensitive to unwanted edges [5]. Some LPs have different colors to differentiate the ownership of the vehicles. Shi et al. [6] proposed an HSI (hue, saturation, intensity) model for LP detection since these color models are insensitive to different illumination.

* Corresponding author.
*E-mail addresses:* yontenjamtsho.gcit@rub.edu.bt (Y. Jamtsho), panomkhawnr@nu.ac.th (P. Riyamongkol), rattapoomw@nu.ac.th (R. Waranusast).
Peer review under responsibility of The Korean Institute of Communications and Information Sciences (KICS).

https://doi.org/10.1016/j.icte.2020.07.008
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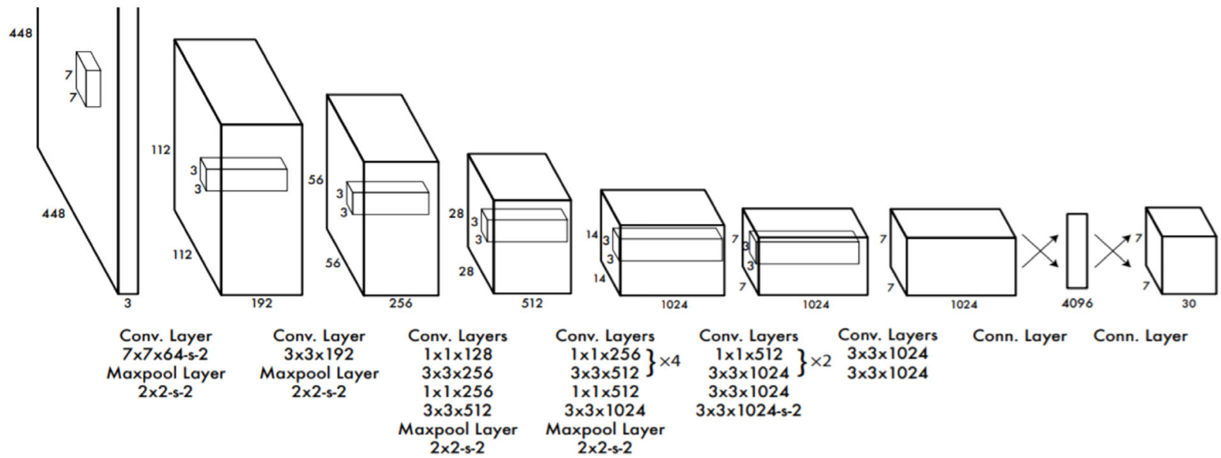


**Fig. 1.** YOLO network architecture.

### *2.2. Helmet detection*

Similarly, many researchers have also proposed a method that involves the detection of motorcyclists, followed by checking whether the motorcyclist wears a helmet or not. For detection of moving objects, the authors in [7] have proposed a background subtraction method to extract the moving object and classify them by extracting features using Local Binary Pattern (LBP) [8]. After getting the motorbike, the 1/5 of the image from the top was cropped to get the helmet section and classified it using HOG, Hough Transform and LBP descriptors. In [9] and [10], the authors have also proposed a background subtraction to detect the object followed by connected component labeling to segment the object. In [9], the object is classified as a motorcycle or another object using a kNN classifier whereas in [10], visual length, visual width and pixel ratio as proposed by Chiu et al. [11] to find the motorcycles. Wen et al. [12] proposed a circular arc detection method based on the modified Hough transform for the detection of a helmet in the ATMs. With the advancement in the computer vision technology, a CNN based LP extraction for non-helmeted biker was proposed in [13]. In their approach, they have used two YOLOv2 [14] model for the detection of a motorcyclist and helmet. Hirota et al. [15] also proposed a CNN based classification of a helmeted and non-helmeted motorcyclist but, different colors of helmet hampered the detection accuracy.

### *2.3. History of YOLO*

YOLO is the latest state-of-the-art real-time object detection algorithm. It is a single convolutional neural network that simultaneously predicts multiple bounding boxes and classes of the entire image in the single scan. The framework was developed by [16]. The network architecture was inspired by the GoogLeNet model for image classification [17]. The network has 24 convolutional layers followed by two fully connected layers. In YOLO, 1 × 1 reduction layers were used followed by 3 × 3 convolutional layers. The full network is shown in Fig. 1 [16].

Currently, there are three versions of YOLO (v1, v2 and v3). The original YOLO network is also termed as YOLOv1. In YOLO v2, it is an improved version of YOLO v1 which keeps the advantage on the speed with the introduction of batch normalization, anchor boxes and high-resolution classifier. In YOLO v3, a better feature extractor was introduced with the introduction of 53 convolutional layers trained on ImageNet. The accuracy of the YOLO v3 is better than YOLO v2 but it is slower than YOLO v2 due to more layers.

