RESEARCH-ARTICLE

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Object-Based Vehicle Color Recognition in Uncontrolled Environment

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Figure 1: Challenge of vehicle color recognition in real-world situations. First row: examples of an uncontrolled environment. Second row: examples of related vehicle colors. Third row: examples of multi-color cars

ABSTRACT

The demand for vehicle recognition significantly increases with impact on many businesses in recent decades. This paper focuses on a vehicle color attribute. A novel method for vehicle color recognition is introduced to overcome three challenges of vehicle color recognition. The first challenge is an uncontrolled environment such as shadow, brightness, and reflection. Second, similar color is hard to be taken into account. Third, few research works dedicate to multi-color vehicle recognition. Previous works can provide only color information of the whole vehicle, but not at vehicle part level. In this study, a new approach for recognizing the colors of vehicles at the part level is introduced. It utilizes object detection techniques to identify the colors based on the different objects (e.g. parts of a vehicle in this research). In addition, a novel generic post-processing is proposed to improve robustness in the uncontrolled environment and support not only single-color but also multi-color vehicles. Experimental results show that it can effectively identify the color under the three challenges addressed above with 99 % accuracy for single-color vehicle and outperforms the other seven baseline models, and 76 % accuracy for multi-color vehicle.

CCS CONCEPTS

• **Computing methodologies** → *Object detection.*

KEYWORDS

image classification, object detection, vehicle color recognition

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1 INTRODUCTION

Vehicle cameras, traffic surveillance camera systems, and mobile cameras have been widely used in recent years, providing ample data and information that can be used to enhance intelligent vehicle technology. The growing availability of images and recordings from these sources has been used and applied in various applications such as driving safety [4], autonomous driving [7], InsurTech [2], and used car valuation [21] etc.

Many applications make use of vehicle attributes, i.e., MAKE (Vehicle brand), MODEL (Model name), YEAR (Year that it was produced), TYPE (sedan, hatchback, pick-up, etc.), and COLOR. Among these attributes, vehicle color is considered to be the easiest attribute to be recognized. However, as stated in several research

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papers [1], [3], vehicle color recognition is not as straightforward as it seems and poses several key challenges.

(1) **Uncontrolled Environments**. Colors can be easily affected by different lighting conditions, perspective, and even parts of the vehicle being occluded. This can cause the color to appear differently in different images or recordings, making it difficult for the algorithms to accurately recognize the color.
(2) **Related Colors**. Two colors that appear similar in terms of hue or color family can be difficult to differentiate, such as black and grey, blue and cyan, orange and red, and pink and purple. This can lead to incorrect recognition of the vehicle color.
(3) **Multi-colored Vehicles**. Vehicles can be comprised of multiple colors, with each section or part potentially painted differently. With the best of our knowledge, existing research has limited capability to identify the colors of individual parts, instead only providing information on the overall color of the vehicle.

In addition, a set of standard vehicle colors defined in the vehicle registration handbook may be different from one country to another. There is no standard model to capture such a variety yet. In Thailand, twelve colors are registered and some vehicles have more than one color, i.e., taxi vehicle usually has two colors as shown in the third row of Figure 1.

On a different note, object detection is a technique in computer vision that aims to identify and locate objects within an image using a bounding box. On the other hand, image segmentation divides an image into multiple segments, each of which corresponds to a different object or region, and representing each segment with a polygon. Compared to image segmentation, object detection is generally faster and requires less computational resources. It is suitable for tasks where a rough estimation of the object location using a bounding box is sufficient.

In this paper, a novel vehicle color recognition method is proposed to tackle such deceptively simple challenges addressed above. The method utilizes an idea of object detection and then propose object-based (e.g., vehicle part) vehicle color recognition. The proposed method consists of two tasks, 1) vehicle part and color detection task and 2) the post-processing task. A multi-color vehicle can be covered in this model.

