THAI TRAFFIC SIGN CLASSIFICATION SYSTEM

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A Thesis Submitted in Partial Fulfillment of the Requirements
for the Degree of Master of Science in Computer Science and Information Technology
Department of Mathematics and Computer Science
FACULTY OF SCIENCE
Chulalongkorn University
Academic Year 2020

ระบบการจำแนกประเภทเครื่องหมายการจราจรไทย

นายณัฐพล นามยัง

วิทยานิพนธ์นี้เป็นส่วนหนึ่งของการศึกษาตามหลักสูตรปริญญาวิทยาศาสตรมหาบัณฑิต
สาขาวิชาวิทยาการคอมพิวเตอร์และเทคโนโลยีสารสนเทศ ภาควิชาคณิตศาสตร์และวิทยาการคอมพิวเตอร์
คณะวิทยาศาสตร์ จุฬาลงกรณ์มหาวิทยาลัย
ปีการศึกษา 2563

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ณัฐพล นามยัง : ระบบการจำแนกประเภทเครื่องหมายการจราจรไทย. (THAI TRAFFIC SIGN CLASSIFICATION SYSTEM) อ.ที่ปรึกษาหลัก : รศ. ดร.ศุภกานต์ พิมลธเรศ

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สาขาวิชา	วิทยาการคอมพิวเตอร์และเทคโนโลยีสารสนเทศ	ลายมือชื่อนิสิต ....
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6278009623 : MAJOR COMPUTER SCIENCE AND INFORMATION TECHNOLOGY
KEYWORD: traffic sign classification, traffic sign recognition, driving assistance technology

Nattapol Namyang : THAI TRAFFIC SIGN CLASSIFICATION SYSTEM. Advisor: Assoc. Prof. SUPHAKANT PHIMOLTARES, Ph.D.

Nowadays, driving assistance technology is continuously developed to serve a comfortable and safe driving experience for the driver. The traffic sign is an important feature to improve the ability of this technology. However, in general, the traffic sign has various structures and details in each specific country for a clearly understanding purpose. Thus, this thesis aims to propose the classification and recognition system for the Thai traffic sign. In this study, the classification process provides the ability to categorize the Thai traffic sign into four classes by using a Support Vector Machine (SVM) and Random Forest (RF) classifier with the combination of two descriptor features that are the Histogram of Oriented Gradients (HOG) and Color Layout Descriptor (CLD) feature. In this proposed classification technique, it is able to reach the accuracy up to 93.98%. Besides, this study also presents the recognition process to recognize the type of each traffic sign. This process using two main techniques: Optical Character Recognition (OCR) and Normalized Correlation Coefficient (NCCoef) template matching to predict the real meaning of each sign in their class after classifying them.

Field of Study:	Computer Science and Information Technology	Student's Signature ....
Academic Year:	2020	Advisor's Signature ....

ACKNOWLEDGEMENTS

It is with great pleasure that I express my gratitude to everyone who has given me the opportunity to complete this thesis.

This completion of this thesis could not have been possible without the expertise of Associate Professor Dr. Suphakant Phimoltares, my beloved thesis advisor. I would like to say that I very much appreciate his attention and dedication to advise me during the period of this study.

Also, I would like to express my appretiate to all thesis committee: Professor Chidchanok Lursinsap and Dr. Prem Junsawangfor their insightful comments and devotion time.

Moreover, I would like to express my extraodinary thanks to my family and friend for their understanding and support.

Finally, I have to say thank you to myself for encouraging myself and the courage to complete this study.

Nattapol Namyang

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CHAPTER I

INTRODUCTION

1.1 Background and Rationale

In this present time, transportation is one of the most important essential factors to make our life more convenient. Numerous vehicle manufacturers develop intelligence software to serve various technologies to modern cars. The driving assistance system is one of the technologies in which manufacturers give a high priority for providing safety and facilitate to the driver.

Traffic signs are widely used as important data for developing car intelligence software: driving assistance system. For example, BMW invents a technology that can detect the relevant traffic sign. For example, the speed limit signs provide the speed limit information to the driver [1]. Moreover, Mercedes-Benz also affords traffic sign assistance technologies. For instance, speed limit or pedestrian crossing signs in the instrument cluster warn the driver in indeed situations [2]. Although traffic signs are widely used for inventing car technology, it is still having a challenging issue for the developer due to the diversity of the format in each country.

To use the traffic signs most beneficially, the traffic signs themselves must provide information that can easily understand by everyone who uses the road or relevant people: driver, passenger, and pedestrian. Besides, the differences in language, culture, and laws of each country also impact the distinctive design of the traffic sign for each country. In Thailand, the traffic signs use various graphics to convey their meanings such as symbols, or colors combining with directional arrows or Thai words to express the meaning of itself to the pedestrians or drivers.

Thailand traffic signs can be classified into four categories which are three main common categories and one minor category. The three main categories consist of regulatory signs, warning signs, and guide signs [3]. Apart from those categories, the final category contains construction signs used for certain objectives [4].

The first category, regulatory signs, is used to instruct both drivers and pedestrians to understand their rights and to be aware of their obligations on the road and nearby area, thereby reducing traffic conflicts and avoiding potential accidents. Therefore, the people who violate the rule of these signs are illegal. Most of the regulatory signs are in a circular shape with a symbol, number, or black alphabet on a white background and red circumference except stop sign, give way sign, etc. Some of the examples of the signs in this category are presented in Figure 1.1.

Figure 1.1 The example of the regulatory signs.

Secondly, the warning signs are intended to alert drivers in advance of road conditions that will change or dangerous. Moreover, it might be used to notify the driver before they meet certain types of traffic control devices. Thus, the chauffeur must be more conscious and decrease the speed when driving under that circumstance. These signs are usually in a square shape with a yellow background and the other elements in black color. Figure 1.2 shows the example of signs in this category.

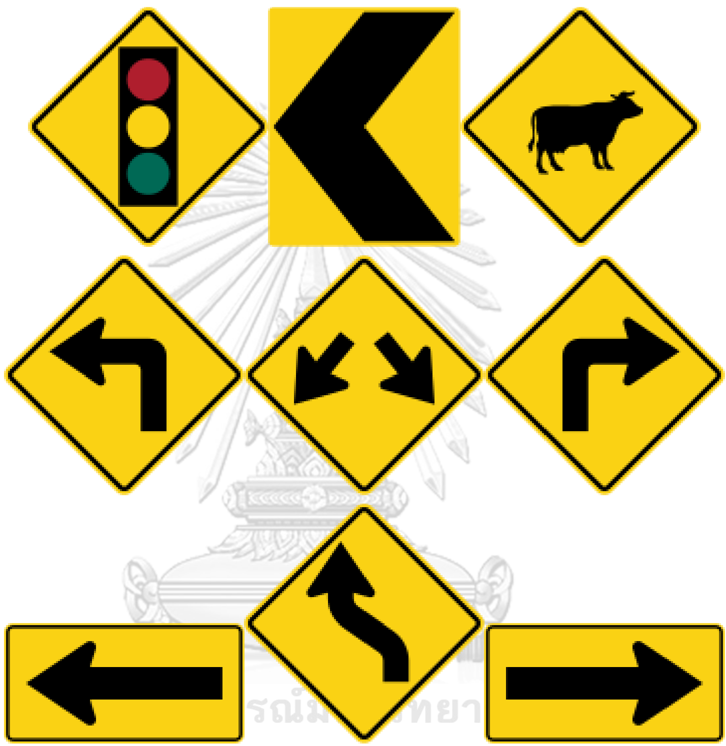


Figure 1.2 The example of the warning signs.

The last main category, the guide signs, informs the driver about supplementary details such as traveling, traffic, and leads to destinations information. To enumerate, the guide signs expose the information about the route to take, direction, distance, places, etc. to the driver. These signs usually use a white, green, or blue background with a rectangle or square shape and diverse types of composed components. The example of the guide signs is shown in figure 1.3.

Figure 1.3 The example of the guide signs.

In addition, another sub-category containing construction signs that are used for an exact purpose. For drivers to be safe and convenient to travel in the construction area, construction signs are different from the previously mentioned traffic signs. Moreover, the other motivation of construction signs is to assure that people who work in the construction area are safe. The signs in this category are designed to use an orange background and black components so that they can be easily distinguished from the other categories. Figure 1.4 presents some of the construction signs.

Figure 1.4 The example of the construction signs.

From many prior works in this field, there are some diverse machine learning techniques and image features that fit this kind of problem. For instance, Convolutional Neural Networks (CNN) that are trained by some global or local features and also Support Vector Machine (SVM) is mostly chosen as a classification model. Nonetheless, the traffic signs in a different country have various information which is hard to develop and adapt a system that can function properly in all domains.

1.2 Research Objectives

1. To classify Thai traffic signs into classes accurately.
2. To measure the efficiency of the proposed model compared with the other classification methods.

1.3 Problem formulation

1. How to classify the Thai traffic signs into their class?

2. How to retrieve their real meaning from Thai traffic signs?

1.4 Scope of the work

There are three issues concerned in this research:

1. The Thai traffic sign images cover only daylight images.
2. The Thai traffic sign images cropped from Google Street View must be removed from their background.
3. The Thai traffic sign images using in this research cover only images from the official Traffic sign standard manual 2018, Department of Highways, Thailand.