## 3. Proposed methodology

### *3.1. YOLO algorithm*

In our approach, we have proposed YOLOv2, which includes 19 convolutional layers and 5 max-pooling layers, followed by softmax activation functions to classify the object [14]. The input image is divided into *SxS* grid cells. The grid cell, which contains the center of the object is responsible for predicting the 5-bounding box (BB) coordinates $(b_x, b_y, b_w, b_h, c)$. The coordinates $(b_x, b_y)$ represent the center of the object relative to the grid cell location and $(b_w, b_h)$ represents the width and height of the object relative to image dimensions. The presence of object in a grid cell is given by confidence score *c*. The illustration of the algorithm is shown in Fig. 2.

In Fig. 2, the yellow grid box is responsible for predicting the LP since it contains the center of the LP (black dot). The coordinates $(c_x, c_y)$ represent the starting grid cell location which contains the center of LP. The actual coordinates of the BB were normalized with relative to grid cell location using Eqs. (1)–(4):

$$\mathrm{b_x} = \frac{(\mathrm{b_x} - \mathrm{c_x})}{\mathrm{c_x}} \tag{1}$$

$$\mathrm{b_y} = \frac{(\mathrm{b_y} - \mathrm{c_y})}{\mathrm{c_y}} \tag{2}$$

$$\mathrm{b_w} = \frac{\mathrm{b_w}}{\mathrm{W}} \tag{3}$$

$$\mathrm{b_h} = \frac{\mathrm{b_h}}{\mathrm{H}} \tag{4}$$

where *W* and *H* are the image dimensions

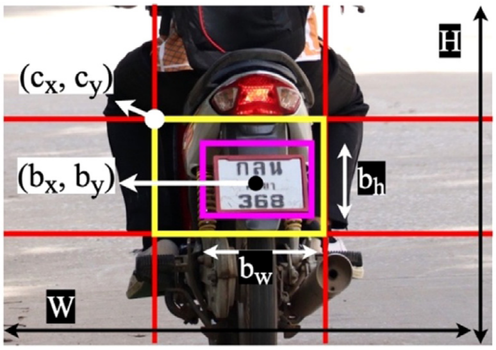


**Fig. 2.** Using 3 × 3 grid cells for illustration of YOLO. . (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

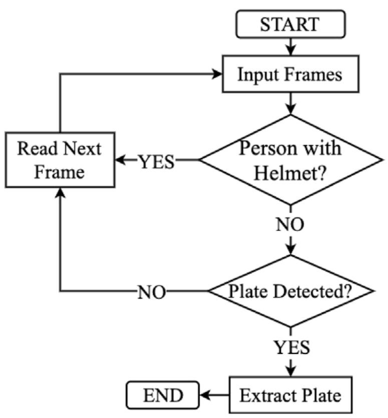


**Fig. 3.** System overview.

### 3.2. System overview

The flow chart that we have implemented in this paper is shown in Fig. 3. The YOLOv2 was used for real-time detection of LP for a non-helmeted motorcyclist. In the system, the video frame is taken as the input, and the expected output is the localized LP for a non-helmet motorcyclist. In our approach, the system checks the presence of a helmet on the motorcyclist. If the motorcyclist is without a helmet, the LP is extracted so that it can be given to ANPR technology for recognition of characters and fine the defaulters.

### 3.3. Data annotation

Before training the model, the training datasets need to be manually annotated with the BB information for three classes (Person, Helmet, Plate). The data annotation was done using *LabelImg* software [18] since YOLO needs a ground truth. The software generates starting coordinates ($x_0$, $y_0$) and ending coordinates ($x_1$, $y_1$). The coordinates were normalized between 0 and 1 to fit into YOLO format *(x, y, w, h)* using Eqs. (5)–(8):

$$x = \frac{(x_0 + x_1)}{2 * W} \tag{5}$$

$$y = \frac{(y_0 + y_1)}{2 * H} \tag{6}$$

$$w = \frac{(x_1 - x_0)}{W} \tag{7}$$

$$h = \frac{(y_1 - y_0)}{H} \tag{8}$$

### 3.4. Algorithm to detect LP for a non-helmeted motorcyclist

While predicting, the YOLO model returns center coordinates (cX, cY) followed by width (w) and height (h) of the bounding box. However, the proposed algorithm for automatic detection LP for non-helmeted motorcyclist needs a starting coordinate ($x_0$, $y_0$) which is derived from Eqs. (9)–(10). After that, the ending coordinate ($x_1$, $y_1$) is calculated using the Eqs. (11)–(12).

$$x_0 = cX - (w/2) \tag{9}$$

$$y_0 = cY - (h/2) \tag{10}$$

$$x_1 = x_0 + w \tag{11}$$

$$y_1 = y_0 + h \tag{12}$$

The list of coordinates representation used in the pseudo-code is shown in Fig. 4.