The main contributions of this paper are as follows:

(1) An idea of object-based (e.g., vehicle part) vehicle color recognition and a generic post-processing formula are introduced. The model overcomes three challenges of vehicle color recognition as stated above.
(2) Business issues in Thai vehicle color recognition have been resolved. It can identify a Thai vehicle color standard including a special case like Thai multi-color taxis. The model can differentiate the vehicle color in a part or a section level. For example, this is a red-yellow car. The upper-half section is yellow and the lower-half section is red.

This paper is organized as follows: Section 2 provides some related knowledge for a vehicle color recognition. In Section 3, our proposed method consists of vehicle part and color detection task and the post-processing task are explained for both single-color and multi-color cases. Next, Section 4 gives an explanation of implementation details and its results for VCoR-TH dataset and Taxi-TH test dataset. Finally, key concluding remarks and future directions are presented in Section 5.

2 RELATED WORK

Recent literature review on vehicle color recognition methods can be divided into two types: a traditional computer vision-based method and a deep learning-based method. These two methods and object detection technique, which will be utilized in our proposed solution, are exclusively reviewed in this section.

[1] evaluated vehicle color recognition which turns into an area segmentation problem. Vehicle color is generally represented with the hood color. Therefore, they proposed a vehicle color classification method using the HSV color system with Support Vector Machine (SVM). [9] analyzed the effect of sunlight. Its reflection transforms the color of vehicle window to white and significantly leads to unexpected results in vehicle color classification. To reduce this effect, a window-removing task is proposed and applied. [6] examined two regions of interest named smooth car hood and semi-front vehicle, and three classification methods consists of K-Nearest Neighbors (K-NN), Artificial Neural Networks (ANN), and support vector machine (SVM) for classifying the vehicle color.

Technically, Convolutional Neural Network (CNN) is designed to learn classification method based on shape information. However, [14] proved that CNN can also learn classification based on color distribution. [13] analyzed the use of CNNs for vehicle color recognition and concluded the importance of alerts on amber and silver colors.

With the state-of-the-art object detection models, one can enrich vehicle color recognition with higher performance. For example, [22] proposed a one-step method for vehicle color recognition using an object detection, named YOLO9000 [15]. [20] introduced the solution by enhancing an object detection with Region-based Convolutional Neural Network (R-CNN), named Faster R-CNN [16]. Their solutions effectively detected the whole car with its color.

However, there is some room of improvement in that of other works. For example, existing object detection model detects the whole car while our technique uses object detection to detect vehicle parts and efficiently post-process them to classify the vehicle color. In addition, we notice that the region proposal is very important for vehicle color recognition. Without this, the model may use improper vehicle parts for recognizing vehicle color, e.g., car grille, headlights, taillights, tires, windows, windshield, etc. Finally, this can lead the result with wrong recognition on vehicle colors. Our novel solution leverages the object detection and overcomes three challenges addressed earlier with correct vehicle color recognition.

3 METHOD

The proposed method consists of two tasks, vehicle part and color detection task and the post-processing task. See Figure 2.

3.1 Vehicle part and color detection task

Given an input image x_i where i is the index of an image, vehicle part detection θ is defined as $\theta(x_i)$. Let J denote the total number of

