LOGO CLASSIFICATION OF AMPHETAMINES BY SURF AND BAG-OF-FEATURES MODEL

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การจำแนกตราสัญลักษณ์ของแอมเฟตามีนโดยใช้เซิร์ฟและตัวแบบถุงฟีเจอร์

นายธารภณ นิธิจิรมน

วิทยานิพนธ์นี้เป็นส่วนหนึ่งของการศึกษาตามหลักสูตรปริญญาวิทยาศาสตรมหาบัณฑิต
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ธารภณ นิธิจิรมน : การจำแนกตราสัญลักษณ์ของแอมเฟตามีนโดยใช้เซิร์ฟและตัวแบบถุงฟีเจอร์. (LOGO CLASSIFICATION OF AMPHETAMINES BY SURF AND BAG-OF-FEATURES MODEL) อ.ที่ปรึกษาหลัก : รศ. ดร.นกุล คูหะโรจนานนท์

แอมเฟตามีนเป็นหนึ่งในยาเสพติดที่ตำรวจจับกุมได้ในประเทศไทย ในปัจจุบันเมื่อผู้ค้ายาบ้าถูกจับ ยาบ้าจะถูกส่งไปยังศูนย์ตรวจพิสูจน์หลักฐาน 1 เพื่อระบุแหล่งที่มาของยาบ้า แอมเฟตามีนแต่ละประเภทมีการจัดประเภทตามตัวอักขระที่พิมพ์ของตำรวจไปยังข้อมูลที่เกี่ยวข้องจากแหล่งของยาบ้า สำหรับแต่ละกรณีแอมเฟตามีนปริมาณมากจะถูกจัดประเภทโดยมีพนักงานเพียงสามคน มันเป็นงานที่ต้องใช้เวลามาก ในงานนี้นำเสนอกรอบการจำแนกภาพของยาบ้าตามตราสัญลักษณ์โดยใช้โมเดล SURF และ Bag-of-features ในงานนี้มีประกอบด้วยข้อมูลภาพสามประเภท Apple 192 ภาพ, R 103 ภาพ และ WY 360 ภาพ พบว่าพื้นผิวแอมเฟตามีนและคอนทราสต์ต่ำเป็นปัจจัยหลักที่ทำให้ความแม่นยำสำหรับการจำแนกประเภทต่ำ ดังนั้นผู้วิจัยจึงเสนอกระบวนการปรับปรุงคุณสมบัติหลักและลดสิ่งรบกวนบนพื้นผิวโดยใช้ฟิลเตอร์แบบปรับได้, Contrast-Limited Adaptive Histogram Equalization (CLAHE), รูปร่างที่ใช้งานและสัณฐานวิทยาของภาพ อัลกอริธึม preprocess ที่เสนอนี้เพิ่มความชัดเจนของตราสัญลักษณ์บนยาบ้าและลดสิ่งรบกวน นอกจากนี้เรายังใช้ SURF เพื่อแยกคุณสมบัติและจัดประเภทโดยใช้ Bag-of-features ผลการทดลองนี้แสดงให้เห็นว่าการประมวลผลล่วงหน้าที่เสนอสำหรับแต่ละขั้นตอนสามารถปรับปรุงความแม่นยำและความแม่นยำของวิธีการที่เสนอมากถึง 97 เปอร์เซ็นต์ จากนั้นเราพิจารณาการจำแนกโลโก้ WY ผลการวิจัยพบว่าความแม่นยำของวิธีการที่เสนอคือ 94 เปอร์เซ็นต์

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An amphetamine is one of the drugs apprehended by the policemen in Thailand. At present, when an amphetamine drug seller is arrested, captured amphetamines are sent to the Scientific Crime Detection Center Region 1 to identify the amphetamines' source. Each drug is classified based on the printed character to relevant information from the source of drugs. For each case, a large volume of drugs is sent to be classified by only three staff members. It is a time-consuming task. In this work, we propose a framework for classifying the image of amphetamines based on their logo using the SURF and Bag-of-features model (BoF). In this work, we have dataset consists of three types: Apple logo for 192 images, R logo for 103 images, and WY logo for 360 images. We found that the unsmooth surface and low contrast are the main factors of low accuracy for this classification. Therefore, we propose a process to enhance the main feature and reduce noise on the surface using an adaptive filter, Contrast-Limited Adaptive Histogram Equalization (CLAHE), active contour, and image morphology. Our proposed algorithm shows that the clarity of the logo on amphetamines is improved. We also then apply SURF to extract features and classify using BoF. This experimental result shows for each step can improve the accuracy and the accuracy of our method is up to 97 percent. The accuracy of the WY logo classification by our proposed method is 94 percent.

Field of Study:	Applied Mathematics and Computational Science	Student's Signature ....
Academic Year:	2019	Advisor's Signature ....

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Tharaphon Nitijiramon

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CHAPTER I

Introduction

The drug problem has been a problem in Thailand for a long time. It is a problem that will lead to various social issues such as crime, prostitution, and gambling. Besides, it is also a problem that affects national security, peace, morality, and economy. One of the common drugs apprehended by policemen in Thailand is amphetamine. The spread of amphetamines in Thailand becomes more severe and tends not to decrease at all.

Figure 1 News of the arrest of amphetamines dealers

Source: https://www.pptvhd36.com

When the amphetamine is consumed, it causes the body to be an alert, fast heartbeat, high blood pressure, palpitations, and nervous tension. After the drug effect is over, the consumer will feel exhausted and nervous. Furthermore, the consumers who consume amphetamine for a long time will cause dementia, hallucinations, delusions, paranoia, self-harm, and death. The appearance of amphetamine is similar to a general medicine pill having approximately 3 millimeters thick. There are many colors of amphetamines, but most popular colors are orange and green. Generally, amphetamine's logos are the WY logo, the R logo, the Apple logo, as shown in Figure 2.

Figure 2 The example logos of amphetamines

When the amphetamine dealers have been arrested, the amphetamines are sent to the Scientific Crime Detection Center for identifying the source of these amphetamines. After that, the collection of evidence, such as the size, the arrest date, and the arrest area, is investigated by the staff of the Scientific Crime Detection Center.

Figure 3 Amphetamines from the Scientific Crime Detection Center

Each amphetamine is recorded by taking a picture of the face of the amphetamine to capture its symbol so that the police officer can sort it by the logo. The symbol information on the amphetamines is unique for each tablet. It is a piece of essential information used to identify the manufacturers and production sources of those drugs. Different traders or production sources represent different characteristics of the logo. Currently, there are only three staff members in the proof center. Therefore, it takes a long time to sort the types of logos, and it is not convenient to consider when there are more amphetamines tablets. Thus, we want to use these photo data and software to identify drug sources more conveniently and rapidly.

Figure 4 The main step for classified each amphetamines

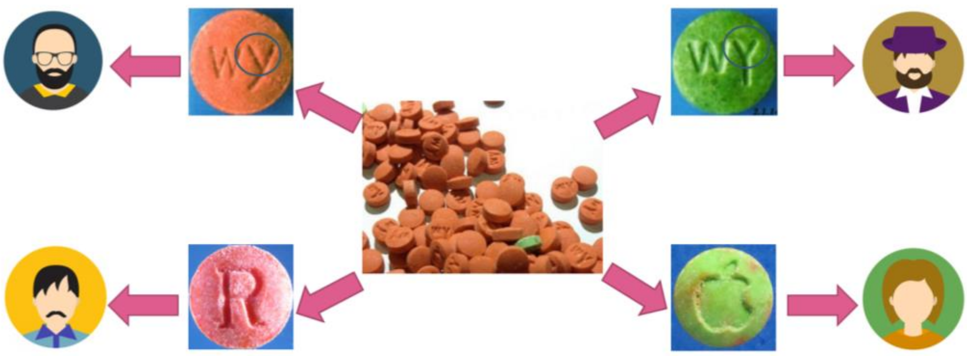


Figure 5 The logo is one of the information of traders or manufacturers of amphetamines

In our work, we propose an algorithm for the logo classification of amphetamines using photo data. Firstly, we select and prepare for amphetamines images. Secondly, we determine the extent of the amphetamines area. Then we separate the amphetamines area from the background. Finally, we extract the internal symbol characteristics of amphetamines and classify the logos using SURF and bag-of-features models.

The overview of background knowledge and details of the standard methods for image preparation and image classification are introduced in Chapter 2. In Chapter 3, we explain the concept of our methods. We want to construct the amphetamine classification process by extracting the features of the amphetamines logo and classify them using SURF and bag-of-features model. The results and our experiment are explained in Chapter 4. Finally, we discuss our proposed method and conclude the proposed method in Chapter 5.

1.1 Objectives

1.1.1 To apply SURF for image extraction from the Scientific Crime Detection Center

1.1.2 To construct an algorithm using the bag-of-features model to classify amphetamines logo based on Thai police officer criteria

1.2 Scopes and Assumptions

1.1.3 The amphetamines images used in this work are representations of a straight face of an amphetamine from the Scientific Crime Detection Center.

1.1.4 Each image contains the whole body of one amphetamine which is put on a sheet of paper with solid background.

1.1.5 The resolution of the images should be at least 124×124 pixels.

1.1.6 In this work, we consider two logo types of amphetamines based on Thai police officer criteria.

1) WY Logo

a. Straight

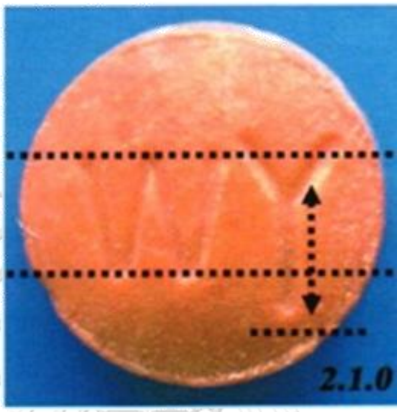


Figure 6 Straight WY Logo

b. Slant

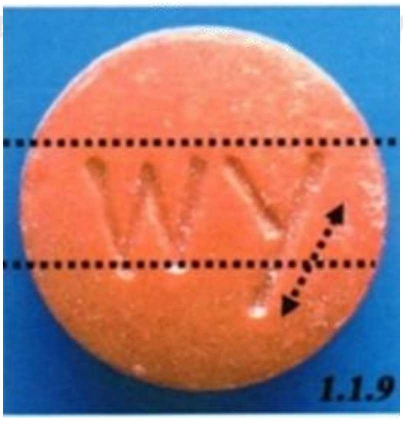


Figure 7 Slant WY Logo

c. Bent

Figure 8 Bent WY Logo

2) Apple Logo

Figure 9 Apple Logo

3) R Logo

Figure 10 R Logo

CHAPTER II

Background Knowledge and Literature Reviews

In this chapter, we will illustrate the background knowledge and literature reviews that are used in our proposed method. We use image processing to represent the image. Then, the adaptive filter and Contrast-Limited Adaptive Histogram Equalization (CLAHE) are used to adjust the picture. After that, we use active contour and erosion to emphasize the amphetamine's logo to be more evident. Finally, we apply two techniques: Speeded Up Robust Features and bag-of-features model for the classification.

2.1 Background Knowledge

2.1.1 Introduction to image processing

Image processing is a technique to perform operations on an image for enhancing pictures and extracting useful information. Generally, the input is an image, and the output may be image or features associated with that photo. Nowadays, image processing is one of the rapid technologies within the engineering and the computing machine science area [1].