1.5 Expected Outcomes

This research aims to propose a classification model for classifying Thai traffic sign images into four categories: regulatory signs, warning signs, construction signs, and guide signs with high accuracy. Thus, this methodology can provide an informative system to help the developer invent the driving assistance system in Thailand.

CHAPTER II

LITERATURE REVIEW

Many of the research presented the study to detect, classify, or recognize traffic signs in the recent past. In this chapter, eight related studies are provided as follows.

The first study aims to detection and recognition of speed limit traffic sign using support vector machines [5]. This study presented a methodology for detection and recognition of speed limit traffic signs in Hochiminh City, Vietnam. This approach consists of eight processes. Firstly, when the source image proceeds into the system, it starts preprocessing the picture by enhancing its quality. After that, the system begins the second process to calculate the color probability of all pixels in the image by using the color probability model. Then, the image is converted into grayscale, and the system proceeds to the third step to select the candidate regions by using the contour technique. After this step, the histogram of the oriented gradient (HOG) feature is extracted, and the authors choose the support vector machine (SVM) to classify the traffic sign image in their study. In this step, the SVM is used to classify each region whether it is a speed limit sign. Finally, digit localization is used to localize the digit area in the selected region, and HOG feature extraction and multi-class SVM are used to classify the localized site numerically. Figure 2.1 refers to these eight main processes.

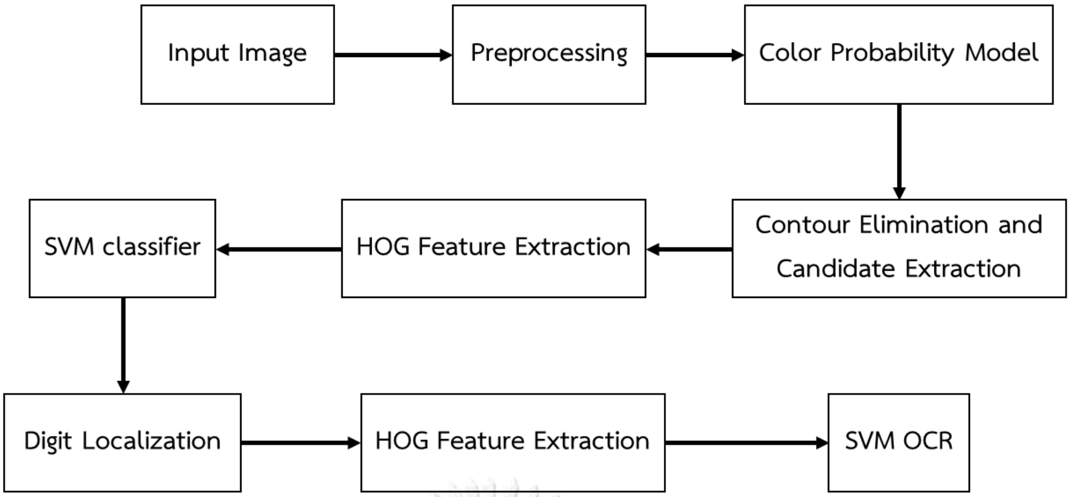


Figure 2.1 The system model of [5].

In conclusion, this paper proposed localizing and recognizing technique of the speed limit traffic sign in Hochiminh City, Vietnam. SVM classifier with HOG feature classifies the speech limit sign, then the second SVM is applied to forecast the integer on speed limit sign.

The second paper is Indonesian traffic sign detection and recognition using color and texture feature extraction and SVM classifier [6]. The detection part starts with normalizing the RGB color space to remove the effects of intensity variations. Then, each color segment of the normalized RGB image is applied by some threshold value to get the binary image. Next, the system identifies the traffic sign region using its size and eliminates the region with a size that is either too small or too large. In case that there is more than one candidate region in the same image, the method analyzes all the candidate regions iteratively. After analyzing the candidate regions, the system draws the bounding box on the original image using the considered traffic sign candidate region from the previous step. Afterward, the recognition part starts extracting the selected area features. In this study, the authors chose the HOG feature to represent the gradient magnitude and gradient orientation of the image and the local binary pattern (LBP) to represent the texture feature. Finally, the SVM is used to determine the category of the traffic sign.

Table 2.1 Recall and Precision results of [6] (a) Result of the detection process (b) Result of the recognition process.

Recall	Precision
95.1%	98.7%

(a)

Method	AUC	Precision	Recall
SVM	100	100	86.7
Random Forest	99.4	96.4	9.00
KNN	91.6	60.5	71.2
Naïve Bayes	93.3	96.4	86.7

(b)

The third paper is a hybrid approach for detection and recognition of traffic text signs using MSER and OCR [7]. The purpose of this paper aims to recognize the text from a traffic sign. The proposed method is divided into two main processes: text area detection and text recognition. The text area detection process starts with removing image noises and de-blurring them by Lucy Richardson's (LR) calculation. Next, the system adjusts an input image intensity by using an enhancement technique to renew its contrast or brightness level. Moreover, the system also converts an input image from RGB color space into grayscale in this step. The system then enhances the image edge and uses maximally stable extremal regions (MSER) to detect all regions. After finishing the text area detection process, the system moves forward to the text recognition process. The text recognition process begins by using morphological segmentation on MSER. The morphological segmentation segments the connected region in an image into subcomponents. After that, the system eliminates the area that is too large or too small. Finally, the system formats the text lines, which are always within straight lines or slight curves. In conclusion, this proposed method can archive 95% of the f1-score in the text area detection process and 93% of the f1-score in the text recognition process. Figure 2.4 shows the steps of this algorithm.

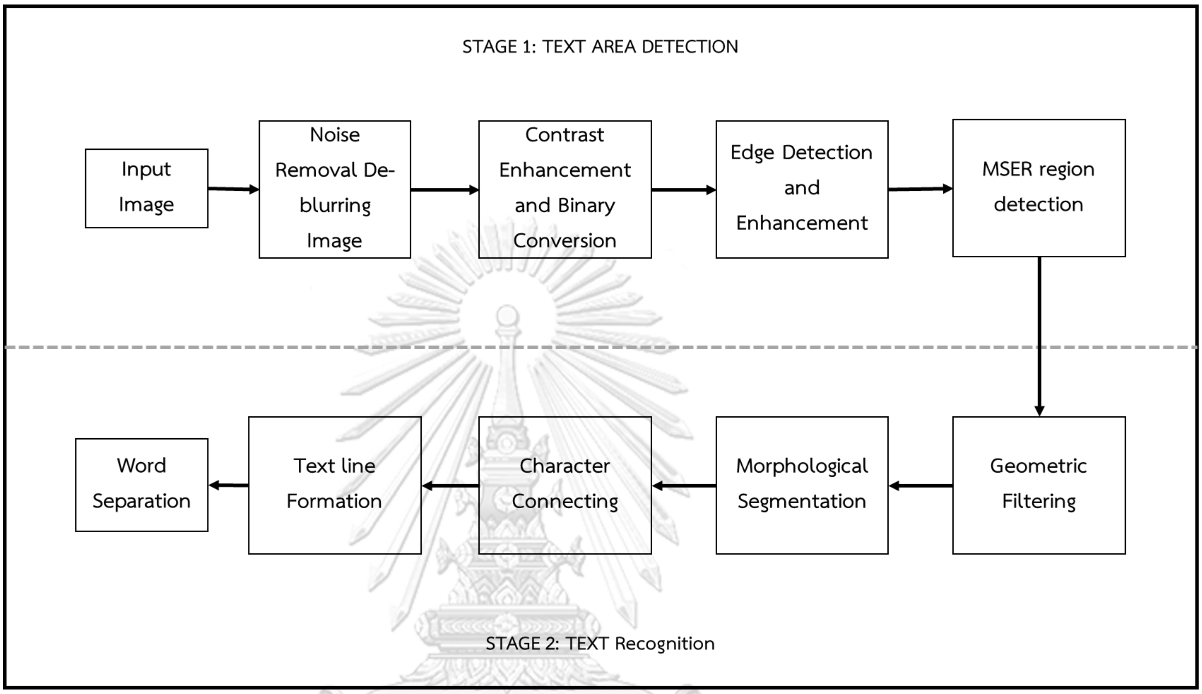


Figure 2.4 The steps of [7].

Fourthly, Ying Sun et al. proposed traffic sign detection and recognition based on convolution neural network [8]. This paper's methodolody is divided into three main parts: preprocessing, detection, and classification. The preprocessing step begins with enhancing image quality to eliminate the image noise by using median filtering. After that, from the enhanced image, the color space is converted from RGB to HSV. Next, the area of interest is detected by using the color and shape datum. Hue value is the most practical when color information is used to extract the area of interest. After the previous step, the system eliminates redundant interference information by a single morphological operation. This mathematical operation, morphology, make image data more comprehensible, collect the fundamental image shape, and reject unrelated pattern. Subsequently, the last step of detection is to find the locale of signs in a circular shape using Hough Transform. For the next method, the classification method, the authors proposed the CNN model that constructs two layers of both pooling layers, and full connection layers, and the activation function that uses in all layers is Rectified Linear Unit (ReLU). Thus, the detected circular traffic sign is identified by this CNN. The traffic sign recognition system process of this research is presented in Figure 2.5.