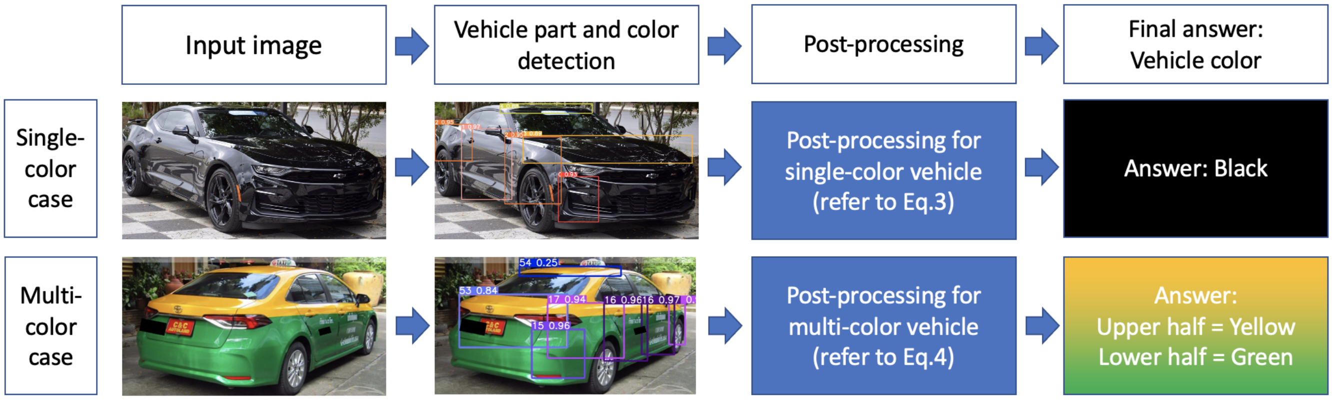

Figure 2: Pipeline of our proposed object-based vehicle color recognition

vehicle parts detected in an image x_i. j denote the index of vehicle part where $j \in \{1, 2, ..., J\}$.

Then, $\theta(x_i)$ contains a vehicle part name p_{ij}, a part color name q_{ij}, a confidence score of the detection s_{ij}, and a coordinate positions which can be transformed into an area a_{ij}. See Equation (1).

$$\theta(x_i) = [(p_{i1}, q_{i1}, s_{i1}, a_{i1}), (p_{i2}, q_{i2}, s_{i2}, a_{i2}), ..., (p_{iJ}, q_{iJ}, s_{iJ}, a_{iJ})] \tag{1}$$

3.2 Post-processing task

The result from vehicle part and color detection task is applied as an input for post-processing task. The output from the post-processing task is the final result of predicted color y. Let C denote a set of possible colors. That means the detected color of a vehicle part q and the predicted color y must be the element of superset C. For example, $C = \{black, blue, brown, cyan, green, grey, orange, pink, purple, red, white, yellow\}$. $c, q \in C$.

Our optimization problem is to determine the element c in superset C maximizing the objective function f. The optimal element c is defined as an optimal element y_i as described in Equation (2).

$$y_i = \underset{c \in C}{\operatorname{argmax}} f(\theta(x_i)) \tag{2}$$

Let p^* denote the appropriate weight of each vehicle part for possible detected vehicle parts P. Let c^* denote the appropriate weight of each vehicle part for all possible colors in C. One of the simple and reasonable f can be calculated by summation of the dot product of p^*_{ij} c^*_{ij} s_{ij} and a_{ij} where p^*, s, and a are normalized as shown in Equation (3). This is because we want to find the main color of the vehicle. Therefore, the area should be multiplied by the confidence score of the predicted bounding box. For p^*, we can adjust based on the dataset. For c^*_{ij}, it will be 1 if $c_{ij} = q_{ij}$, otherwise it will be 0.

$$\begin{gathered} y = \underset{c \in C}{\operatorname{argmax}} \sum_{j \in \mathcal{J}} (p^*_{ij} \cdot c^*_{ij} \cdot s_{ij} \cdot a_{ij}) \\ c^*_{ij} = \begin{cases} 1 & \text{if } c_{ij} = q_{ij} \\ 0 & \text{otherwise} \end{cases} \end{gathered} \tag{3}$$

Next, we focus on solving the multiple-color challenge. First, we create a list of the vehicle parts for each section. For example, Thai taxi in Figure 1 has two sections. The upper half and lower half are yellow and green, respectively. We can define the list of vehicle parts in each section. That means the upper section consists of the vehicle hood, tailgate, and roof. On the other hand, the lower section consists of the bumper, door, and fender.