There are two categories of methods used for effigy processing, namely, parallel and digital prototype processing. Analog image processing can be used for hard copies like printouts and exposure. Image analysts use various fundamentals of interpretation while using these visual techniques. Digital image processing techniques use computation for handling the digital image. All digital image processing techniques compose three general phases: preprocessing, display, and information extraction. [1, 2].

In this work, our input image is a digital image. It is represented by a rectangular region or a matrix of picture elements called pixels. The value of each pixel part represents brightness or color level in a small region surrounding the corresponding point. Typically, pixel values are quantized into an integer value between 1 and 16 bits or 10 bits of digital reporting. The number of bits per component, or per pixel, is called the bit profoundness [3].

For ground substance indexing, axis orderliness is reversed from Cartesian coordinates: A ground substance is indexed by wrangle the column. The top row of a matrix has the smallest index, so the matrix exponent lies in the quadrant quarter. In mathematics, matrix elements are ordinarily identified using 1-origin indexing. Some image processing software packages use 1-origin indexing – in particular, MATLAB, which has deep roots in mathematics. The scan demarcation order of conventional video and image processing usually adheres to the matrix convention. However, with the zero-origin indexing, rows and columns are traditionally numbered [r, c] from [0, 0] at the top left. In other words, the image is in the fourth quadrant (but eliding the negative sign on the y-coordinate), but ordinarily using the zero-origin indexing [2].

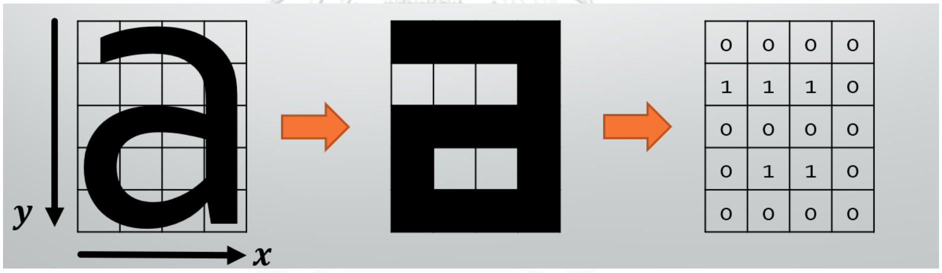


Figure 11 The concept of 2-bit image

So, a grayscale trope is a two-dimensional function $f(x, y)$, where x and y are the spatial (plane) coordinates, and the amplitude at any duo of coordinate (x, y) is called the intensity of the black and white at that level. Grayscale images have many dark levels of gray. In general, it has 256 different intensities or 8-bit grayscale. The example of grayscale image is shown in Figure 12.

$f(2724,2336) = 88$

Figure 12 The amplitude of the example grayscale image at pixel (2724,2336)

A color image is a picture that includes color data for each pixel. The RGB (Red Green Blue) color space is commonly used in computer presentation, but other color spaces such as YCbCr (Yellow Magenta Cyan) and HSV (Hue Saturation Value) are often used in other contexts. The color image has three values per pixel, and they measure the intensity and chrominance of light. The example of color image is shown in Figure 13.

$g(2724,2336) = (10,10,224)$

Figure 13 The amplitude of example color image at pixel (2724,2336)

We can change the color image into a grayscale image. However, in general, the conversion of a color image to a grayscale image is not unique. In this work, we use weighted sum R, G, and B components in this form

$$f(x,y) = 0.2989 \times R + 0.5870 \times G + 0.1140 \times B$$

where $f(x,y)$ is intensity of the greyscale image at pixel (x,y).

2.1.2 Adaptive filters

Adaptive filters are used in image processing to enhance or restore information by removing noise without essentially blurring the image's structures. The evidence behind adaptive image filtering varies the filtering method as the kernel slides across the image to obtain its local properties and structures. They can be cerebration of as self-adjusting digital filters. Certain kinds of adaptive filters may perform better than median filters at removing impulse noise. They have often used for denoising non-stationary photos, which tend to exhibit abrupt intensiveness changes. Because the filtering operation is no longer uniform and instead modulated based on the local properties of the picture, these filters can be employed when there is little a priori cognition of the signal being processed [4, 5].

This method estimates the local mean (μ) and variance (σ^2) around each pixel, follow as these equations:

$$\mu = \frac{1}{MN} \sum_{n_1, n_2 \in \eta} a(n_1, n_2),$$

and

$$\sigma^2 = \frac{1}{MN} \sum_{n_1, n_2 \in \eta} a^2(n_1, n_2) - \mu^2,$$

where η is the filter size *N*-by-*M* local neighborhood of each pixel in the image (a). The filter then creates a pixel-wise adaptive filter using these estimates

$$b(n_1, n_2) = \mu + \frac{\sigma^2 - \nu^2}{\sigma^2}(a(n_1, n_2) - \mu)$$

where ν^2 is the noise variance and b is the output image. If the noise variance is not given, this filter uses the average of all local estimated variances [5].

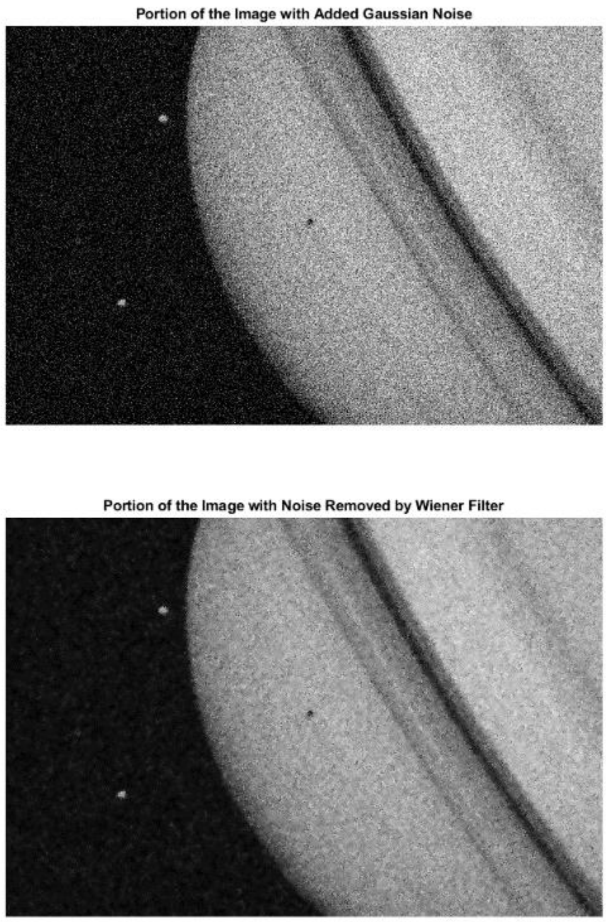


Figure 14 Example image of before and after use adaptive filter

Source: https://www.mathworks.com/help/images/ref/wiener2.html

2.1.3 Contrast-Limited Adaptive Histogram Equalization (CLAHE)

Contrast-Limited Adaptive Histogram Equalization (CLAHE) is the image enhancement process. It is performed to enhance the luminance component of the image. Then this image is reconstructed into gray space. The same white-balanced image is sharpened using unsharp masking, and histogram equalization is applied to the enhanced image. Weight maps are calculated for the processed images. The input images and weight maps are fused using multiscale fusion. It operates on a small part in the image rather than the entire image. The CLAHE algorithm has three parts [6].

1) The image is divided into sections. Each section is called a tile.

2) We construct histogram equalization performed on each tile using a pre-defined clip limit. Histogram equalization consists of five steps.

   a) Histogram computation
   b) Excess calculation
   c) Excess distribution
   d) Surplus redistribution
   e) Scaling and mapping using a cumulative distribution function (CDF).

   This histogram is computed as a set of bins for each tile. Histogram bin values higher than the clip limit are accumulated and distributed into other containers. CDF is then calculated for the histogram values. CDF values of each tile are scaled and mapped using the input image pixel values.

3) The resulting mosaics are stitched together using bilinear interpolation, to generate an output image with improved contrast [7].

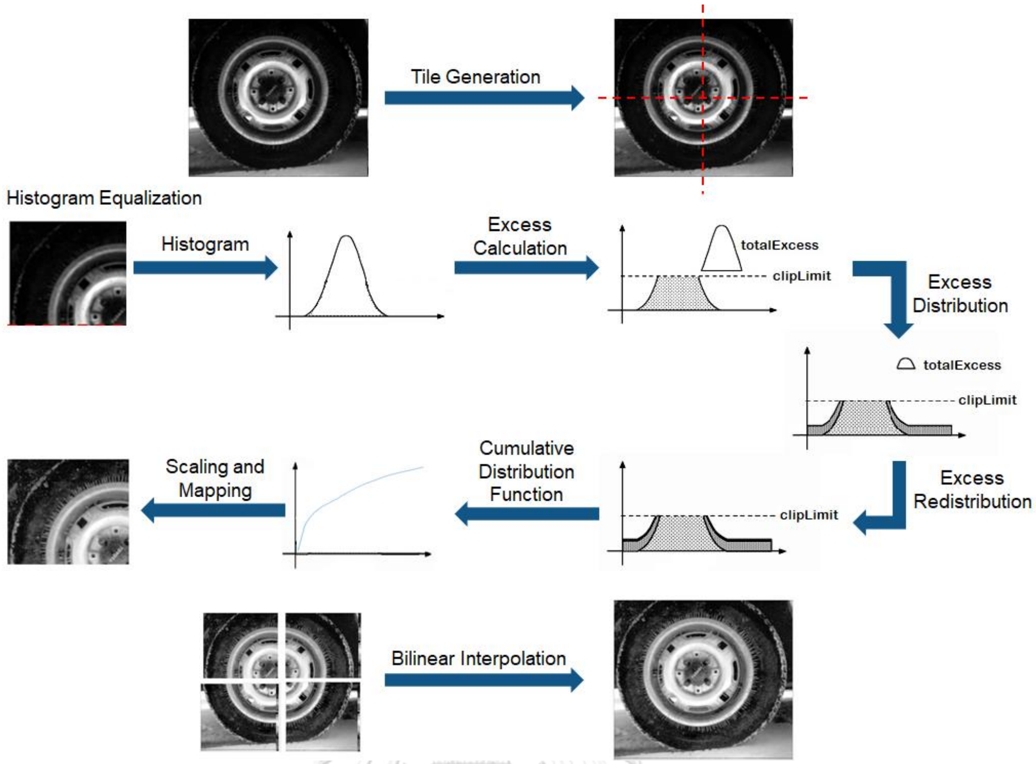


Figure 15 Overview of CLAHE Algorithm

Source: https://www.mathworks.com/help/visionhdl/ug/contrast-adaptive-histogram-equalization.html

2.1.4 Active contour

The well-known methods for image segmentation could be classified as follows: region segmentation, contour segmentation, and texture segmentation [8]. Active contour is a kind of the segmentation technique that can be defined as the use of energy forces and constraints for the segregation of the pixels of interest from the image for further processing and analysis. The interpolation method can be linear, splines, and polynomial, which describes the curve in the image [9]. Different models of active contours are applied for the segmentation technique in image processing [8, 9].

For the set of points in an image, this contour can be defined based on forces and constraints in the image's regions. This contour is used in various applications in the segmentation of the images. Different types of active contour models are used in various applications especially for the separation of required regions from the various images [9].