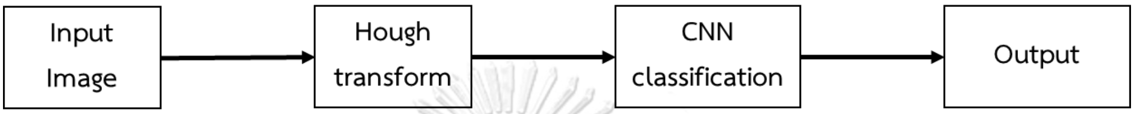


Figure 2.5 Traffic sign recognition system process [8].

In the fifth study, Zhenli He et al. published the article named traffic sign recognition by combining global and local features based on the semi-supervised classification [9]. This paper proposed the classification method that can perform with insufficient training data. The approach starts with extracting the color histogram, HOG, and edge feature from labeled data. Then, three classification models that use the tri-training algorithm were trained by different feature sets. The multi-feature vectors are also obtained from the unlabeled data set. The system will select some of the images with leading confidence score to append to the labeled data set until the unlabeled data set is empty or the labeled data set is no longer change. Thus, the labeled data combined with the unlabeled data with high confidence are used as the CNN training set.

Next, the research, two-stage traffic sign detection and recognition was based on SVM and convolutional neural networks [10]. This paper aims to detect the traffic sign in a circular or triangular shape and recognize it by CNN into their subclass. The detection process starts with convert an RGB image to an HSV image and uses the threshold technique to detect the red and blue color. Next, the system eliminates false candidates by using erosion and dilation. Also, the system eliminates many regions of interest, which are too small or too large. After the regions of interest are detected, the HOG feature is selected to represent this input image. The support vector machine classifier with linear kernel function is used to categorize the detected area to a circular shape, triangular shape, or others. If the shape is classified as a circle or triangle, the recognition process will be started. The recognition process uses the CNN classifier to categorize the German traffic sign in the last step by using ReLU as the activation function of each node. Figure 2.8 presents the block diagram of the system of this study.

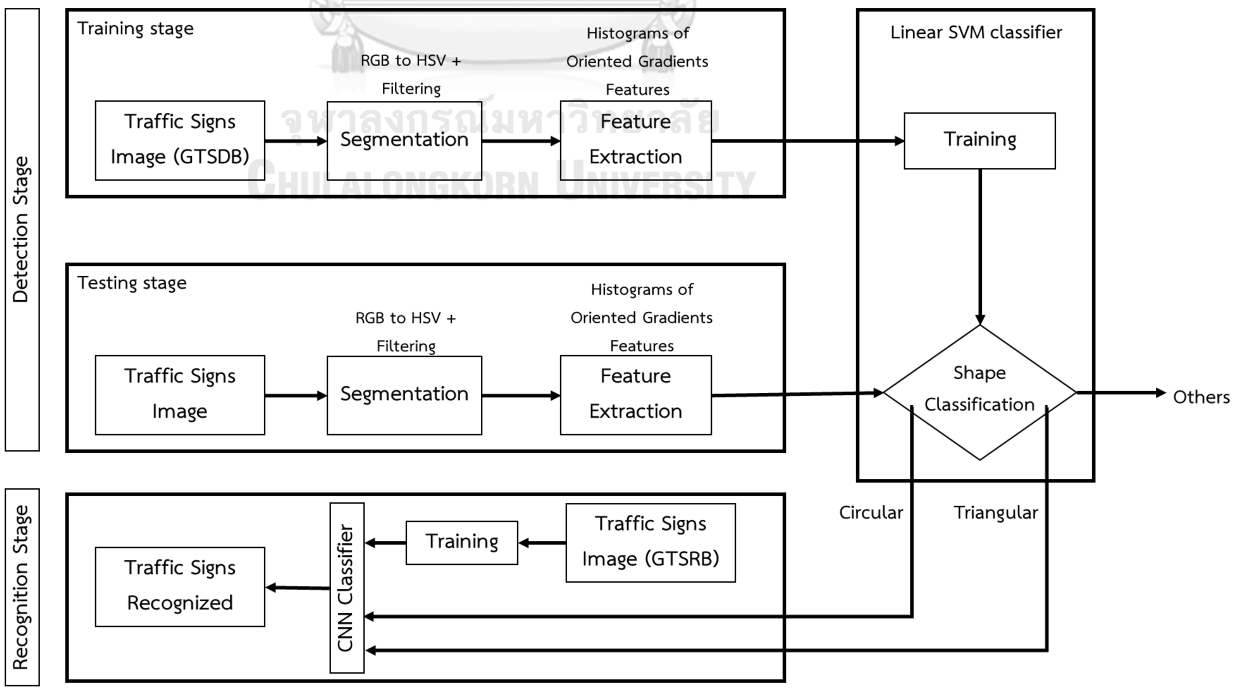


Figure 2.8 Block diagram of the system [10].

For those previous papers, the scope of the data set does not cover the traffic sign in Thailand. The next two articles had used the Thai traffic sign in their data set.

First, the paper named Thai traffic sign detection and recognition for driver-assistance [11] proposed a method for detection and recognition of traffic signs in Thailand. The detection process uses a cascade classifier to train the detection model with two data sets containing positive and negative. The positive data set contains the image with the Thai traffic sign, but the negative data set contains the image without any traffic sign. Then, the system extracts the HOG feature of all images in both positive and negative data sets for use in the cascade classifier. After finish constructing the cascade classifier for the traffic sign detector, the system uses the Viola-Jones cascade detector to localize the traffic sign as a detected region. Simultaneously, the recognition model is trained using the HOG feature retrieved from 32 x 32 pixels grayscale images from both negative and positive data sets with the linear SVM learner. After finishing the detection process, the system resizes the detected sign into 32 x 32 pixels and converts color space from RGB to grayscale. Then, the grayscale detected sign is predicted as the output using the trained traffic sign recognition model. In figure 2.9, the overall framework of this study is presented.

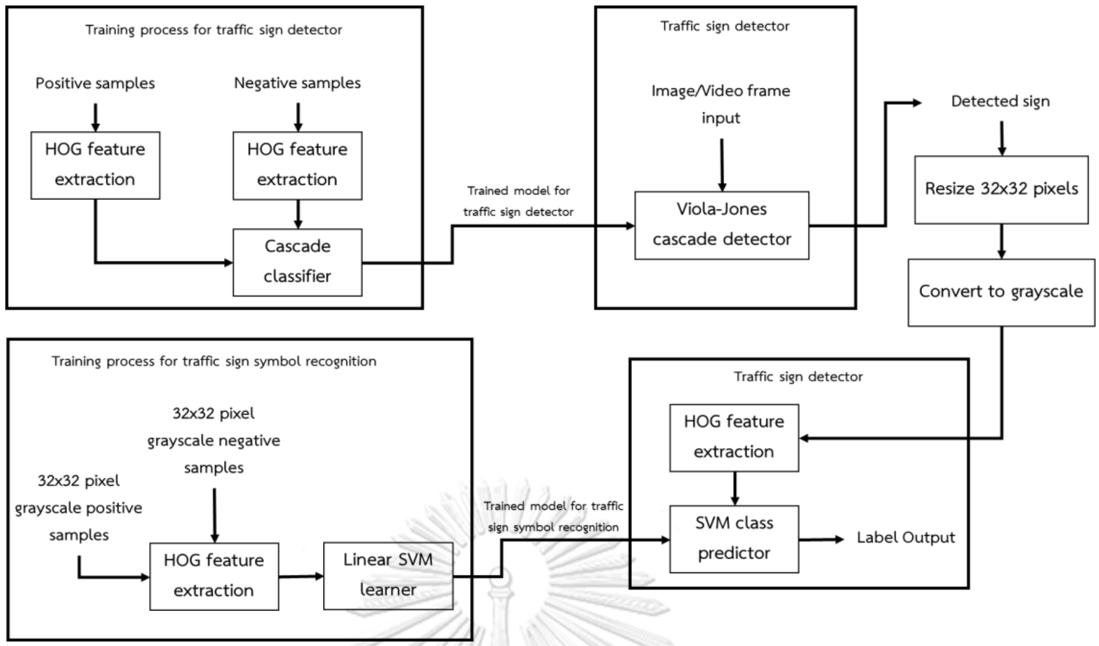


Figure 2.9 An overall framework of the proposed method [11].

The last paper was proposed by Mohamed S. et al. named Thai traffic sign detection and recognition using convolutional neural networks [12]. The Yolov3 library is used to perform the detection and recognition process. For the data set in this paper, the authors collected the images from google street view and some of the images that have little or no difference compared with Thai traffic signs in the Belgium Traffic Sign Data set (BTSD) and German Traffic Sign Detection Benchmark (GTSD). Then, the ten most common traffic signs in Thailand were selected for using in their training and testing processes. The ten chosen Thai traffic signs consist of Highway, Parking, Crosswalk, Stop, Speed bump, School-zone, No entry, No passing for certain width, Speed limit, and Intersection. Before training the models, some effects such as faded, obstruction, or various perspective angles were considered to get higher accuracy. Figure 2.10 shows the confusion matrix of the Yolo library obtained from the recognition process.