Let k denote the index of the section. y_{ik} is the color of image i of section k. P_k is the list of vehicle parts considered in section k. We can define the color of each section as shown in Equation (4).

$$\begin{gathered} y_k = \underset{c \in C}{\operatorname{argmax}} \sum_{j \in \mathcal{J}} (p^*_{ij} \cdot c^*_{ij} \cdot s_{ij} \cdot a_{ij}) \\ c^*_{ij} = \begin{cases} 1 & \text{if } c_{ij} = q_{ij} \\ 0 & \text{otherwise} \end{cases} \quad p^*_{ij} = \begin{cases} 1 & \text{if } p_{ij} \in P_k \\ 0 & \text{otherwise} \end{cases} \end{gathered} \tag{4}$$

4 EXPERIMENTS

First, this section describes the detail of model implementations, i.e, the usage of the object detection model and some parameter settings. Next, the experiment for the single-color vehicle with VCoR-TH dataset is discussed. Lastly, we expand the experiment to the multi-color vehicle with Taxi-TH test dataset.

4.1 Implementations

The detected vehicle part is analyzed in details. We use 5 vehicle parts in this experiment: bumper (both front and rear bumpers are in the same class), doors (every door is in the same class), fender (front, rear, left, and right fenders are in the same class), hood (front hood and tailgate are in the same class), and roof. That means $P = \{bumper, door, fender, hood, roof\}$. The objective function explained in Equation (3) is then applied to achieve the optimal solution. The parameters for single-color and multi-color vehicle scenarios are set and defined as follows:

- For single-color vehicle, p^* is set to 1.
- For multi-color vehicle, according to Taxi-TH test set shown in Figure 5, k is set 2, $P_{upper} = \{hood, roof\}$, and $P_{lower} = \{bumper, door, fender\}$.

In multi-color vehicle, door and fender consist of two colors, i.e., yellow and green. This is technically ambiguous and hard to be recognized. Therefore, we assume $p^*_{door} = 0$ and $p^*_{fender} = 0$ to simplify our experience to achieve practical results.

Due to the performance and ease of use, we exploit one of the state-of-the-art object detection models, named YOLOv5 [10]. We use YOLOv5m which is trained by COCO [11] with a provided pre-trained model.

We label each part with its corresponding color as a class in object detection. For example, black bumper, black door, black fender, black hood, and black roof are labeled as 0, 0, 2, 3 ,4, respectively. If next color is blue, therefore, blue bumper, blue door, blue fender, blue hood, and blue roof, are labeled as 5, 6, 7, 8, and 9, respectively.

4.2 Single-color vehicle with VCoR-TH

4.2.1 Data preparation. The Vehicle Color Recognition (VCoR) dataset [12] is the most diverse and large-scale dataset with 10K images and 15 color classes, including beige, black, blue, brown, gold, green, grey, orange, pink, purple, red, silver, tan, white, and yellow. However, as the focus of this paper is on Thai vehicle color recognition, a new dataset, VCoR-TH, has been proposed and created by filtering and selecting the original VCoR dataset to be comprehensive and better suit the specific requirements and challenges of color recognition in Thailand.

According to Thai vehicle registration book, VCoR-TH consists of 12 colors: black, blue, brown, cyan, green, grey, orange, pink, purple, red, white, and yellow. We set our C as described in Section 3. Key setup for generating certain color set is listed as follows:

- Cyan: Select some light blue images from original VCoR blue images.
- Blue: Select some dark blue images from original VCoR blue images.
- Grey: Combine grey images from the original VCoR dataset with some silver images that looks grey from the same dataset.

Furthermore, images with less than 50KB file size are removed. For each color, there are 30 and 20 images for a test set and a validation set, respectively. The remaining is used as a training set. Moreover, our solution leverages the idea of object detection. Therefore, we also label the vehicle parts. The number shown in Table 1 is the number of bounding boxed for each vehicle part in a training set.

In some colors, vehicle part may have the number of bounding boxes more than the number of images. There are two key points to be taken into account on this. First, there is more than one vehicle part in one image, e.g., two doors, two fenders, etc. Second, a cyan car may possibly have a black roof as shown in the third row of Figure 1. The training dataset is fully described in Table 1.