The main application of active contours in image processing is to define smooth shape in the image and form closed contour for the region. Active contour models involve a snake model, gradient vector flow snake model, balloon model, and geometric or geodesic contours. This contour segments the image into foreground and background. Using the contour algorithm, we specify curves on the icon that move to find object boundaries. The technique evolves the segmentation using an iterative. The argument of the mask is a binary image that specifies the initial state of the contour. The boundaries of the object parts (white) in masks define the initial contour position used for contour evolution to segment the image. The output image is a binary image where the foreground is white (logical true), and the background is black (logical false) [10].

2.1.5 Erosion

Erosion is a primary operator in mathematical morphology. It is ordinarily applied to binary images, but there are versions that work on grayscale images. It removes pixels on object boundaries. The number of pixels removed from the interest object in a picture depends on the size and form of the structuring element used to process the image. In the erosion process, the state of any given point in the output image is determined by applying a rule to the corresponding point and its neighbors in the input image. The rule used to process the pixels defines the operation as an erosion. The significant effect of the operator on a binary image is to erode the boundaries of parts of foreground pixels. Note that the foreground pixels typically are white pixels. Thus, parts of foreground pixels shrink in size, and holes within those areas become larger [11].

For the binary erosion of A by B, denoted $A\,\theta\,B$, it defines as the set operation

$$A\theta B = \{z|(Bz \subseteq A\}$$

where A is a binary image, B is a structuring element, Z is an element of a structuring element, and B_z is a structuring element.

In other words, it is the set of point locations z, where the structuring element translated to location z overlaps only with foreground pixels in A.

In the grayscale erosion, the image f erodes by the structuring element b, where B is the space that b is defined

$$(f \ominus b)(x) = \inf_{y \in B}[f(x+y) - b(y)]$$

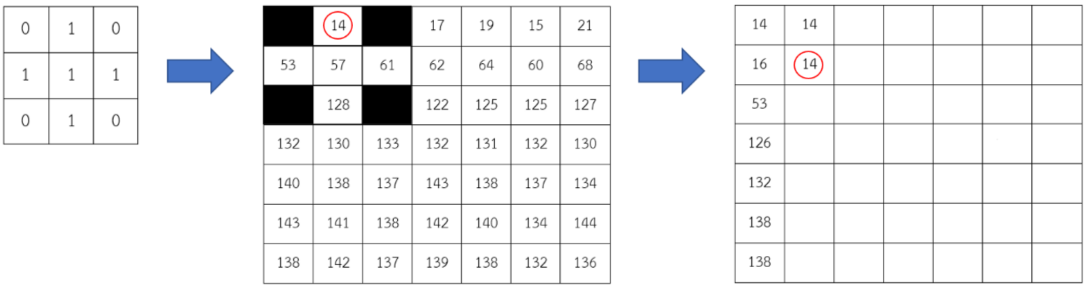
Otherwise, the erosion of a pixel is the minimum pixel in its neighborhood, with that neighborhood defined by the structuring element. Note that erosion removes islands and small regions so that only substantive objects remain [12].

16	14	14	17	19	15	21
53	57	61	62	64	60	68
126	128	124	122	125	125	127
132	130	133	132	131	132	130
140	138	137	143	138	137	134
143	141	138	142	140	134	144
138	142	137	139	138	132	136

(a)

0	1	0
1	1	1
0	1	0

(b)



(c)

14	14	14	14	17	15	15
16	14	14	17	19	15	60
53	57	61	62	64	60	125
126	128	124	122	125	125	130
132	130	133	132	131	132	134
138	138	137	138	134	132	134
138	137	137	137	132	132	132

(d)

Figure 16 (a) the original grayscale image, (b) the structuring element, (c) Erosion step of the image in (a) with the structuring element (b).

(c) the result from erosion of the image in (a) with the structuring element (b).

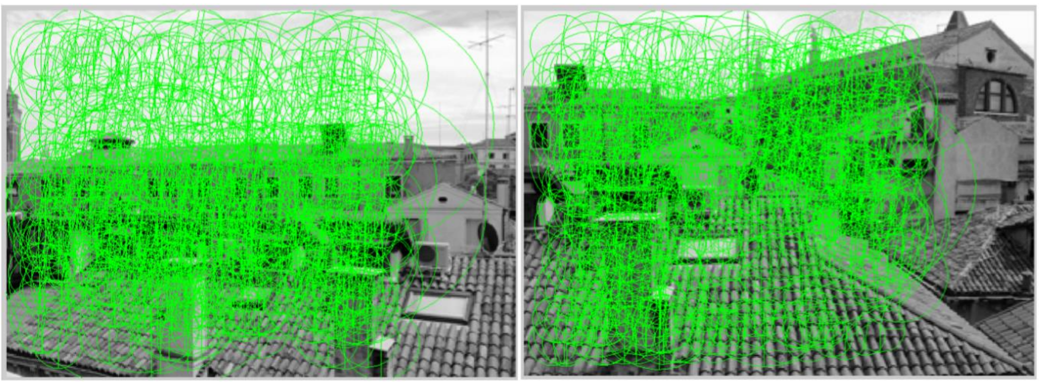
2.2 Literature Reviews

2.2.1 Speeded Up Robust Features (SURF)

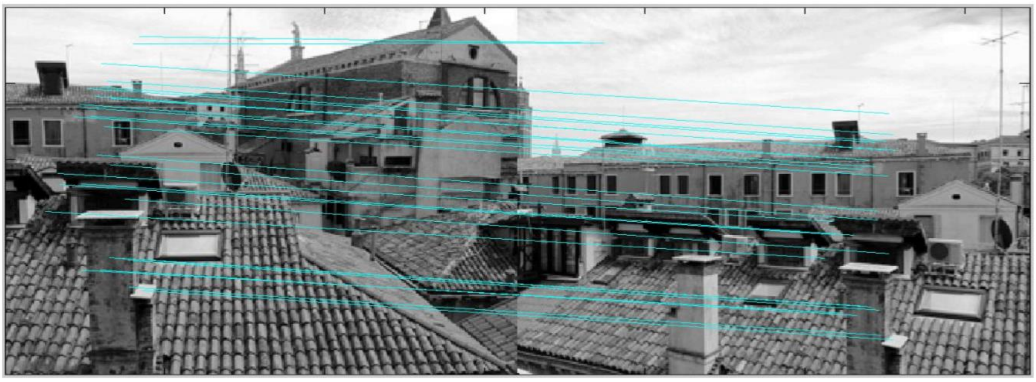
Speeded Up Robust Features (SURF) are a feature detector and descriptor. SURF was published by Herbert Bay, Tinne Tuytelaars, and Luc Van Gool [13, 14]. They present a different scale and rotation-invariant interest point detector and descriptor, coined SURF. It approximates or even outperforms formerly proposed schemes to repeatability, distinctiveness, and robustness, yet it can be computed and compared much faster. SURF is accomplished by relying on integral images for image convolutions; by building on the good point of the leading existing detectors and descriptors and simplifies these methods to the essential. SURF leads to a combination of novel detection, description, and matching steps. This method presents experimental results on a standard evaluation set and imagery obtained in the context of a real-life object recognition application. Both show SURF's strong performance [15].

So, it detects a smaller number of features than Scale Invariant Feature Transform (SIFT), but SURF is fast and has excellent performance the same as SIFT. P. M. Panchal, S. R. Panchal, and S. K. Shah showed that this technique had evaluated two feature detection methods for image registration. Based on the experimental results, it is mentioned that SIFT has detected a more significant number of features than SURF, but it has suffered from speed. SURF is fast and has excellent performance as the same as SIFT. Their future scope is to make these algorithms work for video registration [16]. They showed results are summarized in Figure 17 and Table 1.

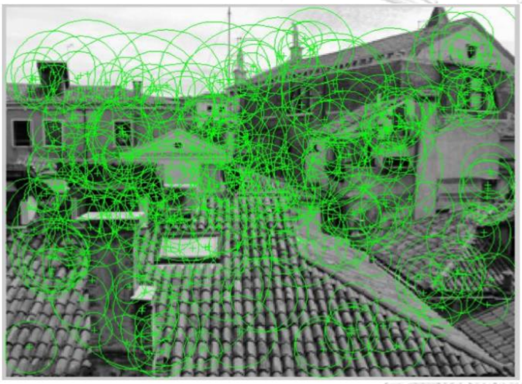
(a) Original Image1 (b) Original Image2

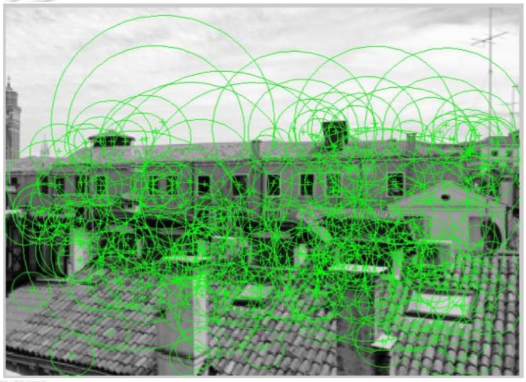


(c) Detected features in image1 using SIFT (d) Detected features in image2 using SIFT

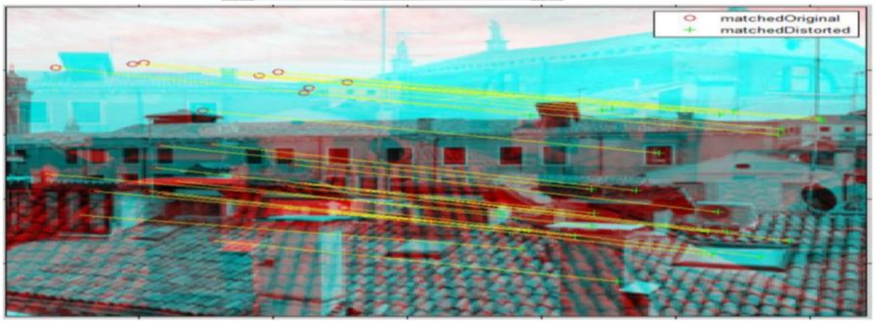


(e) Matching pairs identified between the image1 and image2





(f) Detected features using SURF in image1 (g) Detected features using SURF in image2



(h) Matching pairs identified between the image1 and image2

Figure 17 Comparisons of results of SIFT and SURF algorithm [16]

Table 1 Comparisons of results of SIFT and SURF algorithm [16]

Algorithm	Detected feature Points		Matching feature point	Feature matching Time
	Image1	Image2		
SIFT	892	934	41	1.543 s
SURF	281	245	28	0.546 s

Next, we move to the SURF algorithm part. the SURF algorithm has three main parts: detection, description, and matching.

In the detection section, SURF uses square-shaped filters. Filtering the image with a square is much faster if the integral image is used. An integral image is an equipment that can be used whenever we have a function from pixels to real numbers, and we want to compute the sum of this function over a rectangular region of the image. Examples of the integral images that have been applied include texture mapping that is published by Crow in 1984, face detection in images that are published by Viola and Jones in 2004, and stereo correspondence published by Veksler in 2003.

The sum can be calculated in linear time per rectangle by calculating the value of each pixel's function individually. However, if we need to compute the sum over multiple overlapping rectangular windows, we can use an integral image and achieve a constant number of operations per rectangle with only a linear amount of preprocessing [17, 18]. The integral image at location contains the sum of the pixels above and to the left of, inclusive:

$$if(x, y) = \sum_{x' \leq x, y' \leq y} f(x', y')$$

where $if(x, y)$ is the integral image and $f(x, y)$ is the original image.