Table 2.2 Confusion matrix of Yolo v3-608 [12].

Actual class \ Predicted class	Stop	Parking	Crossing	Bump	Motorway	School Zone	No Entry	No Parking	Speed limit	Intersection
Stop	96.1	0	0	0	0	0	2.9	1	0	0
Parking	0	91.1	0	0	0	0	2.5	5.5	0.9	0
Crossing	0	0	82	2.5	7.9	0	3.6	4	0	0
Bump	0	0	0	95	0	2.6	0	0	0	2.4
Motorway	0	5.6	0	0	91.9	0	0	0	2.5	0
School Zone	5.8	5.4	0	0	0	85.2	0	2.9	0.7	0
No Entry	6.5	0	5.1	0	0	0	79.8	8.6	0	0
No Parking	0	0	0	0	0.8	0	8.9	84.7	0	5.6
Speed limit	0	2.1	0	0	0	0	0	0	92.7	5.2
Intersection	0.7	0	0	3.5	0	0	0	0	5.8	90

From all the abovementioned research, SVM and CNN classifiers are the most selected model to figure out the traffic sign problem; moreover; HOG features are also incredibly famous for overcoming this problem. Nevertheless, this formulated problem still has some more classifiers and features that are able to achieve it with high accuracy score. Therefore, this research methodology proposed the process to classify and recognize the traffic signs in Thailand by using two classifiers namely SVM and Random Forest (RF); moreover; the feature vector of this research consist of structure data of the image using histogram of oriented gradient, and the spatial color in the image using color layout descriptor as described in chapter III.

CHAPTER III
PROPOSED METHOD

The research approach is designed to cope with two principal tasks: classification and recognition. The first task is to categorize a given image of Thai traffic signs into classes: regulatory class, warning class, guide class, and construction class. For the second task, this research proposed recognizing the type of each Thai traffic sign image in their class. The system workflow is shown in Fig.1.

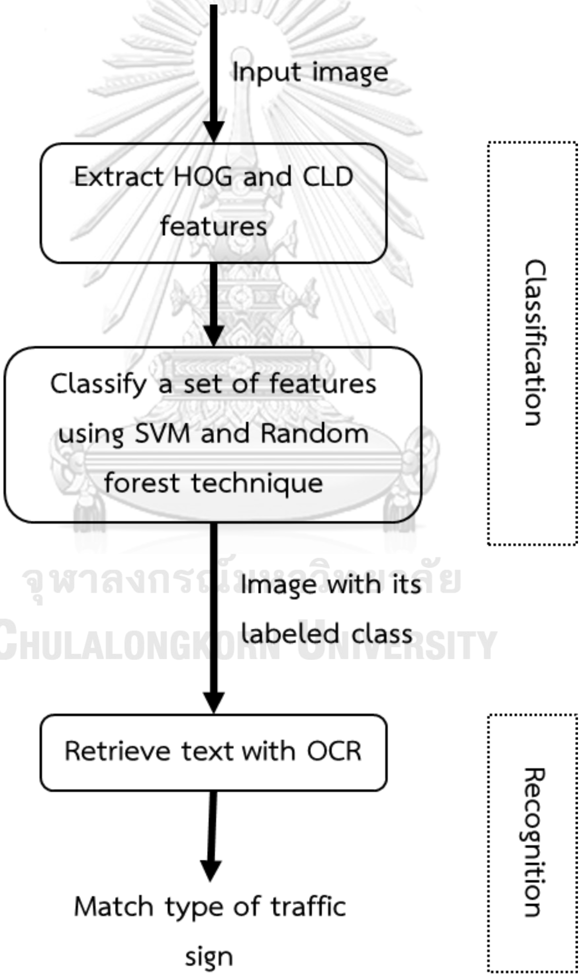


Figure 3.1 System workflow.

3.1 Classification task

The classification task of this study aims to arrange the Thai traffic sign into the defined classes by using the ability of support vector machine and random forest by using two different features to describe all the images.

3.1.1 Feature extraction

The features used in this research are Histogram of gradients (HOG) and Color Layout Descriptor (CLD) features. The HOG is used to describe the shape, texture, and dense of the images. In addition, the color of images is described using the CLD feature.

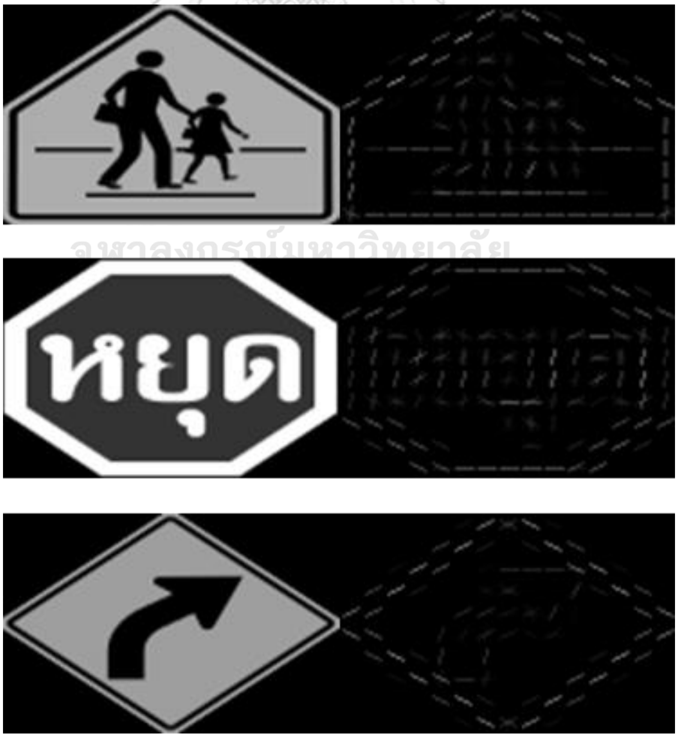
3.1.1.1 Histogram of oriented gradients (HOG)

The HOG feature is famous in the image processing and computer vision fields. To be more concise, the HOG feature can express the distribution of oriented gradients in the image. Before the feature extraction task begins, the images are resized into the pre-defined size as 120 x 80, then transforming their color space from RGB to a grayscale image.

The algorithm to extract the HOG feature starts with the global normalizing of the image. This step is to reduce the impact of illumination effects. The function will calculate each color channel's square root for minimizing the impact of illumination variations and shadows. Then, the system computes the gradient image on the x and y-axes. This step aims to calculate the image's gradient value using 1D centered point discrete derivative mask in two directions of images. For a gradient image, each value of a pixel represents change of intensity correponding to the pixel at the same position of the original image, in the specified direction. Next, the third step computes the gradient histogram by partitioning the image into cells containing 8 x 8 pixels. It means that each cell has 64 values of gradient magnitude and 64 values of gradient direction. For each cell, the system gathers a local 1D histogram of gradient, where each histogram spreads the gradient angle from 0 to 360 degrees. Next, the fourth step is normalizing across blocks, each of which contains 2 x 2 cells, or four local histograms and the system calculates the block normalization by using the L2-norm method to decrease the impact of light conditions on the interested area of 16 x 16 pixels. The L2-norm method is shown in equation (3.1).

$$f = \frac{v}{\sqrt{\|v\|_2^2 + e^2}} \tag{3.1}$$

where f is a normalized vector of one block, v is an original vector, $\|v\|_2$ is L2-norm of v, and e is a small real number. The normalized vectors from all blocks are combined as a histogram of oriented gradient descriptors. Fig.3.2 shows the example of original images with the images after extracting the HOG feature.



(a)

(b)

Figure 3.2 The original image (left) and image after extracting the HOG feature (right). (a) Example images from the training set. (b) Example images from the test set.

3.1.1.2 Color layout descriptor (CLD)

The CLD feature represents the image's spatial color distribution. The extraction of this feature consists of two main approaches: representative color selection based on grid and discrete cosine transform with quantization.

The grid-based substitutive color selection algorithm starts with partitioning the input image of size P x Q into 16 blocks where the size of each block is P/4 x Q/4. After that, the averaged RGB color value is calculated as a representative of each block. Then, the averaged RGB image is converted to the YCbCr color space. The Y is the luma component that represents the brightness in an image. Cb and Cr mean the blue component and red component associated with the green chroma component, respectively. In other words, the Cb means blue component without luma and the Cr means red component without luma. After finishing calculate YCbCr color space, the system applies the discrete cosine transform (DCT); thus, this step computes DCT coefficients in form of matrix of each color layer. In the last step for constructing the feature vector, the system uses zigzag-scanning to the DCT matrices to create the one output vector with 48 values as the CLD feature vector. The CLD feature extraction process is shown in Fig.3.3.

