AUTOMATIC ACNE DETECTION AND QUANTIFICATION FOR MEDICAL TREATMENT THROUGH IMAGE PROCESSING

BY

NATCHAPOL KITTIGUL

A THESIS SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF MASTER OF SCIENCE (ENGINEERING AND TECHNOLOGY)
SIRINDHORN INTERNATIONAL INSTITUTE OF TECHNOLOGY
THAMMASAT UNIVERSITY
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A Thesis Presented

By

NATCHAPOL KITTIGUL

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Abstract

AUTOMATIC ACNE DETECTION FOR MEDICAL TREATMENT
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by

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Master of Science (Engineering and Technology), Sirindhorn International Institute of Technology, 2017

About 85% of people age between 12 and 24 experience acne while the acne treatment cost exceed $3 billion in U.S.A. Currently, dermatologists use manual skin assessment method such as visual and photography then manually mark and count acne on patient face which is time-consuming and subjective. This thesis proposed automatic acne segmentation method using adaptive thresholding, detection and quantification using Speeded Up Robust Features with novel feature extraction. The system applied supervised learning with Train and Test algorithm. After the training process, the correlated 6 designed features were found: Standard Deviation (SD) of Red, SD of Green, SD of Blue, Circularity, Entropy and Saturation Average that should be used for acne classification. The System classified and quantified acnes using K-Nearest Neighbors algorithm. The results showed that the proposed method could efficiently detected acne with 73% accuracy, 78% sensitivity and 90% precision on average.

Keywords: Acne detection, Acne quantification, Speeded Up Robust Features (SURF), K-Nearest Neighbor (KNN), Feature Extraction.

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Chapter 1
Introduction

Acne is a chronic skin disease occurring from inflammation of pilosebaceous units which are hair follicles under skin and their surrounding sebaceous gland (fatty gland) clog up [1]. Currently, dermatologist has to manually mark a location of acnes on the sheet, then count to quantify and measure treatment progress. This is an unreliable and inaccurate method. Moreover, this method requires dermatologist's excessive effort [2]. In the present study, a novel automatic acne detection and quantification method using Image processing technique is proposed. This chapter mainly describes basic knowledge for this research. Motivation and Objectives are introduced in this chapter. Lastly, Thesis structure is presented for reviewing the overall structure of this thesis.

1.1 Acne

Acne is a chronic inflammatory skin disease occurring from disorder of pilosebaceous units, follicular epidermal hyper-proliferation and propionic bacteria (p-acne) activity [3] characterized by blackheads or whiteheads pimples, oily skin and scar. Acne primarily affects face, upper part of chest and back which have high numbers of oil glands.

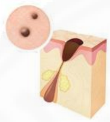
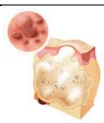
Acne causes significant physical and psychological problems for patients such as permanent scarring, depression and anxiety from poor self-image [4]. When you have acnes, go to see dermatologist early is the safest way to heal and prevent future permanent scars.

Acne can be caused by many factors such as overactive oil glands that produce too much oil, combine with skin cells to make pores in the skin, become plugged, and p-acne bacteria cause skin lesions.

Food with high glycemic ingredients such as rice, sweets, bread and pasta have been linked to be the cause of acne [5]. To prevent acne and for overall good health, balanced diet and eating a healthy food can prevent acne.

Acne is categorized into 6 different types which are shown in Table 1.1:

Table 1.1 Acne types

Acne type	Illustration Image	Real Image	Description
1. Whitehead			This acne occurs when sebum and dead skin cells get plugged in follicles. Small blemishes with white head.
2. Blackhead			Black head or comedone: follicles get clogged by sebum, the only difference from whitehead is that the debris inside the follicle becomes oxidized and the hair follicles are clogged.
3. Papules			When whiteheads are advancing to further stage: P-acnes bacteria, sebum and dead skin cells cause inflammation. These acnes characters are red and swelling.
4. Pustules			Pustules are similar to papules, but with the presence of white or yellow sebum on the surface.
5. Nodules			Nodules are one of the severe types of acne, characterized by red and inflamed blemished. This can cause permanent damage to skin if left untreated.
6. Cysts			Cysts are one of the severe types of acne, characterized by red and inflamed blemished. The difference from nodules is that cysts are more severe and tend to have larger size. This can cause permanent damage to skin if left untreated.