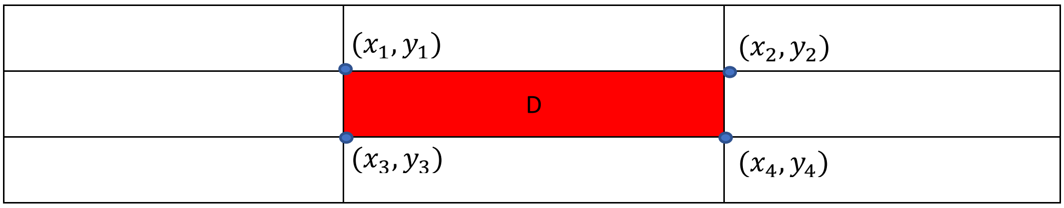


Figure 18 Example of calculation of the integral image at area D

The sum of the initial image within a rectangle can be evaluated rapidly using the integral image, requiring the value of an integral image at the rectangle's four corners. For example, we can calculate an integral image at area D in Figure 18 by

$$if(x_4, y_4) - if(x_3, y_3) - if(x_2, y_2) + if(x_1, y_1)$$

SURF uses the hessian matrix to look for points of interest. The hessian matrix explains the second-order variations of local intensity around a pixel, thereby encoding the shape information. It describes the local curve of the spatial structures over the whole picture. It has been used to detect structure orientation, noise, and structure brightness and differentiate blob-like, sheet-like, and tubular structures. The hessian matrix is suited for corner detection, which can be used for interest object localization and shape to detect [19]. It is the square matrix defined follows

$$\begin{bmatrix} \frac{\partial^2 f}{\partial x_1^2} & \cdots & \frac{\partial^2 f}{\partial x_1 \partial x_n} \\ \vdots & \ddots & \vdots \\ \frac{\partial^2 f}{\partial x_n \partial x_1} & \cdots & \frac{\partial^2 f}{\partial x_n^2} \end{bmatrix}$$

where f is a function from $\mathbb{R}^n$ to $\mathbb{R}$.

And the derivative of image I at pixel $p = (x, y)$ (x-direction) is

$$\frac{\partial I}{\partial x} = I(x+1, y) - I(x-1, y).$$

Similarly,

$$\frac{\partial I}{\partial y} = I(x, y+1) - I(x, y-1).$$

Then we can calculate the second-order derivative of Gaussian as follow

$$L_{xy}(p) = \frac{\partial^2 I}{\partial x^2} + \frac{\partial^2 I}{\partial y^2}.$$

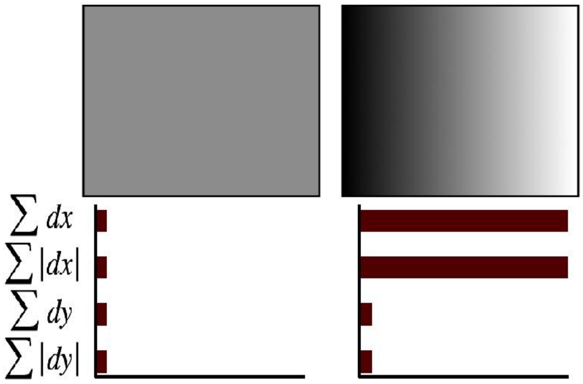
The hessian matrix $H(p)$ at point $p = (x, y)$ is

$$H(p) = \begin{bmatrix} L_{xx}(p) & L_{xy}(p) \\ L_{xy}(p) & L_{yy}(p) \end{bmatrix}$$

where $L_{xx}(p)$ is the second-order derivative of Gaussian with image I at point $p$and similarly for $L_{xy}(p)$ and $L_{yy}(p)$.

In the description section, a descriptor is based on the sum of wavelet responses. The wavelet responses dx and dy are summed up over each small region and form the first set of entries to the feature vector. We also extract the sum of the absolute values of the responses, $|dx|$,and $|dy|$. Hence, each sub-region has a four-dimensional descriptor vector $\boldsymbol{v}$ for its underlying intensity structure $v = (dx , dy , |dx |, |dy |)$.

In the matching section, we only compare features if they have the same kind of contrast. For example, the picture below.



No match

Figure 19 Example of matching of both difference images

Source: SURF: Speeded Up Robust Features by Herbert Bay, Andreas Ess, Tinne Tuytelaars, and Luc Van Gool

2.2.2 Bag-of-features model

The early decade has seen the growing popularity of Bag of Features model approaches to many computer visions tasks, including texture recognition, robot localization, video search, and image classification. Part of the appeal is simplicity. This model is based on orderless collections of quantized local image descriptors; they discard spatial data and are therefore conceptually and computationally easier than many alternative methods [20-22].

Bag-of-features model was presented by Gabriella Csurka, Christopher R. Dance, Lixin Fan, Jutta Willamowski, Cédric Bray. They showed this model in visual categorization with bags of key points. They presented a novel method for generic visual classification: identifying the object content of original images while generalizing across variations fundamental to the object class. This model was based on vector quantization of affine invariant descriptors of image patches. They proposed and compared two alternative implementations using different classifiers: Naïve Bayes and SVM. The main advantages of the model were that it was simple, computationally efficient, and intrinsically invariant. They presented results for simultaneously classifying seven semantic visual categories. These results demonstrated that the method was robust to background and produces good categorization accuracy without exploiting geometric information [23-25].

It also often referred to as Bag-of-words. It is a method of assigning a group label to an image under test. The advantages of this method are works for image classification that we have limited data. It can be learning object types from a few training data [26-28]. This benefit of this model suitable for our work with limited images.

The key idea is to treat images as loose sets of independent patches, sampling a representative set of pieces from the picture, properly evaluating a descriptor vector for each part independently, and using the resulting distribution of available samples in descriptor space characterization of the image [29]. The algorithm has four main steps:

Step 1: Organize and partition the images into the training set and test set then separate the collections into training and test image subsets.

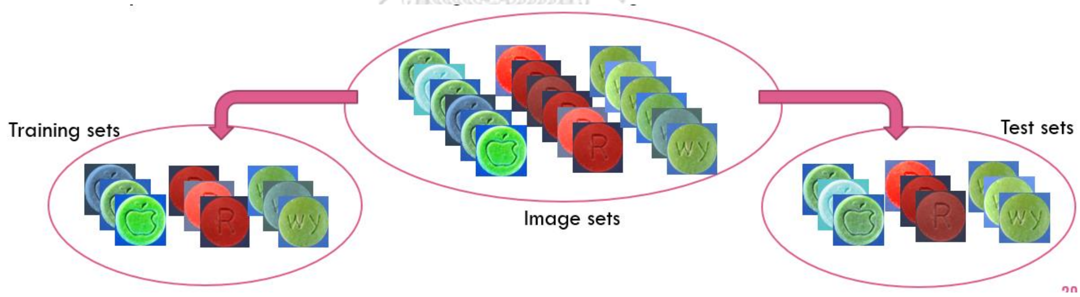


Figure 20 Step 1 of bag-of-features model

Step 2: Create a visual feature by extracting feature descriptors from representative photos of each kind.

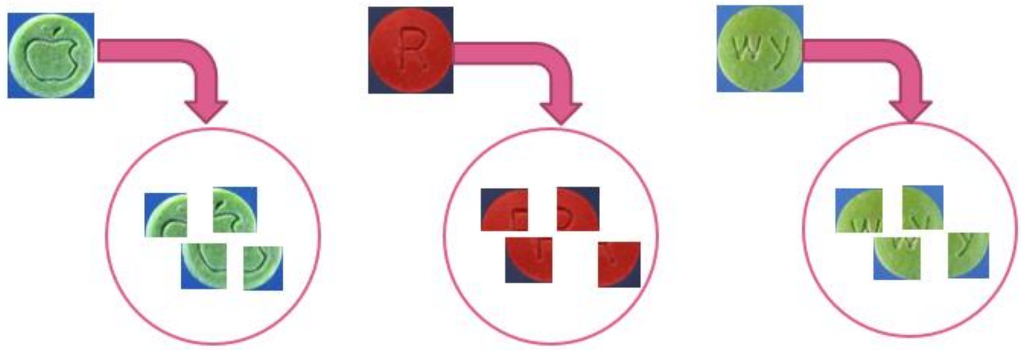


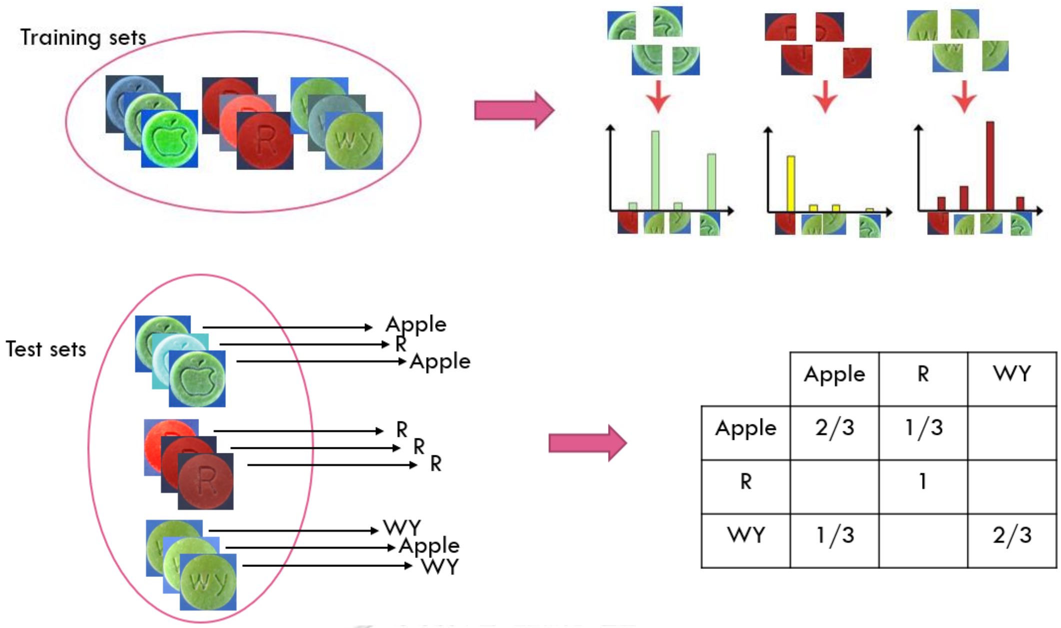
Figure 21 Step 2 of bag-of-features model

Step 3: Train an image classifier with bag-of-visual-features. This step has three sub-steps:

1. Apply the bag of features method to each image from the training set. This method accurately detects and extracts features from the photo and then uses the approximate neighbor algorithm to create a feature histogram for each image. The number of visual features corresponds to the histogram length that the bag of features objects constructed. The histogram can represent a feature vector for the picture.

2. Repeat step 1 for each data in training set to create the training data.

3. Check the quality of the classifier by testing the classifier against the validation data set. The output is a confusion matrix that represents the analysis of the forecast. The best image classification result is a matrix consisting of 1s on the diagonal.