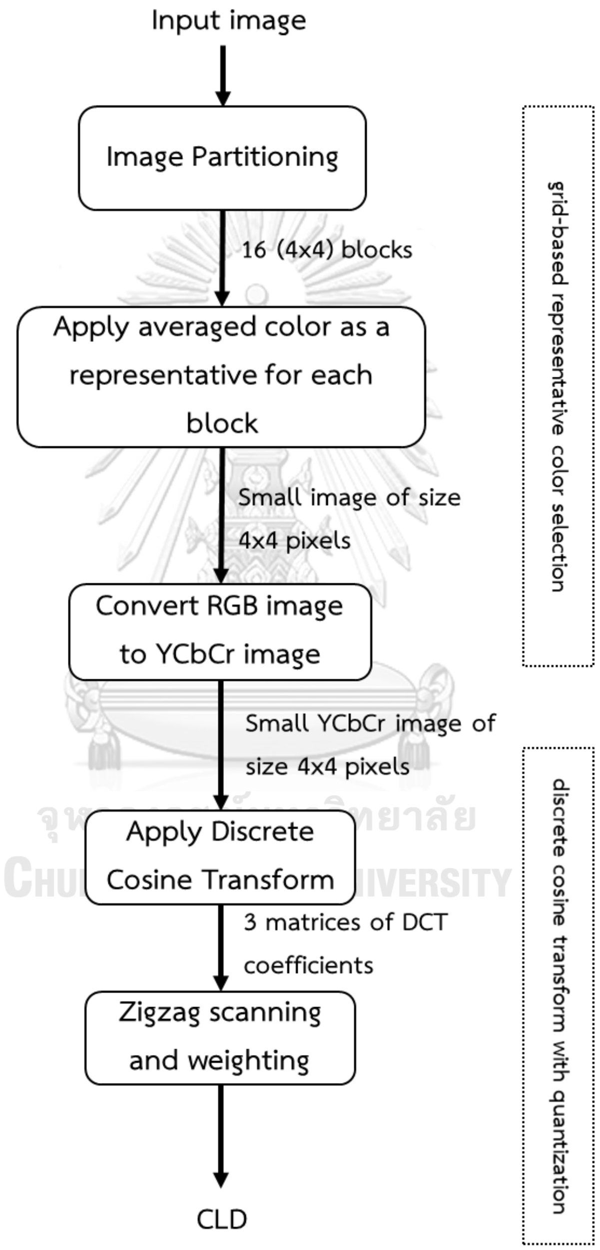


Figure 3.3 CLD feature extraction process.

3.1.2 Classification models

The classification models selected to classify the Thai traffic signs in this research are Support Vector Machine (SVM) and Random Forest (RF).

3.1.2.1 Support Vector Machine (SVM)

The support vector machine is known as a famous classification model used to achieve the traffic sign classification problem. The SVM classifier uses a hyperplane to partition the group of data in high dimensional space. The idea to find the decision line that separates the group of data is to find the decision line, which is to have the maximum distance between the decision line and the closest data points of any class. So, the data points at the boundaries are called support vectors. For this research problem, the SVM has to classify the multi-class data. Thus, the one-versus-rest approach performs as a classification strategy in this study. Using this approach, the SVM model trains model by pick one class of data compare with one another class. The one-versus-rest approach creates *n* SVM models if data have *n* classes. The example of the SVM model by using the one-versus-rest approach is shown in Fig.3.4.

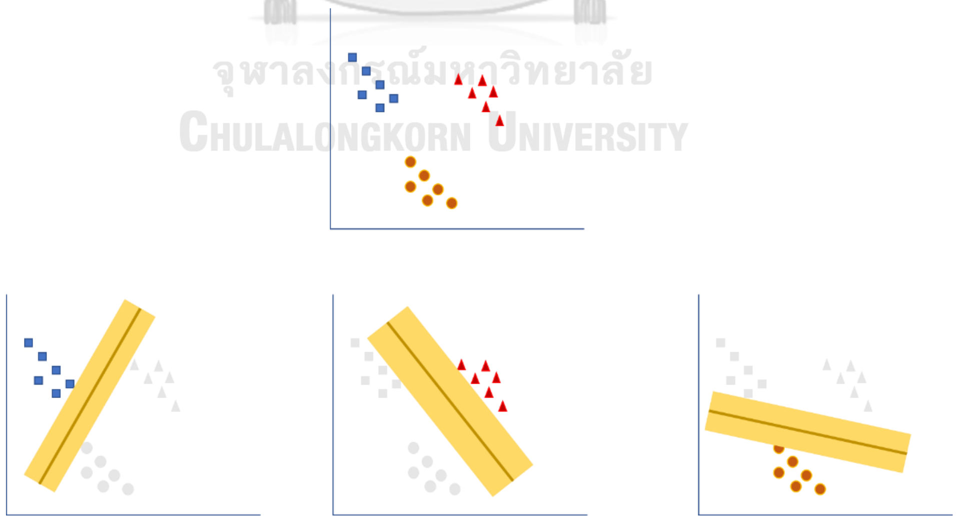


Figure 3.4 Illustration of training linearly multi-class SVM with a one-versus-rest approach.

Moreover, the SVM is able to modify its kernel function to fit the shape of the data. So that, in this research, the Radial Basis Function (RBF) is deployed as the kernel function to calculate the value that inversely proportional to the distance between a data point and the center of data using equation (3.2).

$$f(x) = e^{(-\gamma \|x-x'\|^2)} \tag{3.2}$$

where x is the point, x' is the center of data, and γ is a constant greater than 0.

3.1.2.2 Random forest (RF)

The random forest classifier is a model to classify the multi-class data. A random forest classifier aims to create the number of decision trees by using bootstrapping data. Before constructing the decision tree, the data set is separated into *n* sub-datasets for *n* sub-decision trees by different features and different instances. After finish partitioning the data set, each decision tree is trained separately using its sub-data set. For testing, when all decision trees finish their prediction, the most voting result will be the random forest output. Figure 3.5 shows the methodology of the random forest.

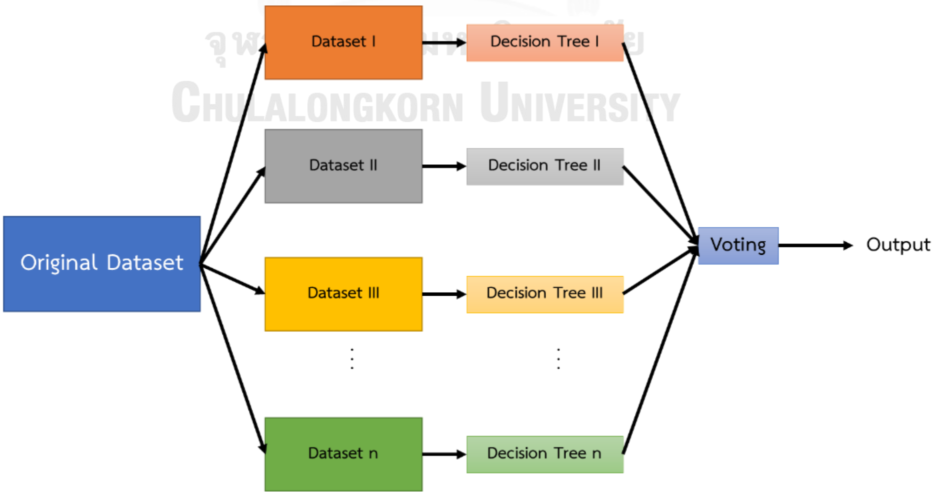


Figure 3.5 Methodology of Random Forest classifier

3.1.3 Classification methodology

The classification method in this study combines the feature and classification techniques from the previous section to construct the hierarchical classification model. This hierarchical classification model is shown in fig.3.6. The model is used to categorize the Thai traffic sign into four different classes: regulatory sign as class 1, warning sign as class 2, construction sign as class 3, and guide sign as class 4.