1.2 Image Processing

Image Processing is a signal processing which is applied on image input [6]. Image processing has two main types: digital and analog. The processes of image processing are shown in Figure 1.1. In this study, only digital image processing is focused. Digital image processing is superior to analog image processing in such many ways, for example, digital image processing allows more algorithms to be applied to the input image. Furthermore, noise problem and signal distortion can be avoided.

Computer Vision is an interdisciplinary field, the objective of this field is to make computer understand high-level detail from digital images or videos resulting in automate human visual system tasks [7–9]. The main tasks include acquiring, processing, analyzing and understanding digital images. The discipline focuses on theory to extract information from images and construct models for computer vision system.

The first step of image processing is digital image acquisition using sensors in optical or thermal wavelengths. Due to range sensors, ultra-sonic cameras, tomography devices, radar, etc. [10] the image can be captured in 2 Dimensions or 3 Dimensions or image sequence. The pixel values obtained from quantization represent light intensity in one or multi-spectral bands. Other physical measures such as depth, nuclear magnetic resonance or wave absorption can be related.

Pre-processing is the step to enhance and refine acquired image to get better result visual quality of the image. The key objective is to improve image qualities to increase success chances for other processes [6]. The Pre-processing steps include:

- Re-sampling
- Noise reduction
- Contrast enhancement
- Scale space

Feature Extraction is the process to extract meaningful features: the related piece of information for solving specific task, features represent quantitative information of interest that are used for object's class differentiation from another, for example: character recognition use descriptors such as lakes (holes) and bays to differentiate one alphabet from another [6]. Feature has various levels of complexity such as lines, edges, ridges, corners, BLOBs, points, color value, texture, roundness etc. Moreover, each feature can be represented into different forms such as scalars, function, Boolean etc. For example, color will be represent in three scalars (average values of R, G, and B). Edge can be represent as Boolean or certainty measure of the edge's existences.

Feature vectors and feature spaces: features are extracted from the image. Each feature will have feature descriptor at each image point. Feature vector contains organized information and set of all features vectors is called a feature space.

Classification is the process to determine classes for image points or regions. The Region of Interest (ROI) is assessed again model from feature extraction process. If the condition is satisfied, the detected object will be classified into different categories, also called "Image recognition".

Post-processing is the last step in Image processing, the application will draw results on original image, and the results depend on application. If the application is automatic inspection, the result is Pass or Fail. For recognition application, the result is match/no-match. Lastly, for medical, military, security or some recognition applications the results will be flagged for further human inspection.

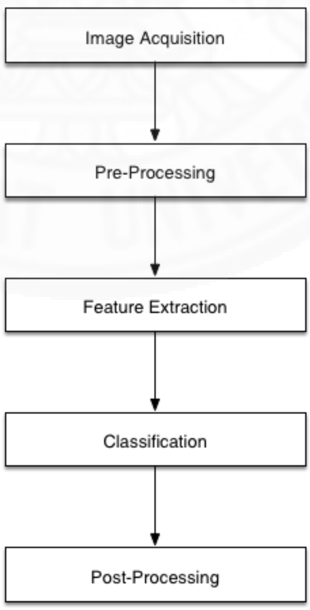


Figure 1.1 Image processing processes

1.3 Motivation

Currently, there are more than 3,000 beauty clinics in Thailand with more than 2 billion baht revenue. About 85% of people age between 12 and 24 experience acne and the acne treatment cost exceed $3 billion in U.S.A. [11]

In acne treatment, dermatologist diagnoses acne quantity and severity by manual counting and classifying into following lesion types: comedo, papule, pustule, nodule and cyst. Dermatologist has to mark the spot of acne on the sheet to show acne's location and count them manually. This method has high degree of unreliability, inaccuracy and requires doctor's excessive effort [12]. Therefore, a Computer assisted - Image processing system for acne detection has been proposed to overcome manual counting in recent years [2].