	Apple	R	WY
Apple	2/3	1/3	
R		1	
WY	1/3		2/3

Figure 22 Step 3 of bag-of-features model

Step 4: Classify a data or data set

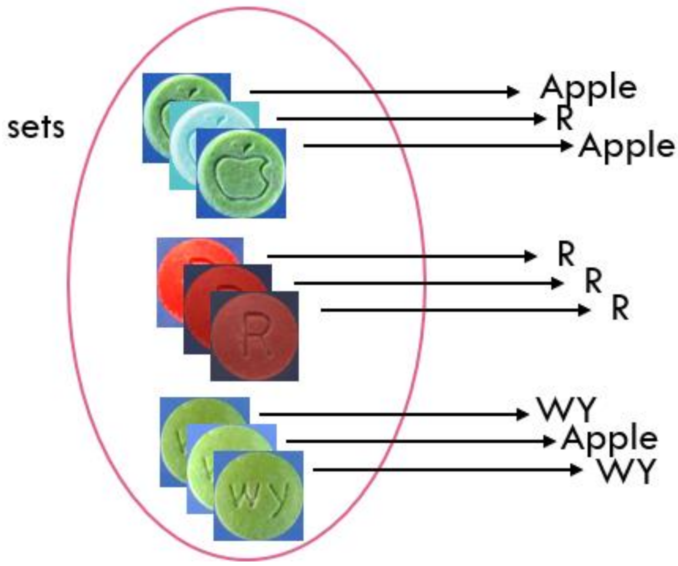


Figure 23 Step 4 of bag-of-features model

CHAPTER III

Methodology

In this work, we propose an alternative process to improve amphetamine images for logo amphetamine classification. We separate our process into two main steps. The first step is preprocessing. We convert the input image from RGB into grayscale. Then the image is blurred and enhanced to reduce noise and clean logo groove. Next, we emphasize the logo groove by using contour segmentation and erosion. The second step is image classification by applying two techniques: SURF and Bag-of-features model. Figure 24 shows the primary stage of our method.

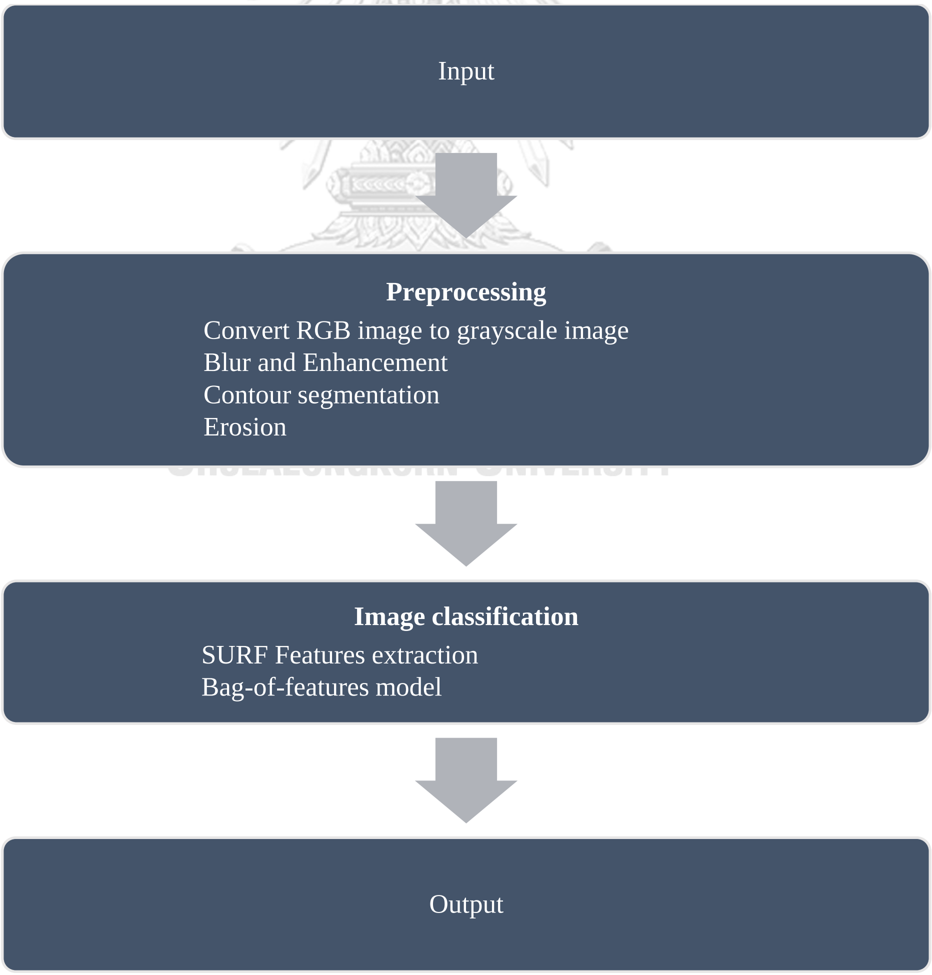


Figure 24 The main step of our method.

Before the classification step, we select amphetamine images which contain the whole body of one drug. The drug is put on a flat plane with a solid background. The resolution of the images is 124×124 pixels, as shown in Figure 25. Since the color of the drug does not affect the editing of images, we then convert the RGB color images that we have stored into black and white images. After that, it is selected for use in the next step for the selection of images. We consider the area of potholes that are mixed on the surface. The image contains more than half of the pitting area of the drug we do not use as training photos. We rotate the logo not to tilt more than $\frac{\pi}{18}$ radians relative to the center of the logo and cut the background to see the full tablet as in Figure 26 We consider three logotypes of amphetamines based on Thai police officer criteria: WY, R, and Apple.

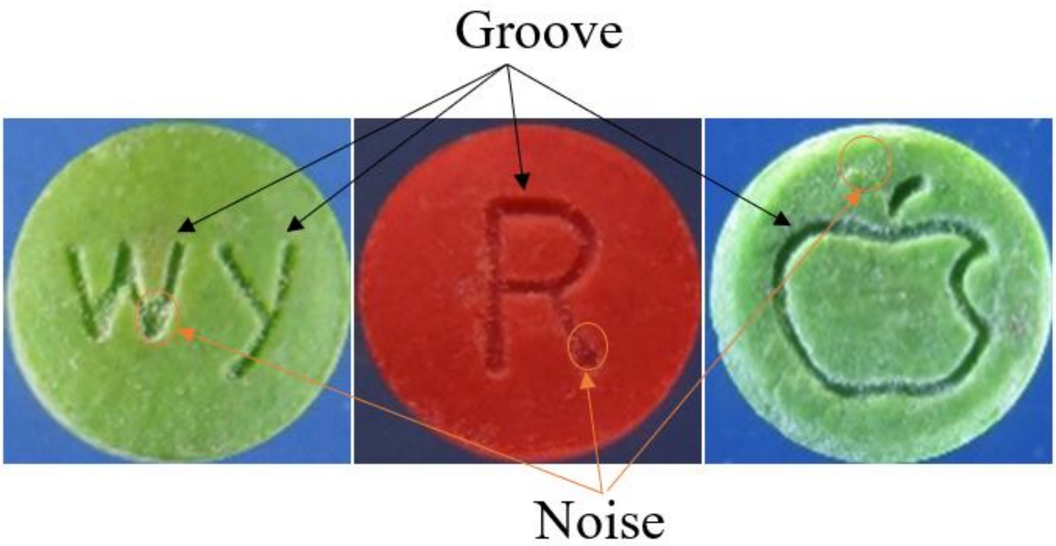


Figure 25 Example amphetamines images in our work

Figure 26 Example amphetamines images before they are improved

3.1 Proposed method for preprocessing

In the preprocessing step, this is the first part of adjusting amphetamines images. We improve amphetamines images by the adaptive filter, Contrast-Limited Adaptive Histogram Equalization (CLAHE), Active contour, and Erosion using a disk-shaped structuring element. Figure 27 shows the proposed method.

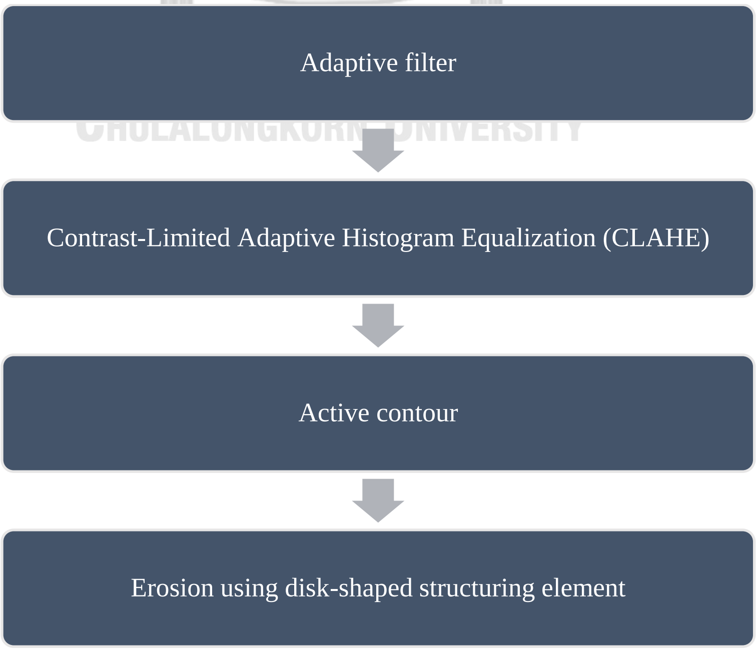


Figure 27 The process of the preprocessing.

In this part, we improve images four steps. The first step is to get rid of the noise on the surface. Notice that the noise characteristics we encounter are usually salt-pepper noise, so we choose the adaptive filter for this work. We try to use the adaptive filter of size 3x3, 5x5, 7x7, 9x9, and 11x11. We choose the adaptive filter of size 9x9 because it gives the best result for this work. The example of amphetamine images after they are improved by the adaptive filter are shown in Figure 28.

Figure 28 Example amphetamines images after they are improved by adaptive filter

Next, we want to adjust the picture so that only the boundaries of the groove are clear. We need to adjust the image to make the logo more clearly by using Contrast-Limited Adaptive Histogram Equalization (CLAHE). This algorithm has the following steps [6, 7].

1) We divide the image into non-overlapping contextual regions. The number of tiles is equal to 8x8, which is an excellent value to preserve the chromatic image data.

2) We calculate the histogram of each contextual area according to gray tiers present in the array image.

3) We calculating the limited contrast histogram of the contextual area by clip limit value as

$$N_{arg} = \frac{(NrX \times NrY)}{N_{gray}}$$

where N_{avg} is the average number of pixels, N_{gray} is the number of gray levels in the contextual area, NrX and NrY are the numbers of pixels in the X dimension and Y dimension of the contextual space. The actual clip limit can be expressed as

$$N_{CL} = N_{clip} \times N_{avg}$$

where N_{CL} is the actual clip limit, N_{clip} is the normalized clip limit in the range of [0, 1]. Note that we choose 0.01. If the number of pixels is more significant than N_{CL}, the pixels will be clipped. The total number of clipped pixels is defined as $N_{\sum clip}$, then the average of the remaining pixel to distribute to each gray level is

$$N_{avggray} = \frac{N_{\sum clip}}{N_{gray}}$$

The following statements give the histogram clipping rule

If $H_{region}(i) > N_{CL}$ then $H_{region\_clip}(i) = N_{CL}$

Else if $\left(H_{region}(i) + N_{avggray}\right) > N_{CL}$ then $H_{region\_clip}(i) = N_{CL}$

Else $H_{region\_clip}(i) = H_{region} + N_{CL}$

where H_{region} and H_{region_clip} are original histogram and clipped histogram of each region at i-th gray level.