Table 1: VCoR-TH Dataset

	image	bumper	door	fender	hood	roof
black	136	141	218	240	139	274
blue	139	132	235	260	132	86
brown	119	99	199	220	110	65
cyan	54	54	83	98	52	29
green	173	152	227	318	157	85
grey	93	76	175	177	83	54
orange	63	51	96	120	56	20
pink	97	77	132	167	91	38
purple	169	153	215	297	143	75
red	194	186	309	372	186	116
white	117	114	222	221	116	88
yellow	136	130	186	249	126	55
sum	1490	1365	2297	2739	1391	985

4.2.2 Experimental results. A set of seven baseline models consists of traditional computer vision methods such as KNN, SVM, decision tree, RandomForest, and a deep learning with a CNN such as Resnet50 [8] and MobileNetV2 [17], and fine-grained image classification EfficientnetB3 [19], is used and experimented as an image classification task. Pre-trained deep learning weight is trained and computed by Imagenet [5].

Table 2: Comparison between our proposed algorithm and baseline methods

	accuracy
DecisionTree	0.381
KNN	0.394
RandomForest	0.642
SVM	0.681
Resnet50	0.911
MobileNetV2	0.897
EfficientnetB3	0.928
Ours	0.986

According to Table 4, our proposed solution significantly outperforms other baseline models. The confusion matrix of EfficientnetB3, which is the best in the baseline model, and ours are shown in Table 3 and Table 4.

4.2.3 Discussion. The proposed solution has false recognition with only 5 images from total of 360 testing images. The main reason is vehicle part detection cannot recognize the target vehicle parts. This is because detection model is trained by limited dataset of 1490 images for 60 classes (12 colors and 5 vehicle parts per color) which is insufficient to achieve concrete results. However, detecting only a few vehicle parts may lead to wrong detected color as a result in wrong answer. On the other hand, few vehicle parts can be efficiently detected with the correct color. Not only the proposed model, but also the baseline model EfficientnetB3 fails to recognize the vehicle color of those five images. Moreover, EfficientnetB3 cannot correctly detect color in certain conditions of related colors such as grey-white, grey-black, cyan-blue, and pink-purple. To

Table 3: Confusion maxtrix of EfficientnetB3

label\pred	black	blue	brown	cyan	green	grey	orange	pink	purple	red	white	yellow
black	28	1	0	0	0	1	0	0	0	0	0	0
blue	0	27	0	2	0	0	0	0	1	0	0	0
brown	0	0	28	0	0	2	0	0	0	0	0	0
cyan	0	3	0	26	0	1	0	0	0	0	0	0
green	0	0	0	1	29	0	0	0	0	0	0	0
grey	3	0	1	0	0	24	0	0	0	0	2	0
orange	0	0	2	0	0	0	27	0	0	0	0	1
pink	0	0	0	0	0	1	0	26	2	0	1	0
purple	0	0	0	0	0	0	0	0	30	0	0	0
red	0	0	0	0	0	0	0	0	0	30	0	0
white	0	0	0	0	0	0	0	0	0	0	30	0
yellow	0	0	0	0	1	0	0	0	0	0	0	29

Table 4: Confusion matrix of proposed solution

label\pred	black	blue	brown	cyan	green	grey	orange	pink	purple	red	white	yellow
black	30	0	0	0	0	0	0	0	0	0	0	0
blue	0	30	0	0	0	0	0	0	0	0	0	0
brown	0	0	30	0	0	0	0	0	0	0	0	0
cyan	0	0	0	30	0	0	0	0	0	0	0	0
green	0	0	0	0	30	0	0	0	0	0	0	0
grey	0	0	0	0	0	29	0	0	0	0	1	0
orange	0	0	2	0	0	0	28	0	0	0	0	0
pink	0	0	0	0	0	0	0	28	1	1	0	0
purple	0	0	0	0	0	0	0	0	30	0	0	0
red	0	0	0	0	0	0	0	0	0	30	0	0
white	0	0	0	0	0	0	0	0	0	0	30	0
yellow	0	0	0	0	0	0	0	0	0	0	0	30

analyze in details, Grad-CAM [18], the popular visualization tool of deep neural network using gradient-based localization, is used for further investigation.