In the pseudo-code, ***P*** (Person), ***H*** (Helmet) and ***LP*** (License Plate) are the 2D-array containing the bounding box information. **P** (Person class) contains the BB coordinates of a motorcyclist with and without a helmet. The pseudo-code is divided into three parts, each having different functionality. The similar pseudo-code to accomplish the task was discussed in [19].

**M** ← Length (P)
**N** ← Length (H)
**O** ← Length (LP)

#### 3.4.1. Pseudo-code to check person motorcyclist wearing helmet

```
for i ← 0 to M do
  for j ← 0 to N do
    x0 ← P[i][0];        p0 ← H[j][0];
    y0 ← P[i][1];        q1 ← H[j][1];
    x1 ← P[i][2];        p1 ← H[j][2];
    y1 ← P[i][3];        q1 ← H[j][3];
    if (x0 < p0 & y0 < q1) & (x1 > p1 & y1 > q1) then
      pwh ← (x0, y0, x1, y1)
      break
    End If
  End For
End For
```

where ***pwd*** is a variable used to store the BB of *Person* wearing a helmet

#### 3.4.2. Pseudo-code to check person motorcyclist not wearing a helmet

```
for x in P do
  if x not in pwd then
     pwoh ← (x)
  End If
End For
```

where ***pwoh*** *is a* variable used to store the BB of *Person* without a helmet.

#### 3.4.3. Pseudo-code to detect LP of motorcyclist not wearing a helmet

```
S ← Length(pwoh)
for i ← 0 to S do
  for j ← 0 to O do
    x0 ← pwoh[i][0];       a0 ← LP[j][0];
    y0 ← pwoh [i][1];      b0 ← LP[j][1];
    x1 ← pwoh [i][2];      a1 ← LP[j][2];
    y1 ← pwoh [i][3];      b0 ← LP[j][3];
    if (a0 > x0 & b0 > y0) & (a1 < x1 & b0 < y1) then
        Extract the license plate
    End If
  End For
End For
```

### 3.5. Centroid tracking method to eliminate false positive

When the motorcyclist wearing helmet (Fig. 5(a)) leaves the video frame, the proposed system detects the LP (false positives) since the helmet is out of video frame as shown in Fig. 5(b). Therefore, to overcome this problem, a horizontal line was introduced in the video frame. The horizontal line act as a reference line which is drawn at the 3/10 (30% of height) of the frame. When the model performs detections in the video frame, the centroid (white dot in Fig. 5(c)) of the PERSON class is grabbed. The system makes sure that the detection of a license plate for non-helmeted motorcyclist are performed before centroid crosses the horizontal line, as shown in Fig. 5(c). The threshold value of 30% is selected so that the system gets enough detections before the centroid crosses the horizontal line.

## 4. Experimental results

The datasets for this study were collected from Naresuan University, Phitsanulok, Thailand. The datasets were separated into 80%–20%, where 80% was treated as the train set and 20% as the test set. The Darknet-19 framework [14], which defines the YOLOv2 network, was used to train the model in the Google Collaboratory. Google Collaboratory is an online

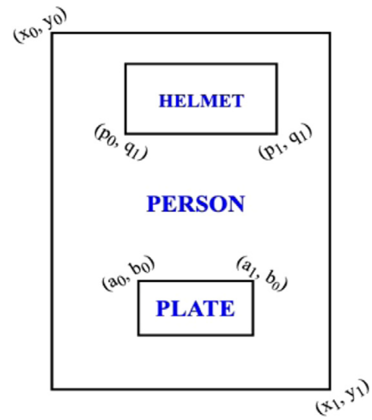


**Fig. 4.** Bounding box coordinate representation of three classes.

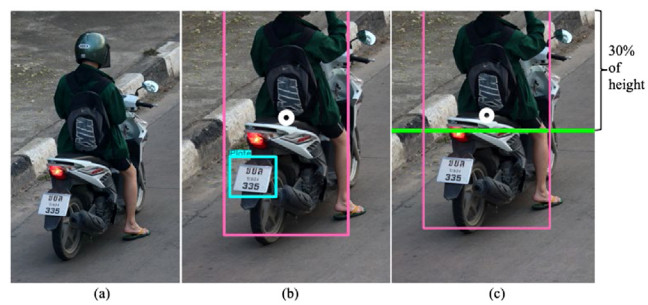


**Fig. 5.** (a) LP is not detected due to presence of helmet, (b) LP is detected since the helmet is out of frame, (c) LP is not detected with the introduction of centroid tracking.