4) Redistribute the remaining pixels until the remaining pixels have been all distributed. The step of redistribution pixels is given by

$$Step = \frac{N_{gray}}{N_{remain}}$$

where N_{remain} is the remaining number of clipped pixels.

5) The intensity values in each region are enhanced by Rayleigh transform. The clipped histogram is transformed into cumulative probability, $P_{input}(i)$, which is provided to create the transfer function [30]. Rayleigh forward transform is given by

$$y(i) = y_{min} + \sqrt{2\alpha^2 \ln\left(\frac{1}{1 - P_{input}(i)}\right)}$$

where y_{min} is the lower bound of the pixel value, and α is a scaling parameter of Rayleigh distribution that is defined depending on each input data. From [7], The good α value in Rayleigh function is 0.04. The output probability density of each intensity value can be expressed as

$$p\big(y(i)\big) = \frac{(y(i)) - y_{min}}{\alpha^2} \cdot exp\left(-\frac{(y(i) - y_{min})^2}{2\alpha^2}\right) \text{ for } y(i) \geq y_{min}$$

6) We reduce the changing effect. The output from the transfer function is re-scaled using linear contrast stretch. The linear contrast stretch can be given as

$$y(i) = \frac{x(i) - x_{min}}{x_{max} - x_{min}}$$

where $x(i)$ is the input value from the transfer function, x_{min} and x_{max} denote the minimum and maximum value of the transfer function.

7) We calculate the new grayscale assignment of pixels within a matrix contextual area using a bilinear interpolation between different mappings to eliminate boundary artifacts.

The example amphetamines images after they are improved by CLAHE are shown in Figure 30.

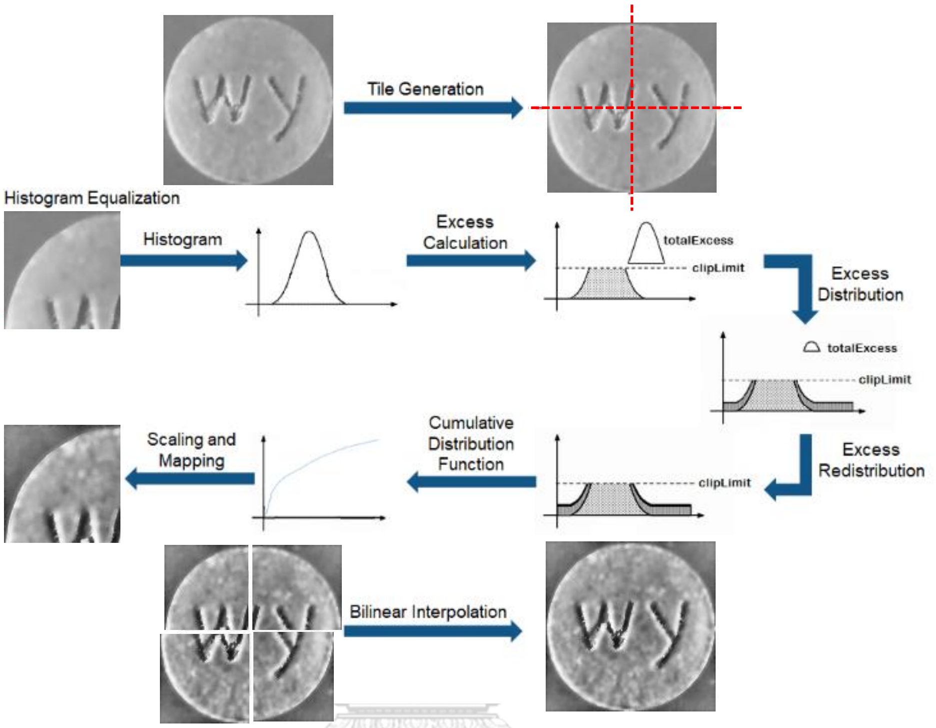


Figure 29 Overview of CLAHE with amphetamines image

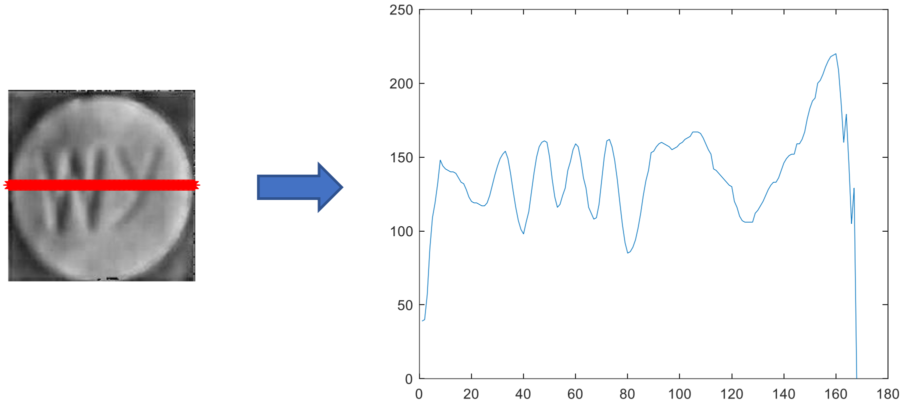
Figure 30 Example amphetamines images after they are improved by CLAHE

Then, we want to focus on the areas with more logos to narrow the scope of the amphetamines. In this work, we use the active contour method, call contour. The technique spits out the segmentation using an iterative process. For this work, it performs 100 iterations. The mask argument is a black and white image that specifies the initial status of the contour. The boundaries of the object parts (white) in masks define the initial contour position used for the contour process to segment the image. The output image is a black and white image where black is the background, and white is the foreground [8, 10]. The example amphetamines images after they are improved by active contour are shown in Figure 31.

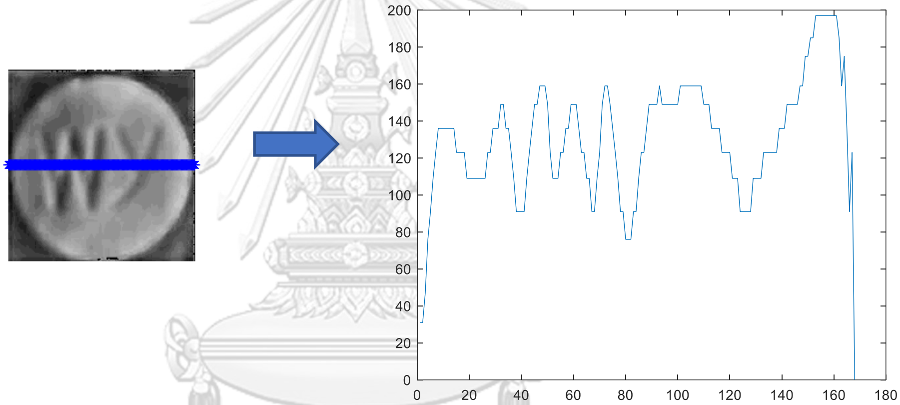
Figure 31 Example amphetamines images after they are improved by active contour

In the last step of the preprocessing part, we need to emphasize the amphetamines logo to be more evident. We have applied erosion to customize images with quantized images using specified quantization levels, with the following steps:

1) We quantize the image from the previous step using specified quantization in the threshold grayscale image from 256 to 16. Because it guarantees we can find the value of the mode. For example, we plot the intensity of the red line through the drug of origin image. The graph is hard to find the mode. But we plot the intensity of the blue line through the drug same red line of quantizing image. The graph is a step graph. It easy to find mode and guarantee that we have the value of the mode. Figure 32 shows the comparison of (a) and (b).



1) The origin image with its intensity at red line through



2) quantizing image with its intensity at blue line through

Figure 32 The comparison intensity value of (a) and (b).

2) We determine the mode of the image's grayscale value to store the intensity of the drug surface. We do not count the intensity equal to zero because we get a background with magnitude the same to zero after performing the previous steps.

3) We specify the line through the drug order to keep the x-position with an intensity equal to mode, which grayscale value of surface, and find the period x-position. We can see that the period of x-position is the hole of the logo groove. In

this work, we use three lines in the approximate size of the drug groove are $y=\frac{Y}{4}$, $y=\frac{Y}{2}$, and $y=\frac{3Y}{4}$, where Y is the vertical width in pixels.

4) We choose the smallest width range (R) as the width of the seal groove that is suitable to determine the radius than we construct a disk-shaped structuring element with a radius of $\frac{R}{4}$.

The examples of amphetamine images after they are improved by erosion are shown in Figure 33.

Figure 33 Example amphetamines images after they are improved by erosion

Recall, we adjust the grayscale image. We want to reduce distractions on the drug surface and focus more clearly on the amphetamines mark. It shows in Figure 34.

(a) (b) (c) (d) (e)

Figure 34 Amphetamines image during each preprocessing: (a) grayscale image, (b) blur images of (a) using adaptive filter, (c) enchanced images of (b) using CLAHE, (d) contour images of (c), and (e) eroded images of (d) using disk shaped structure element

3.2 Classification by Bag-of-features model with SURF

In classifying the amphetamines logo, we use the concept of the Bag-of-features model with the following steps.

Step 1: we partition the images into category each training and test.

Step 2: we construct a visual feature by extracting feature descriptors from representative data of each category. In this step, we construct a extracting feature descriptors by SURF.

Step 3: we train an image classifier with bag-of-visual-features. This step has three sub-steps:

1) Apply the Bag-of-features method to each image from the training set. This process accurately detects and extracts features from the data and then uses the approximate nearest neighbor process to construct a feature histogram for each model. The histogram's length corresponds to the number of visual features that the Bag-of- features objects built. The histogram is a feature vector for the image.

2) Repeat the previous step in the training set to create the training data for each image.

3) Test the classifier against the image from the test set to check the quality of the classifier. The output confusion matrix represents the analysis of the forecast—a perfect classification results in a normalized form consisting of 1s on the diagonal.

CHAPTER IV

Results and Discussion

We applied our method using 655 of amphetamines images from the narcotics sub-division, Police Forensic Science Center 1, Office of Police Forensic Science. This dataset consists of three types: Apple logo for 192 images, R logo for 103 images, and WY logo for 360 images. For this work, we will compare four classification experiments as follows Figure 35 - 38.