Figure 3 shows that EfficientnetB3 provides an incorrect answer. For example, it is an orange car but EfficientnetB3 returns the result with a yellow car. It is because EfficientnetB3 mainly focuses the middle position of the image such as left headlight more than the other parts. See the visualization resulting using Grad-Cam in Figure 3b. This investigation corresponds with what [1] explains such that the vehicle color recognition can turn into area segmentation problem. YOLOV5, shown in Figure 3c, detects each part as an orange color (class numbers 25-29 based on vehicle parts). Thus, final answer from proposed solution is indeed orange color. Figure 4 shows more samples of incorrect recognition from EfficientnetB3 while our solution detects it correctly.

4.3 Multi-color vehicle with Taxi-TH

4.3.1 Data preparation. Thai taxi usually consists of two colors, e.g., yellow-green, yellow-red, blue-red, pink-white, etc. Yellow-green taxi is the only type of taxis that are owned by individuals. Other colors are run by taxi companies, taxi co-ops, and their alliances. In this experiment, we collect 100 images of a yellow-green Thai taxi, named Taxi-TH test set as shown in Figure 5.

4.3.2 Experimental results. We use the model trained in section 4.2 without further fine-tuning process. The result from our proposed solution with Taxi-TH test set is shown in Table 5. The table denotes the number of true positive predictions. 100 images are used in the experiment. 81 images and 95 images are correctly detected with upper-half and lower-half sections, respectively. Overall, 76 out of 100 images are mutually correct for both upper and lower-half sections.

Table 5: Taxi-TH dataset and its results with proposed solution

	Number of images
Total images	100
Upper section	81
Lower section	95
All	76

(a) Original input image

(b) Visualization of EfficientnetB3 using Grad-Cam

(c) YOLOV5 vehicle part detection result

Figure 3: Error analysis by comparing our method with the baseline method

Figure 4: Samples of incorrect images with baseline method EfficientnetB3

Figure 5: Samples of Taxi-TH test set

4.3.3 Discussion. With detailed analysis on experimental results, the upper-half section has higher wrong detection than the lower-half section. Main root cause is insufficient training dataset on yellow vehicle parts. Only 136 images are applied for 5 classes of object detection tasks as mentioned in Table 1. Moreover, we have only 55 bounding boxes of yellow roofs and 126 bounding boxes of yellow hood. The roof is hard to see compared to other vehicle parts. The roof area is typically small if the image is taken from the perspective of side view, not from the top view. Although a hood can be easily detected, it is also easy to be influenced with an impact on predictions by the light as stated in previous works. See Figure 1 for more results.

5 CONCLUSIONS

In this paper, the modern vehicle color recognition model is proposed. The model efficiently works under difficult circumstances, i.e., uncontrolled environment, related vehicle color, and multi-color vehicle. The object detection technique has been exploited in identifying vehicle parts with its corresponding color. Additional generic post-processing formula for vehicle color recognition is also proposed. Our proposed method significantly outperforms conventional models with 99% accuracy for single-color vehicle. Moreover, we expand our experiment to multi-color vehicle with 76% accuracy. According to our analysis, the conventional image classification model may use the improper vehicle parts such as headlights, tires, windows, etc. In contrast, our model utilizes various proper vehicle parts so it can surpass the challenges stated above.

Future work involves furthering the proposed object-based vehicle color recognition by exploring additional datasets for training and addressing novel implementations from others in the field of computer vision. Additionally, we aim to extend the object-based method to include the detection and recognition of colors in other objects, beyond just vehicle parts. This could broaden the scope of the object-based method and demonstrate its versatility for use in a wider range of applications and scenarios.

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