The motivation of this thesis was to create and implement effective Image processing system for acne detection to overcome dermatologist excessive effort of manual counting, and classification to diagnose acne's quantity and severity.

1.4 Objectives and Scope of the Study

1. To develop and implement more efficient and more accurate approach of acne segmentation using Adaptive Thresholding approach.
2. To develop and implement more efficient and more accurate approach of acne detection which includes acne feature extraction and classification using K-Nearest Neighbors (KNN) Algorithm.
3. To design and implement a practical acne detection system from end to end, that has user-friendly front-end User Interface and User Experience.

1.5 Thesis Organization

The thesis is organized into 6 chapters as follows:

- Chapter 1 Introduction, this chapter introduces definition of acne, image processing steps, existing problems motivation and necessity of this thesis.
- Chapter 2 Literature Review, this chapter provides a review of existing literatures and notable existing performance evaluation techniques.
- Chapter 3 describes Acne Detection using Adaptive Thresholding approach.

- Chapter 4 describes Acne Detection using Speeded Up Robust Features and Quantification Using K-Nearest Neighbors algorithm approach.
- Chapter 5 Results and Discussion: this chapter presents experimental design and performance results for Acne Detection using Speeded Up Robust Features and Quantification Using K-Nearest Neighbors algorithm.
- Chapter 6 Conclusions and Recommendations. The important points are summarized and recommendations for future work are discussed.

Chapter 2

Literature Review

In this chapter, existing image processing technique for acne detection and existing performance evaluation techniques are reviewed to provide background knowledge of existing works and how to evaluate the performance of the system.

2.1 Existing Image Processing Techniques for Acne Detection

In previous image processing approaches to detect acne, Ramli et al. [13] used CIELAB color space to do skin lesion segmentation. Firstly, sample images were converted from RGB color space to CIELAB color space by calculating the Euclidean distance. They applied Otsu's thresholding method to extract foreground (acnes) from background (skin). The system had 80% sensitivity and specificity.

Khan et al. [3] applied Fuzzy C-means (FCM) Clustering Technique which clustered associated pixel in one or more clusters. They applied FCM on 4 color spaces which were RGB, OHTA, YIQ and I1I2I3. They noted that RGB was very sensitive to illumination variations. YIQ color space solved illumination problem by separating the luminance (Y) from chrominance information (I, Q). The results showed that optimum clusters number was 3. Specificity / sensitivity and accuracy is varying in different clusters number from 45-95%.

Alamdari et al. [14] used k-means clustering (2 levels) with Hue Saturation Value (HSV) color space, which had more meaningful color component over RGB. They achieved 70% accuracy. They also used Fuzzy c-means (FCM) clustering technique and Support Vector Machine (SVM) to differentiate acne scar from inflammatory lesions with 80% and 66.6% accuracy, respectively. They found that the accuracy of classifying detected acne from normal skin was 100% using FCM. In addition, they applied wathershed segmentation and multi thresholding but the application was failed to detect acne properly.

Liu and Zerubia [15] used Markov random fields (MRFs) with Chromophore Descriptors by applying iterated conditional modes (ICM). The algorithm was robust to large-dynamic-range intensity that would work on images captured under uncontrolled environment. The result highly agreed to human visual inspection (estimated).

Chen et al. [16] developed imaging system on Android device as an alternative to expensive skin probe. They used normal and Ultraviolet (UV) lighting with YCbCr color space. The system used simple thresholding to extract acne features. Their systems had drawback that required user to manually mark Region of Interest (ROI). They achieved 82% accuracy by simply counting positive and negative samples.

Malik et al. [17] used K-means clustering and SVM classifier to detect and classify acnes into 4 categories: comedo, papule, pustule, and nodule with severity level, and resulted in 93% accuracy in average (with post processing).