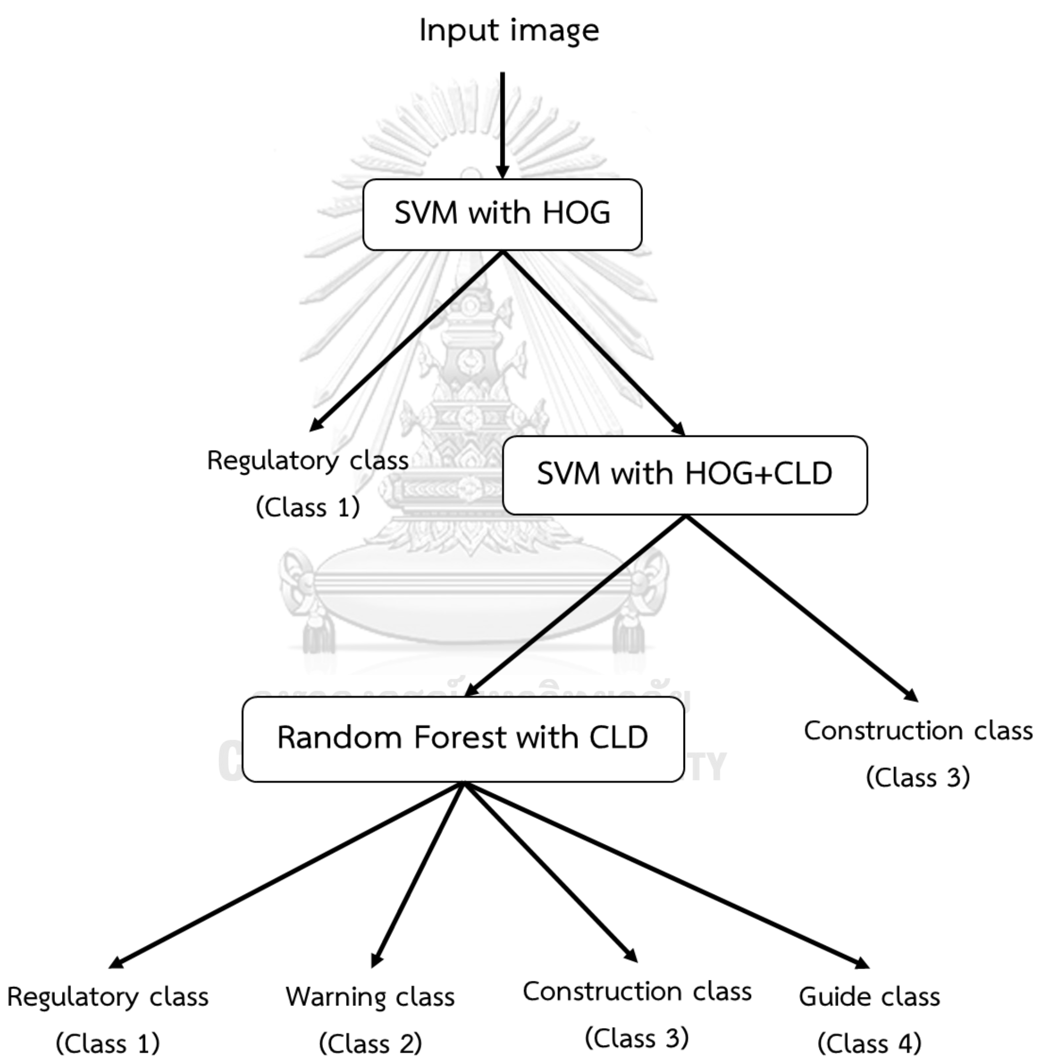


Figure 3.1 The hierarchical classification model for Thai traffic sign images.

This model procedure starts with the beginning step under the assumption that edge, shape, and density affect Class 1 with regulatory sign separation from a set of images. Therefore, the HOG feature using an SVM classifier with RBF is used to determine the sign image that fits in Class 1. Unless the sign image was in Class 1, the system will be passed the images into the second classifier. In this step, the two selected features: HOG and CLD were collaborated to allow color properties to be highlighted while retaining the shape properties. A construction sign in Class 3, can be filtered out at this step using an SVM classifier. The images that go through this process can be either Class 2 or Class 4 as a warning or guide signs respectively. From the consideration, Class 2 and Class 4 can be separated by the color property. Therefore, the CLD feature is used as the feature vector to comply with the RF classifier to flag an appropriate image class. In addition, certain images of Class 1 and Class 3 which are not specified by two prior SVMs, will also be classified according to the RF at the final step.

3.2 Recognition task

This task aims to distinguish the type of Thai traffic sign in this study. After finishing this task, each Thai traffic sign will be labeled with its real meaning. To identify their type, this recognition task uses the integration ability of two different techniques which are optical character recognition to recognize the character and template matching to find the most suitable matching template.

3.2.1 Optical Character Recognition (OCR)

The OCR is the technology that is widely used to recognize text inside images. In other words, OCR technology provides the ability to distinguish handwritten, printed, or painted characters from digital images. Thus, this benefit of OCR can apply to this study to take the Thai character out from the Thai traffic sign images.

Generally, OCR systems were constructed from a diverse combination of technology both software and hardware. In this study, the Pytesseract python library was chosen to use as an OCR tool to reach out the Thai character from input images. Pytesseract is the wrapper of Google's tesseract-OCR [13, 14]. The structure of this OCR engine was comprised by using various techniques including long-short-term memory (LSTM) line recognizer, character classifier, and language model. The brief system architecture shows in figure 3.7.

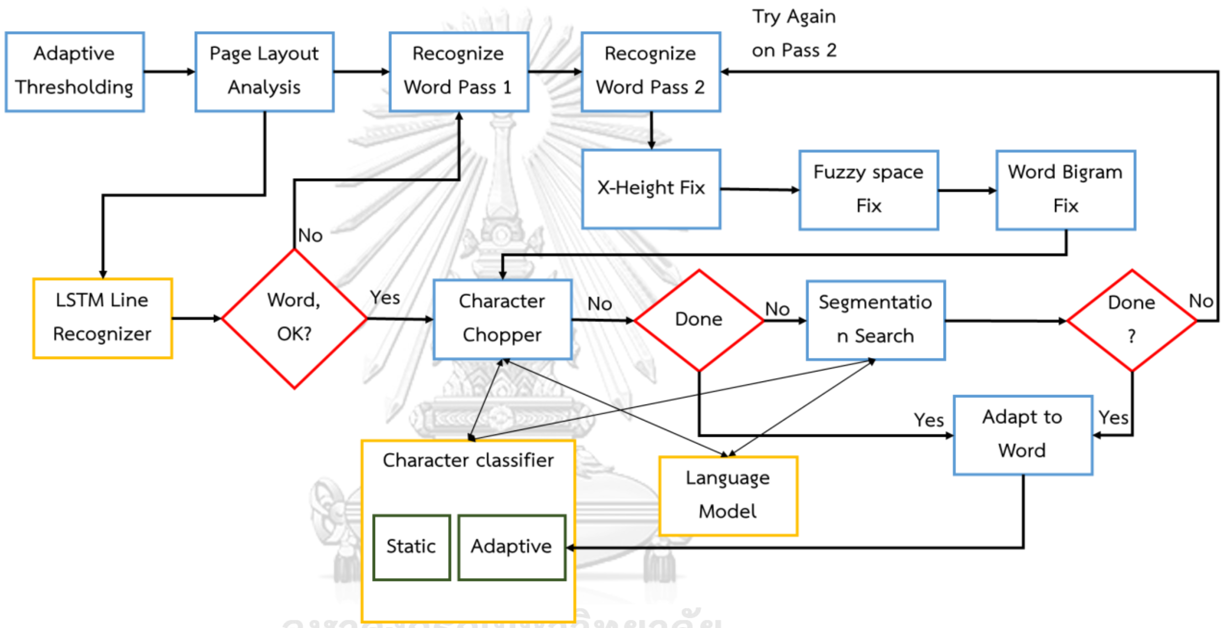


Figure 3.2 Abbreviated illustration of Google's Tesseract OCR system architecture

3.2.2 Template matching process

After extracting Thai character by OCR process, the images which were not considered as character image will send to the template matching process. In this process, the system finds out the most matching sign which is similar to the input image.

To match the template with the input image, the OpenCV template matching method was selected to use in this study [15]. The template matching method was used to find the area of the image that is similar to a template image. The template will simply slide into the image 2D dimensions and compute the matching score by the specific comparison approach.

To compare the template with input image in this proposed recognition task, the similarity value is calculated by using the Normalized Correlation Coefficient (NCCoef) method which is a comparison method that measure the matching score between the template image, which has no defect, and the input image with some real-world affections. Thus, equation (3.2) shows the computation of the score between the template T_i and the image I [16]

$$Score(T_i, I) = \frac{\sum_{x,y}(T_i'(x,y)\ I'(x,y))}{\sqrt{\sum_{x,y}(T_i'(x,y)^2)\sum_{x,y}(I'(x,y)^2)}} \quad (3.1)$$

where T_i' and I' are the normalized matrices from those two images. The image I is associted with the template T_j when $j = \underset{i}{argmax}\ Score(T_i, I)$

3.2.3 Recognition methodology

The recognition task in this research begins with the OCR method. In preparation for the OCR process, the colorspace is converted from the RGB colorspace to a grayscale. Then, Pytessaract which is an OCR engine will extract the Thai character from the source image. After finishing the OCR process, the image which has a Thai character will determine as wordy images of its predicted class. In contrast, the image which is not detected any Thai character from the OCR process will be proceeded further in the template matching.

For template matching, the system resizes the size of the input image to the pre-defined size of 320 x 160 pixels, which is the identical ratio to the template image. Then, the NCCoef method is used to compute the matching scores between the input and each template. Lastly, the template which has the highest matching score is used to identify the final output of this recognition task.

CHAPTER IV
EXPERIMENTAL RESULTS

The experiments and results of the classification task and recognition task are presented in this chapter. Moreover, the preparation of data sets used in this research is also shown.

4.1 Data set preparation

The Thai traffic sign images used in this research were retrieved from two data sources. Firstly, the images used for training the classification model and used as a template in the recognition task were assembled from the clear images in the manual of official traffic signs from the Department of Highways, Thailand.

On contrary, the images in the test set were screenshotted and cropped from Google Street View which has no differentiation. However, before the images were collected to the test set, all images background was manually removed. The examples of images from the training set and test set are shown in figure 4.1.

(a)

(b)

Figure 4.1 The images from a training data set (left) and the test data set with the same type (right)

(a) Regulatory class (b) Warning class (c) Construction class (d) Guide class

(c)

(d)

Figure 4.1 (cont'd) The images from a training data set (left) and the test data set with the same type (right)

(a) Regulatory class (b) Warning class (c) Construction class (d) Guide class

These two data sets consist of 4 classes: regulatory signs (class 1), warning signs (class 2),, construction signs (class 3), and guide signs (class 4). Each image in the data sets was labeled by one of these four classes.

The training data set consists of 408 images and there are 216 images in the test data set. The number of traffic sign images in each class is shown in Table. 4.1.