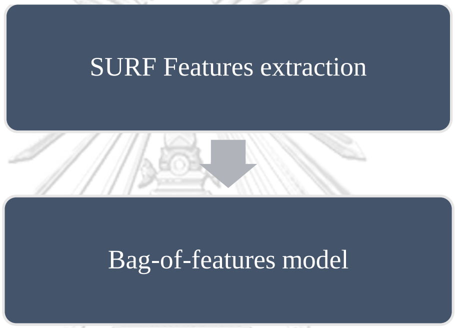


Figure 35 Format of experiments 1

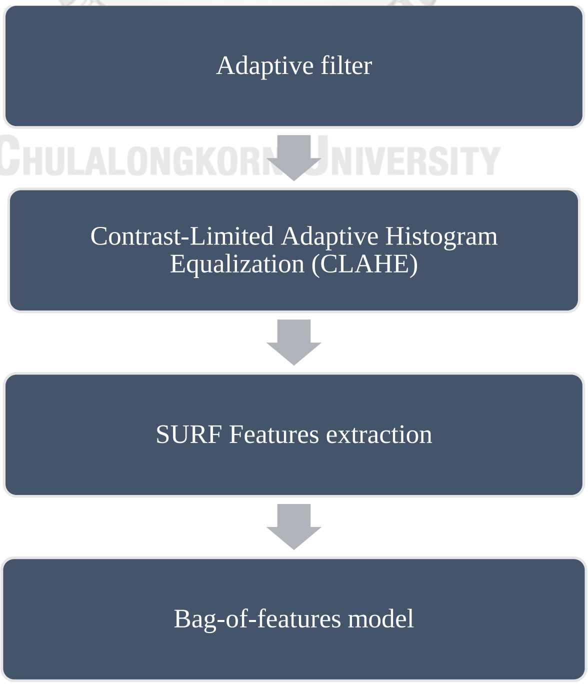


Figure 36 Format of experiments 2 (add adaptive filter and CLAHE)

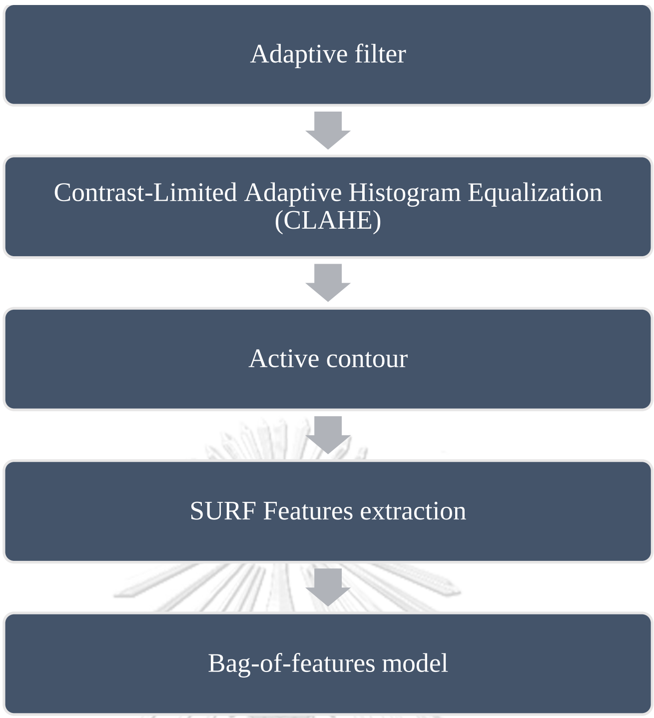


Figure 37 Format of experiments 3 (add active contour)

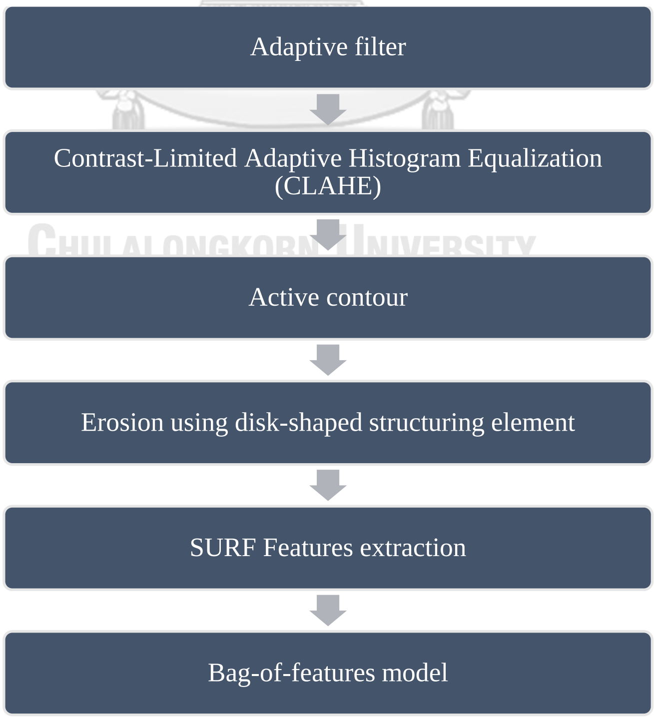


Figure 38 Format of experiments 4 (add erosion)

The result from logo classification by the Bag-of-features model with our proposed method for each format is shown in Table. 4.1 – 4.4. The first row to the third row of each type of confusion matrix shows the ratio of the number of predicted images in line with the column with the total number of amphetamines images for each logo in line with the row. We compute the average accuracy show in the final row.

Table 2 The confusion matrix of format of experiments 1

Actual	Predicted		
	Apple logo	*R logo*	*WY logo*
Apple logo	0.96	0.04	0.00
R logo	0.16	0.84	0.00
WY logo	0.10	0.03	0.87
Average Accuracy = 0.89			

From Table 2, we classified grayscale images of logo amphetamines by the bag-of-features model with SURF. The number of accuracies of Apple logo is 0.96. we have falsity is 0.04 which is predicted to R logo. For R logo, the number of accuracies is 0.84. we have falsity is 0.16 which is predicted to Apple logo. And we have the number of accuracies is 0.87 for WY logo. It is predicted to Apple logo is 0.10 and R logo is 0.03. We have average accuracy is 0.89.

Figure 39 Example amphetamines images for classification of experiments 1

Table 3 The confusion matrix of format of experiments 2

Actual	Predicted		
	Apple logo	*R logo*	*WY logo*
Apple logo	0.96	0.03	0.01
R logo	0.11	0.89	0.00
WY logo	0.12	0.01	0.87
Average Accuracy = 0.91			

From Table 3, we adjusted grayscale images of logo amphetamines by adaptive filter and Contrast-Limited Adaptive Histogram Equalization (CLAHE). Then we classified them by the bag-of-features model with SURF. The number of accuracies of Apple logo is 0.96. we have falsity is 0.02 which is predicted to R logo and 0.01 which is predicted to WY logo. For R logo, the number of accuracies is 0.89. we have falsity is 0.11 which it predicted to Apple logo. We have the number of accuracies is 0.87 for WY logo. It is predicted to Apple logo is 0.12 and R logo is 0.02. We have average accuracy is 0.91.

Figure 40 Example amphetamines images for classification of experiments 2

Table 4 The confusion matrix of format of experiments 3

Actual	Predicted		
	Apple logo	*R logo*	*WY logo*
Apple logo	0.96	0.04	0.00
R logo	0.05	0.95	0.00
WY logo	0.04	0.01	0.95
Average Accuracy = 0.95			

From Table 4, we adjusted grayscale images of logo amphetamines by adaptive filter, Contrast-Limited Adaptive Histogram Equalization (CLAHE), and active contour. We classified them by the bag-of-features model with SURF. The number of accuracies of Apple logo is 0.96. we have falsity is 0.04 which is predicted to R logo. For R logo, the number of accuracies is 0.95. We have falsity is 0.05 which it predicted to Apple logo. We have the number of accuracies is 0.95 for WY logo. It is predicted to Apple logo is 0.04 and R logo is 0.01. We have average accuracy is 0.95.

Figure 41 Example amphetamines images for classification of experiments 3

Table 5 The confusion matrix of format of experiments 4

Actual	Predicted		
	Apple logo	*R logo*	*WY logo*
Apple logo	0.97	0.03	0.00
R logo	0.02	0.98	0.00
WY logo	0.04	0.01	0.95
Average Accuracy = 0.97			

From Table 5, we adjusted grayscale images of logo amphetamines by adaptive filter, Contrast-Limited Adaptive Histogram Equalization (CLAHE), active contour, and erosion using the disk-shaped structuring element. We classified them by the bag-of-features model with SURF. The number of accuracies of Apple logo is 0.97. We have falsity is 0.03 which is predicted to R logo. For R logo, the number of accuracies is 0.98. We have falsity is 0.02 which it predicted to Apple logo. We have the number of accuracies is 0.95 for WY logo. It is predicted to Apple logo is 0.04 and R logo is 0.01. We have average accuracy is 0.97.

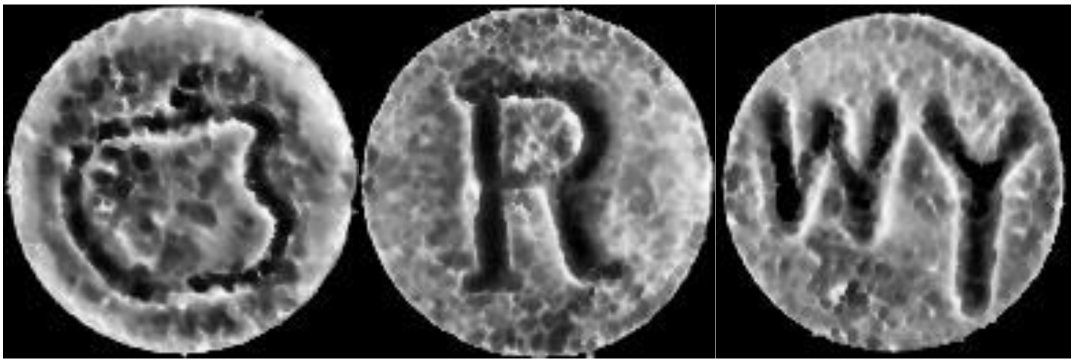


Figure 42 Example amphetamines images for classification of experiments 4

The result shows that the average accuracy of our proposed method is higher than a conventional method for this logo classification of amphetamines. But there still some failure cases shown in Figure 43, which depend on the visibility of the logo in each image. The reason for this failure is that the intensity value between the groove and surface almost similar, but they are not the same.