**Table 1**
Tabulation of AP with average IOU of each class.

| Epochs | Person | Helmet | Plate | Avg IOU |
|---|---|---|---|---|
| 1000 | 97.78 | 96.08 | 98.17 | 71.58 |
| 2000 | 96.79 | 97.36 | 98.53 | 73.12 |
| 3000 | 96.56 | 98.19 | 98.16 | 74.12 |
| 4000 | 97.15 | 98.17 | 98.39 | 74.59 |
| 5000 | 96.97 | 98.18 | 98.24 | 74.5 |
| 6000 | 97.05 | 97.86 | 98.21 | 74.53 |
| **7000** | **96.97** | **97.85** | **98.4** | **74.72** |
| 8000 | 97 | 97.84 | 98.41 | 74.62 |
| 9000 | 97.02 | 97.85 | 98.39 | 74.52 |
| 10,000 | 97.3 | 97.85 | 98.42 | 74.5 |

GPU which provides Tesla K80 GPU with 12 GB RAM. The programs used in automatic detection of LP for non-helmeted motorcyclist were written in Python 3.7.2 with OpenCV library. For training of YOLO model, around 1365 datasets were annotated with the bounding box information including the class labels for three classes. The original YOLOv2 model uses 13 × 13 grid cells, but in our approach, we have used 17 × 17 grid cells to increase the predictions. The model was trained for 10,000 iterations with the input image dimensions of 544 × 544 pixels. Table 1 shows the average IOU and the average precision (AP) generated by each iteration for three classes.

From Table 1, we can select the epoch having higher average IOU since it has the highest area of overlap between the

**Table 2**
The Confusion matrix obtained from the experiments.

| | With helmet | Without helmet |
|---|---|---|
| With helmet | 78 | 7 |
| Without helmet | 2 | **135** |

**Table 3**
Precision, recall and F1-score generated from the confusion matrix.

| | Precision (%) | Recall (%) | F1-Score (%) |
|---|---|---|---|
| With helmet | 97.5 | 91.76 | 94.54 |
| Without helmet | 95.07 | 98.54 | 96.77 |
| Weighted avg | 96 | 95.94 | 95.92 |

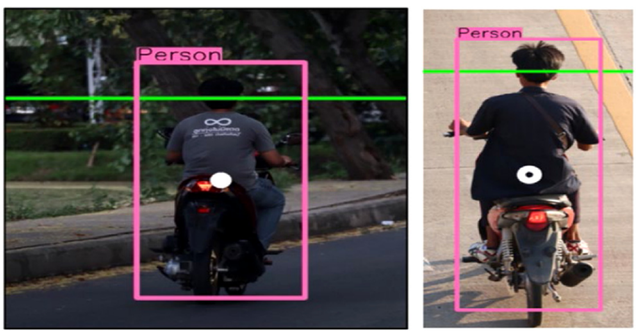


**Fig. 6.** LP for a non-helmeted motorcyclist is not detected due to absence of LP.

ground truth and the predicted bounding box. The overall mean precision (mAP) for three classes is 97.9% with the average training loss of 0.0829 for 64 batch size with 8 subdivisions.

### *4.1. Evaluation metrics*

To check the overall detection rate of LP for non-helmeted motorcyclists from the video, we have selected 222 bikers (with helmet = 85, without helmet = 137). Since we have the unbalanced number of motorcyclists, the accuracy of the system will be given by F1-score, which takes care of precision and recall rate. The confusion matrix generated by the experiment is shown in Table 2 and, the tabulation of precision, recall and F1-score is given in Table 3.

In Table 2, out of 137 non-helmeted motorcyclists, the system was able to detect 135 motorcyclists as non-helmeted, and rest 2 was detected as a helmeted motorcyclist. In both cases, the recall rate is higher than 90%, which relates to low false-positives rates. The LP detection rate for non-helmeted motorcyclists was 98.52% (out of 135 non-helmeted motorcyclists from the confusion matrix, 133 LPs were detected). We could not achieve 100% accuracy due to the absence of LP on some motorbikes, as shown in Fig. 6 . The system relies on the LP located at the rear position due to non-availability of LP on the front position. The system draws the bounding box of a non-helmeted motorcyclist along with the LP. The overall accuracy of the proposed method given by f1-score was 95.92%.