Table 4.1 The number of images in each class in the training and test data set.

Class	Training data set (images)	Test data set (images)
1	65	56
2	131	70
3	55	33
4	157	57
Total	408	216

4.2 Evaluation methods

4.2.1 Confusion matrix

To evaluate the accuracy of our model, the confusion matrix is used to visualize the achievement of the model. Each column shows the amount of data in the predicted class and each row shows the amount of data in the actual class.

From the data in the confusion matrix, it can be described in terms of metrics shown in table 4.2. The terms True Positive (TP), False Negative (FN), False Positive (FP), and True Negative (TN) represent the result of the correctness of the classification.

Table 4.2 Confusion Matrix

Actual \ Predicted	**Positive**	**Negative**
Positive	True Positive	False Negative
Negative	False Positive	True Negative

True Positive, TP, is the value that represents the predicted instances that are assigned correctly to the correct class which is the target class.

False Negative, FN, is the value that represents the predicted instances that are predicted to the incorrect class which is the nontarget class.

False Positive, FP, is the value that represents the predicted instances that are predicted to the incorrect class which is the target class.

True Negative, TN, is the value that represents the predicted instances that are assigned correctly to the correct class which is the nontarget class.

4.2.2 Precision

Precision measures the correctness of model prediction results that focuses on the target class only. In other words, it is the comparison of the number of correct prediction results of the target class and the total number of prediction results of the target class no matter what the result is correct or not. Equation (4.1) shows the formula for calculating precision.

$$precision = \frac{TP}{TP+FP} \tag{4.1}$$

4.2.3 Recall

The recall represents the accuracy of the actual value of the target class. It can be calculated from the division of the number of correct prediction results of the target class and the number of actual instances of the target class in both correct and incorrect results. This formulation shows in equation 4.2.

$$recall = \frac{TP}{TP+FN} \tag{4.2}$$

4.2.4 F-measure

F-measure is used as a single metric that can reflect the performance of the model. It can be calculated by using the value of precision and recall as equation 4.3.

$$F - measure = 2 * \frac{precision*recall}{precision+recall} \tag{4.3}$$

4.2.5 Accuracy

The accuracy score is used to represent the overall correctness which can be calculated by using equation 4.4

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{4.4}$$

4.3 Experimental methodology

The system workflow starts with extracting all features from both training and testing Thai traffic sign images. The step to extract the HOG feature starts with transforming a color image to a grayscale image. Next, the system resizes the image to 120 x 80 pixels. Next, the HOG feature extraction method is applied according to the details mentioned above in chapter 3. After finish extracting the HOG step, the system has already prepared the HOG feature for the training set and test set. In addition, to extract the CLD feature for both data sets, the system uses a RGB color image of a traffic sign to form a CLD feature vector by using the method in 3.1.1.2.

The feature vectors from those two techniques for each image: HOG and CLD are formed in the size of 4536 and 48 values respectively. Moreover, to classify class 3 in the hierarchical classification model, the system must merge two feature vectors to obtain the feature vector in size of 4584 values.

After preparing the feature vector, the proposed hierarchical classification model in section 3.1.3 is used to classify all images to their appropriate class. Besides classification by the proposed model, several models and features are trained and tested to compare with the proposed models. Those models and features include SVM using HOG feature, SVM using CLD feature, RF using HOG feature, RF using CLD feature, SVM using Discrete Fourier transform feature, and RF with Discrete Fourier transform feature. Hence, in this study, the scikit-learn library will be used to build the SVM [17][18] and RF [19] models. The important configuration parameters of SVM models in this hierarchical classification model are shown in table 4.3; in addition, the parameters for RF models are presented in table 4.4. All these experimental results are presented in the next section.

Table 4.3 The parameters list of SVM models

Parameter Name	Value	Meaning
decision_function_shape	ovr	Using one-versus-rest as a classification strategy
kernel	rbf	Using radial basis function as a kernel function
max_iter	-1	No limit on the number of iterations within the solver

Table 4.4 The parameters list of the RF model

Parameter Name	Value	Meaning
bootstrap	True	Decision trees are implemented by using bootstrap data
criterion	gini	Using Gini impurity to measure the quality of separation
max_depth	None	All nodes in the decision tree are spread until all leaves are pure
max_features	auto	The criterion number for considering when searching the best separation is equal to the square root of the total number of features.

Following the classification task, the system moves forward to the recognition task. The recognition containing OCR for extracting Thai characters and template matching for finding the most suitable template is used to determine the real meaning of a Thai traffic sign. For instance, whenever the cattle crossing sign is proceeded through the system, this image is firstly classified into the warning class and then the system indicates the sign type as cattle crossing warning sign in the final output.

As abovementioned, the recognition contains two sub-processes in this proposed approach. The OCR process determines whether the input image contains a Thai character or not. The OCR method in this study starts with converting an input image into a grayscale image. Then, the ability of Pytesseract, wrapper Google engine, as mentioned in section 3.2.1 is used to perform this OCR task. The image will be labeled as a wordy sign in their class if and only if it contains characters. In contrast, if characters are not detectable, the input image will be forwarded to the template matching process. The examples of results after applying the OCR process are shown in figure 4.2.

(a) (b)

Figure 4.2 Example of OCR results of Thai traffic signs in each class

(a) Regulatory class (b) Warning class (c) Construction class (d) Guide class

(c) (d)

Figure 4.2 (cont'd) Example of OCR results of Thai traffic signs in each class

(a) Regulatory class (b) Warning class (c) Construction class (d) Guide class

The template matching process is used to find the template image which is able to achieve the highest similarity score to compare with the input image from the test set. To compare these two RGB images, the system has to calculate the similarity score by using the Normalized Correlation Coefficient (NCCoef) as mentioned in equation 3.1.

The template matching begins with resizing both template and input image to 320 x 160 pixels. After this resizing, the similarity score will be calculated by using the NCCoef method. Meanwhile, the other comparative similarity scoring model namely the Sum of Squared Differences (SSD), the Normalized Sum of Squared Differences (NSSD), Cross-Correlation (CCor), Normalized Cross-Correlation (NCCor), and Correlation Coefficient (CCoef) methods are also calculated. The example of the template matching process using NCCoef is shown in Figure 4.3.

Finally, the final results after applying the recognition task are presented in the next section with comparative results of other similarity scoring models. Note that the results are presented in two different sets. The first set contains the results using the initial classes of the test set while the second set contains the results using the predicted classes of the test set from the classification task. The system workflow of this experiment shows in figure 4.4.

Figure 4.3 Example of template matching results of Thai traffic signs

(a) Regulatory class (b) Warning class (c) Construction class (d) Guide class

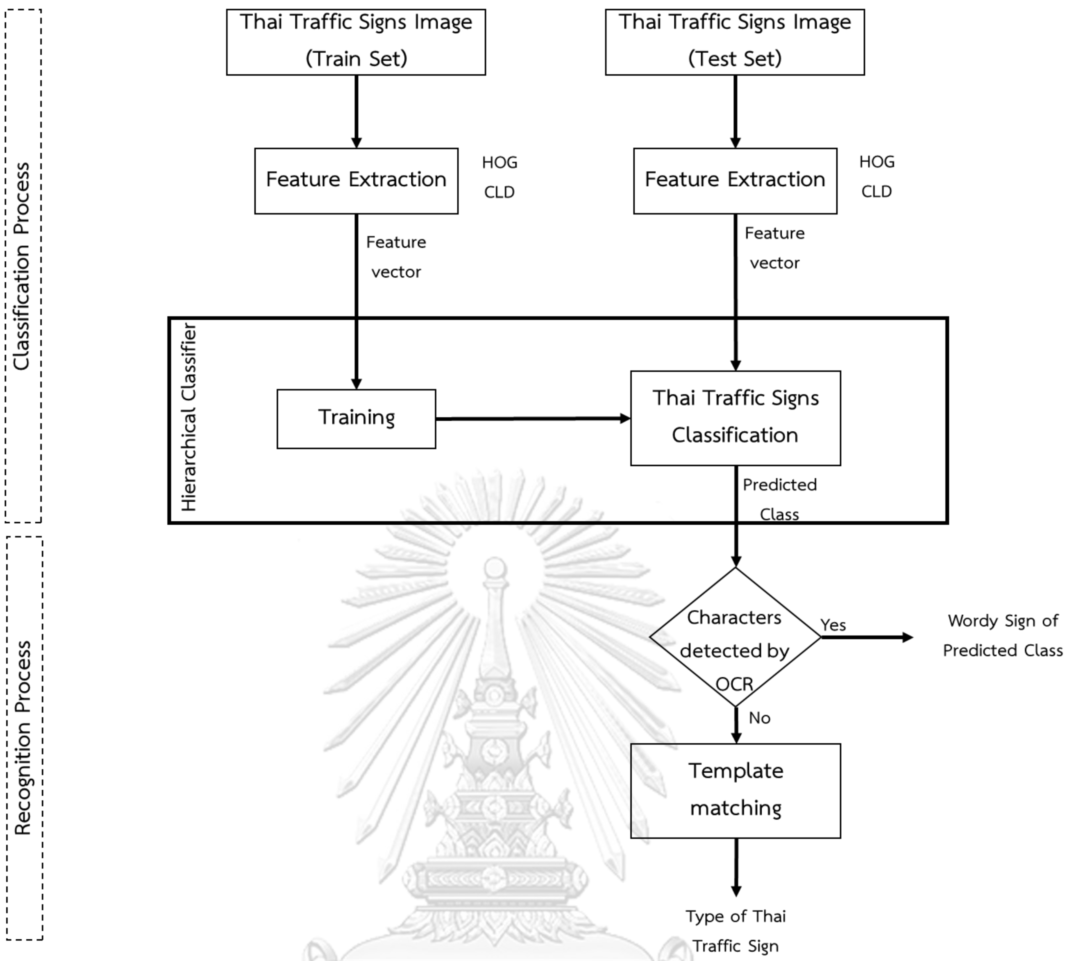


Figure 4.4 The overall system of this study.