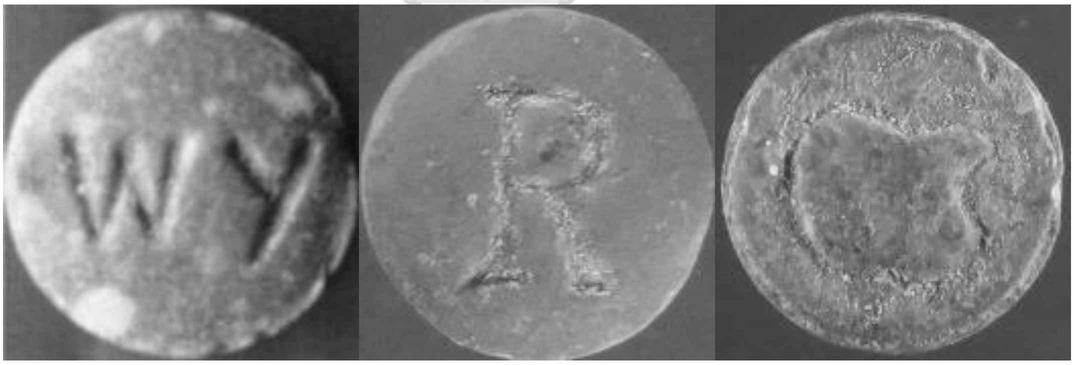


Figure 43 Example of images which low contrast between groove and surface

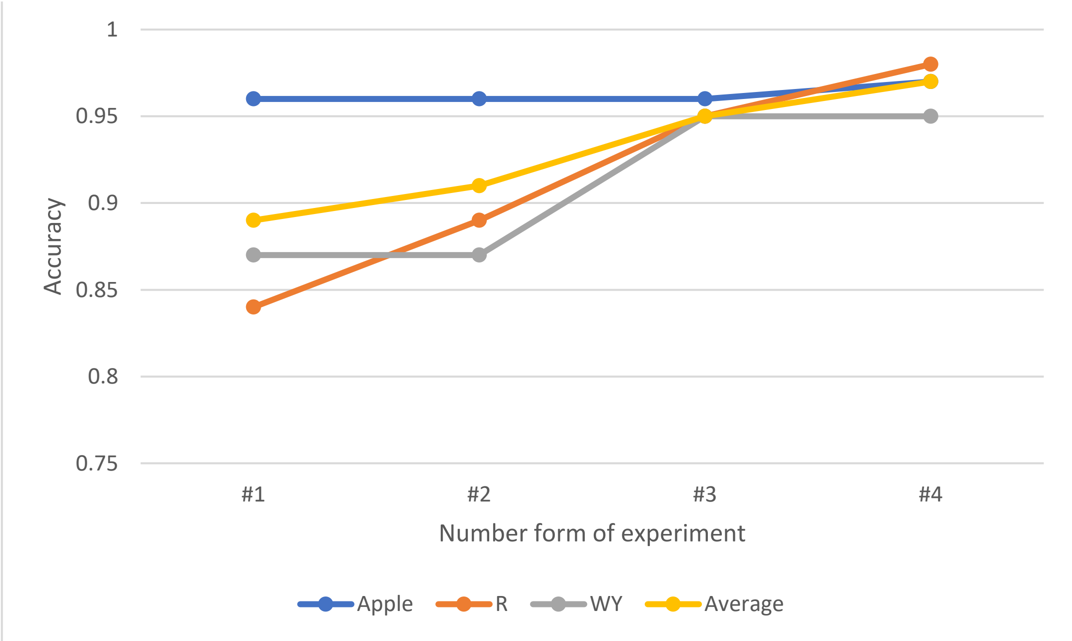


Figure 44 The accuracy of the logo classification of amphetamines images

However, from Figure 44, our proposed method is efficient for logo classification of amphetamines. The run time is taken in seconds to identify the logo of amphetamines. We can improve the average accuracy of the logo classification of amphetamines images. Since the intensity number of groove and surface more distinct significantly then the average accuracy in the logo classification increase. Therefore, our proposed process is suitable for the image that has the number of a solution is higher than 124x124. Moreover, when the image after erosion by our method, it is sufficient to eliminate noise and identify logo amphetamines. By our concept, we can handle the noise on the surface and groove in the amphetamines region.

After that, we apply this technique format of experiments 4 (adaptive filter, Contrast-Limited Adaptive Histogram Equalization (CLAHE), active contour, and erosion) to classify only the WY logo which has three types which are straight slant and bent with results as in Table 6.

Table 6 The confusion matrix of WY classification

Actual	Predicted		
	Bent	*Slant*	*Straight*
Bent	0.98	0.00	0.02
Slant	0.01	0.95	0.04
Straight	0.09	0.02	0.89
Average Accuracy = 0.94			

From Table 6, we adjusted grayscale images of WY logo by adaptive filter, Contrast-Limited Adaptive Histogram Equalization (CLAHE), active contour, and erosion using disk-shaped structuring element. We classified them by the bag-of-features model with SURF. The number of accuracies of bent form is 0.98. we have falsity is 0.02 which is predicted to straight form. For slant form, the number of accuracies is 0.95. We have falsity is 0.02 which it predicted to bent form and 0.04 which is predicted to straight form. We have the number of accuracies is 0.89 for straight form. It is predicted to bent form is 0.09 and slant form is 0.02. We have average accuracy is 0.94.

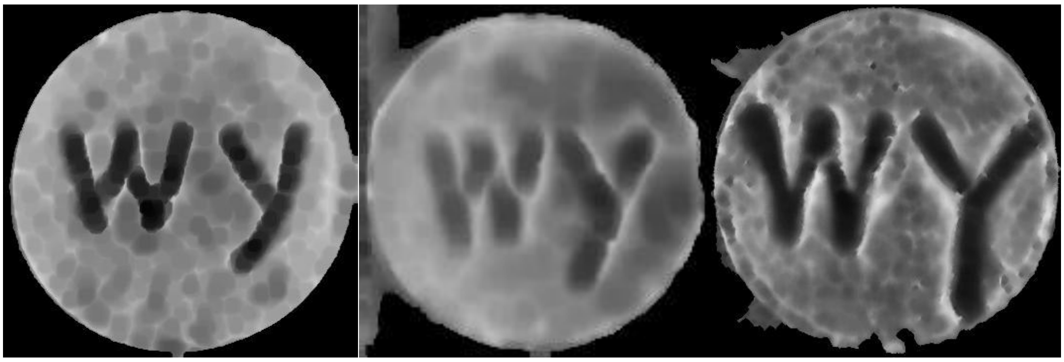
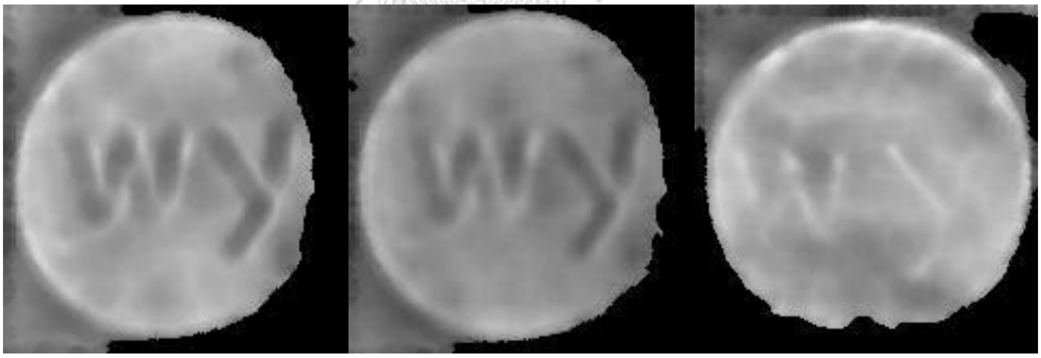


Figure 45 Example amphetamines images for classification in WY logo case

For WY logo classification, there are two bad cases for separating the specific logos from the WY logo. The first is the main improvement of the image. The difference between the seal groove and the surface on the tablet is not much different. Resulting in the same result as the previous logo separation and the second case is after the image enhancement causing only the distinctive features of the WY logo to disappear, resulting in the classification of that logo in error.

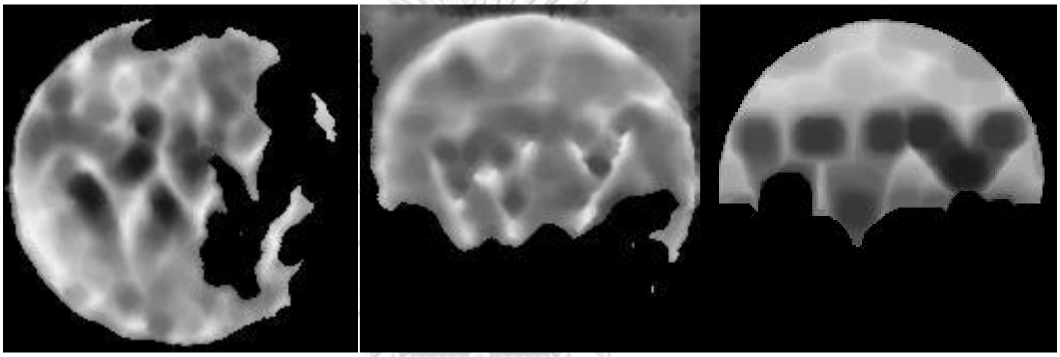
(a) Amphetamines images before preprocessing step by our method



(b) Amphetamines images after preprocessing step by our method

Figure 46 Example of images of WY logo in the first case

(a) Amphetamines images before preprocessing step by our method



(b) Amphetamines images after preprocessing step by our method

Figure 47 Example of images of WY logo in the second case

CHAPTER V
Conclusions

In summary, we proposed a modified amphetamines image for logo classification using the Bag-of-features model. We applied our method using amphetamines images from the narcotics sub-division, police forensic science center 1 office of police forensic science.

In this work, we compared four results of logo amphetamines classification. First, we classified grayscale images of logo amphetamines by the bag-of-features model with SURF. The number of accuracies of Apple logo is 0.96. For R logo, the number of accuracies is 0.84. We have the number of accuracies is 0.87 for WY logo. We have average accuracy is 0.89.

Second, we adjusted grayscale images of logo amphetamines by adaptive filter and Contrast-Limited Adaptive Histogram Equalization (CLAHE). We classified them by the bag-of-features model with SURF. The number of accuracies of Apple logo is 0.96. For R logo, the number of accuracies is 0.89. And we have the number of accuracies is 0.87 for WY logo. And then we have average accuracy is 0.91.

Third, we adjusted grayscale images of logo amphetamines by adaptive filter, Contrast-Limited Adaptive Histogram Equalization (CLAHE), and active contour. We classified them by the bag-of-features model with SURF. The number of accuracies of Apple logo is 0.96. For R logo, the number of accuracies is 0.95. We have the number of accuracies is 0.95 for WY logo. We have average accuracy is 0.95.

Fourth, we adjusted grayscale images of logo amphetamines by adaptive filter, Contrast-Limited Adaptive Histogram Equalization (CLAHE), active contour, and erosion using disk-shaped structuring element. We classified them by the bag-of-features model with SURF. The number of accuracies of Apple logo is 0.97. For R logo, the number of accuracies is 0.98. We have the number of accuracies is 0.95 for WY logo. We have average accuracy is 0.97.

Finally, we adjusted grayscale images of the WY logo by adaptive filter, Contrast-Limited Adaptive Histogram Equalization (CLAHE), active contour, and erosion using disk-shaped structuring element. We classified them by the bag-of-features model with SURF. The number of accuracies of bent form is 0.98. For slant form, the number of accuracies is 0.95. We have the number of accuracies is 0.89 for straight form. We have average accuracy is 0.94.

The main idea that our proposed method can improve the accuracy of prediction of the logo classification of amphetamines images. Our method can identify the logo of the amphetamines. Even if only about half a thousand of information has been learned. Thus, the result of our proposed method would classify the logo of the amphetamines images.

Bag-of-features can classify the logo of amphetamines, although it has limited learning examples. It created a feature histogram to represent each set of logo amphetamines images. However, there is still some failure possible cases which depend on the visibility of the logo in each image. The reason for this failure is that the intensity value between the groove and surface almost similar, but there is not the same. For the WY logo classification, there are two bad cases. First, the difference between the seal groove and the surface on the drug is not much different. Second, it is after the image enhancement causing only the distinctive features of the WY logo to disappear, resulting in the classification of that logo in error.

Nevertheless, our proposed method helped in clustering the logo of amphetamines by the image in a dataset. This method support identifies the logo more unique detail. We can improve their image more obviously.

5.1 Further work

In this work, our proposed method concentrates on dealing with the main feature and noise on the surface of amphetamines images causes retrieved an undesirable result. The proposed method is able to clear the logo on amphetamines and reduces the noise on the drug. We also then apply SURF to extract features and classify using Bag-of-features model. However, the method can be improved by modifying other filters, adjusting the enhanced method, reform segmentation, changing the technique of erosion, and trying another image classification model. For further work, if we can find other filters, the enhanced method, segmentation, the technique of erosion, and image classification model., it probably improves the efficiency for amphetamines images base on the idea of image classification.

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