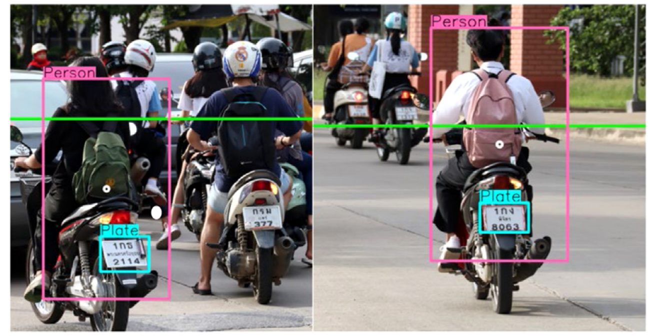


**Fig. 7.** LP detected for a non-helmeted motorcyclist.

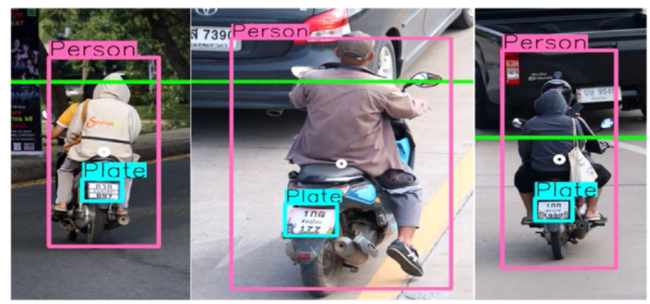


**Fig. 8.** Motorcyclists wearing hood/cap.

To check the robustness of the algorithm used in the system, we have tested the system having both helmeted and non-helmeted motorcyclists. As we can see from Fig. 7, the system detected the LPs for non-helmeted motorcyclists. The proposed system can also distinguish between the motorcyclists wearing a helmet or cap/hood, as shown in Fig. 8 . For helmeted motorcyclists, the system does not draw a bounding box for the detection.

The proposed algorithm is better than the existing algorithm because our algorithm uses a CNN-based YOLO model which is more robust to noise and can generalize on new data. Many researchers have used two layers of CNN to accomplish the tasks, but our proposed model uses a single CNN to fulfill the objective of the study. In the license plate detection, the proposed method outperforms some of the traditional methods such as boundary and color based approaches. In the boundary-based approaches, the input image should have a visible boundary and it is sensitive to unwanted edges. Similarly, in the color based approaches [6], the RGB color model is limited to illumination condition and the HLS (Hue, Lightness, Saturation) is sensitive to noise, making it difficult for color-based techniques to localize the license plates. The helmet detection rate of the proposed method is 94.54% (F1-score) which is better when compared with [7] and [9]. In our approach, we have introduced a reference line which tracks the centroid of the PERSON class and helps to perform detections before the centroid crosses the line. This helps to reduce the false positives generated by the helmeted motorcyclist.

The significant difference between the proposed method and methods discussed in related work is in our approach, we have introduced single convolutional neural network for automatic localization of license plate whereas in [13], the authors have used two YOLOv2 algorithms to accomplish the same task. Similarly, the authors in [7] and [9] have used boundary-based approaches which is sensitive to unwanted edges and need good quality images for generalization of an algorithm. The proposed algorithm is better than the color-based approach since it does not need to depend on the color information of the license plates and different quality of images were included for the training. This helps to generalize on the unseen data.

## 5. Conclusion

The main objective of the study was to develop an algorithm for automatic detection of LP for non-helmeted motorcyclists. A single convolutional neural network was implemented to accomplish the task. The detected license plate can be used in the ANPR technology to recognize the LP characters, which can be further used in analyzing the information. A centroid tracking method was also proposed to reduce the number of false positives generated by the helmeted bikers when their helmet is out of video frame. The proposed system was able to detect the license plate of those motorcyclists who wears a hood or cap. The overall LP detection rate for non-helmeted motorcyclists was 98.52%. The system relies on the LP located at the rear position since Thai motorcyclist does not have LP on the front area.

## CRediT authorship contribution statement

**Yonten Jamtsho:** Conceptualization, Methodology, Software, Formal analysis, Investigation, Resources, Data curation, Writing - original draft, Writing - review & editing, Visualization. **Panomkhawn Riyamongkol:** Conceptualization, Validation, Investigation, Writing - original draft, Writing - review & editing, Supervision, Project administration. **Rattapoom Waranusast:** Conceptualization, Validation, Investigation, Writing - original draft, Writing - review & editing, Project administration.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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