4.4 Result

As mentioned above, this research aims to classify and recognize the Thai traffic signs. For the classification task, the proposed hierarchical classification model was performed classifying the input images into four classes using images for training and test with different data sets. The results of this classification model in terms of method accuracy and three metrics are presented in the next table.

Table 4.5 Classification results

Overall Accuracy 93.98%			
Class	**Precision**	**Recall**	**F-measure**
1	100.00%	89.29%	94.34%
2	97.01%	92.86%	94.89%
3	91.18%	93.94%	92.54%
4	87.69%	100.00%	93.44%

In Table 4.5, classification results are shown in terms of precision, recall, and f-measure of each class, and method accuracy. It shows that the overall accuracy of the proposed method is 93.98%. To be more precise, this hierarchical classification method can apply to the traffic sign images in real-world conditions while each class yields the f1-score of more than 92%. In addition, the precision of class 1, class 2, and class 3 are more than 90% but in class 4 the precision of 87.69% is quite less than those of the other classes. Besides, the highest precision at 100% in this experiment can be achieved by warning class, class 1. Furthermore, the recall scores of classes 2, 3, and 4 are greater than 92% while class 4 achieves 100% of recall. However, the recall rate of class 1 is quite less than the others even though it achieves nearly 90%. The last metric is the f1-score where the warning class, class 2, can achieve the highest f1-score at 94.89%.

In figure 4.5, the confusion matrix shows the correctness of the proposed hierarchical classification model. The information of this table can be used to analyze the performance of the models shown in table 4.5. Besides the information that has already been presented above in Table 4.5, the accuracy of individual class can be described by using the value in this confusion matrix.

Firstly, class 1, regulatory class, has 50 true-positive instances, 6 false-negative instances, none of the false-positive instances, and 153 true-negative instances so that from equation 4.4, the accuracy of class 1 achieves 97.13%.

Secondly, the accuracy of class 2 can calculate by 65 true-positive instances, 5 false-negative instances, 2 false-positive instances, and 138 true-negative instances. These four measurements represent the class 2 accuracy at 96.67%.

Next, the accuracy of class 3 is 97.60% calculated by 31 instances of true-positive, 2 instances of false-negative, 3 instances of false-positive, and 172 instances of true negative.

Lastly, the guide class, class 4, can achieve the accuracy at 97.60% from true-positive, false-negative, false-positive, and true-negative as 57, 0, 8, and 146 respectively.

Actual class \ Predicted class	Class 1	Class 2	Class 3	Class 4
Class 1	50	0	0	6
Class 2	0	65	3	2
Class 3	0	2	31	0
Class 4	0	0	0	57

Figure 4.5 Confusion matrix

Furthermore, the accuracy score comparison of proposed method against other combinations of classification model and feature is given as shown in Table 4.6

Table 4.6 Comparison of proposed method against other combinations of classification model and feature

Model and Feature	Accuracy
SVM with the HOG feature	75.46%
RF with the HOG feature	69.91%
SVM with the CLD feature	84.72%
RF with the CLD feature	85.18%
SVM with the Discrete Fourier Transform feature	26.39%
RF with the Discrete Fourier Transform feature	33.80%
Hierarchical classification model with HOG and CLD features	**93.98%**

.

From the table 4.6, the proposed method presented in bold can achieve the highest accuracy at 93.98%. Moreover, in the case of using either only CLD or both CLD and HOG can achieve an accuracy of more than 84%. On the other hand, when using only the HOG feature, SVM has a significant accuracy higher than RF. Finally, the least accuracy appears when using on Discrete Fourier Transform feature not only in SVM but also in RF.

After the proposed hierarchical classification model has been applied, the OCR and template matching in the recognition task are used to find out the real meaning of Thai traffic sign image. Thus, the final result after these two tasks using the actual class of each image is shown in Table 4.7 in terms of comparison among different matching methods.

Table 4.7 Comparison among different matching methods using actual class

Method	Accuracy			
	Class 1	Class 2	Class 3	Class 4
SSD	32.14%	52.86%	78.79%	64.91%
NSSD	35.71%	54.29%	78.79%	71.93%
CCor	14.29%	20.00%	63.64%	64.91%
NCCor	48.21%	50.00%	75.76%	73.68%
CCoef	51.79%	55.71%	75.76%	**80.70%**
NCCoef	**55.36%**	**58.57%**	**78.79%**	**80.70%**

From table 4.7, when comparing the NCCoef to the other classification methods it can yield the most significant accuracy of more than 78% in class 3 and class 4. However, class 1 and class 2 still maintain the highest accuracies when comparing with the other competitive matching methods.

Besides, the results after applying the recognition task by using the results from the classification task are shown in table 4.8.

Table 4.8 Comparison among different matching methods using classification result

Method	Accuracy			
	Class 1	Class 2	Class 3	Class 4
SSD	25.00%	50.00%	75.76%	64.91%
NSSD	28.57%	51.43%	75.76%	71.93%
CCor	7.143%	18.57%	63.64%	64.91%
NCCor	39.29%	47.14%	72.73%	73.68%
CCoef	44.64%	52.86%	72.73%	**80.70%**
NCCoef	**48.21%**	**55.71%**	**75.76%**	**80.70%**

From the above table, the trend of all data is in the same pattern as in table 4.7. When using the result from the classification task the accumulated errors affect the accuracies except class 4. Since class 4 is obtained 100% of recall, so the accuracies from both tables are all the same. In this table, the NCCoef combine with OCR can achieve the highest accuracies in all classes against the other matching methodologies.

CHAPTER V
CONCLUSION

From the experimental results of this study in the previous section, many perspectives will be shown in this chapter.

5.1 Discussion and Conclusion

To discuss in detail of classification task, it can be assumed that instances in class 4 have the most correct result when using the proposed hierarchical model, followed by class 3, class 2, and class 1 respectively. The proposed classification model can classify all instances of class four to their actual class, so the recall of this class is 100%. Besides, class 1 can achieve 100% precision. It seems that the classification model can reject all other classes from class 1 in this experiment. Although the proposed technique outperforms all other classification models and also accomplishes the recall of class 4 at 100%, this proposed model still needs some advanced development to achieve 100% of overall accuracy.

To focus on the classification results based on the results in the confusion matrix as shown in figure 4.5, it can be shown that some images are misclassified by this proposed hierarchical classification model due to various reasons such as the completeness of each traffic sign image. Figure 5.1 shows some examples of falsely predicted results from the proposed classification model.

(a)

(b)

(c)

Figure 5.1 The examples of the traffic signs yielding incorrect results

(a) Regulatory class (b) Warning class (c) Construction class

From figure 5.1, it can be noticed that the sign figure (a) has the object which partially occludes the traffic sign, resulting in the failure case. Another possible reason is that the sign has many characters that differ from the original pattern such that the classifier is not able to classify it correctly. For figure (b), the color tone is likely more orange than the actual tone, causing the present model to classify this traffic sign into class 3 instead of class 2 because most of the traffic signs in class 3 are dominated by orange color. Finally, the proposed classification model classified the sign figure (c) in the wrong class because it has a complicated texture and the lined pattern significantly different from the original appearance.

Moreover, in the final results after applying the classification and recognition task as shown in table 4.6, it is obvious that applying the proposed recognition technique based on Normalized Correlation Coefficient (NCCoef) can yield the most accurate matching score.

In conclusion of this study, there are two principal tasks. Firstly, the classification uses the proposed hierarchical classification model to indicate the category of the Thai traffic signs. This model uses the ability of two classification models: Support Vector Machine (SVM) and Random Forest (RF) to classify the real-world Thai traffic signs images captured from Google street view. This classification task uses two features Histogram of Oriented Gradient (HOG) and Color Layout Descriptor (CLD) to describe the image for both training and testing data sets. The accuracy result for classifying the Thai traffic sign images in this study is 93.98%. Then, the recognition task is mainly to label the Thai traffic sign images into their type. This task contains two sub-processes OCR and template matching. After applying all these steps, the accuracy of class 4 can achieve the highest percentage value at 80.70%.

5.2 Suggestion

To improve the system, future work might be required as follows:

1. Increasing the performance of classification to reduce the accumulated error from classification result to recognition task
2. Improving the ability of OCR by using the ability of natural language processing (NLP) techniques to improve its accuracy and output
3. Adding the step of the sign detection task before applying the current method.

4. Adding the extension of the method to cope with the real-time video.

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