Huamyun and Malik [18] used Multilevel thresholding on RGB images. The result needed more improvement and they suggested a use of Multispectral and Thermal images with more color bands. There would be an improvement in detection result.

Lucut and Smith [19] proposed their own K-means clustering algorithm that applied Hough Transform and First Order Derivative to find thresholding point. This approach automatically found actual number of clusters, resulting in 59-99% accuracy.

Chantharaphaichit et al. [1] detected acnes by using image processing technique in MATLAB module. They converted the image from RGB color space to Gray Scale, applied normalization with maximum intensity, converted RGB to HSV color space then applied brightness extraction process. The system marked the Region of Interest (ROI) by image subtraction then applied Binary thresholding with user defined value to apply spot and region. Lastly, acnes detection result was marked on original image. The system had fair accuracy.

Chantharaphaichit et al. [2] applied feature extraction with supervised learning: “Training” and “Testing” algorithm on 10 acne images. The system did Blob detection, Feature extraction for each candidate and then applied Bayesian Classification, Supervised Training and Unsupervised Testing. The system had accuracy at 70.65%.

Chang and Liao [20] did facial region extraction from captured image by using skin color filtering and region-filling method to detect the largest connected region and remove unrelated facial feature which were eyes, eyebrows, nostrils and mouth through Fourier descriptor. Then, they used feature extraction with co-occurrence matrix and the sequential floating forward selection (SFFS) to select features. They used Support

Vector Machine (SVM) to classify normal patterns, acnes and spot. They applied a decision tree structure which consisted of two SVMs. Chang's methods worked effectively at 98% accuracy. The system sensitivity was medium at 64% because of the different features in various types of acnes.

Chandra et al. [21] used segmentation with color-based technique, Mahalanobis distance (MD) Minimum distance classifier, then compared with Bayesian Classifier. The experimental result showed that Mahalanobis distance was superior to Bayesian Classifier but with limitations such as photographic session ambience light.

Khongsuwan et al. [22] applied Ultra-Violet fluorescence lighting in image capturing process to detect *P. acne*, a gram positive anaerobic microorganism, which causes the acne, They converted UV image to RGB and to Gray-Scale, applied adaptive histogram equalization which used a bilinear interpolation to eliminate artificially induced boundaries of the acne, and then applied extended maxima transform to separate close objects from each other. The experiment was done on cropped-part of the skin area only. The system had 83.75% accuracy.

Singh and Kanwal [23] did facial marks detection techniques comparison survey. They found that to extract facial features, Active Apperance Model (AAM) was the most efficiency technique. For acnes detection, various techniques were reviewed such as Laplacian-of-Gaussian (LoG), Speeded Up Robust Features (SURF), BLOB detection and Morphological operators. They could identify various types of acne [8].

Fujii et al. [12] applied image processing techniques on Multispectral Image captured from 16 bands and 12 bits depth multispectral camera. Two tungsten lamps were used to illuminate Patient's face. The measurement of spectral energy distribution was done by Spectroradiometer. The classification process was done by Fisher linear discriminant function (LDF's) and thresholding. The 3 Fisher LDF's and thresholding value were experimentally calculated. The system showed good results.

2.2 Existing Performance Evaluation Techniques

Although acne vulgaris is easy to be diagnosed, the polymorphic aspect and its property variation do not permit simple severity evaluation [24]. There are two main types of diagnostic approaches: grading and lesion counting. The comparison of them is shown in Table 2.1. Grading of acne is a subjective method, the dermatologist determines acne severity by observing the dominant lesions and evaluates them by estimating inflammation and amount of involvement. Lesion counting requires dermatologist effort in counting and recording number of acnes in different types and overall severity.

Table 2.1 Comparison of grading and lesion counting

Grading	**Lesion counting**
Involves observing the dominant lesions, and estimating the extent of involvement	Involves recording the number of each type of acne lesion and determining the overall severity
Subjective method	Objective method
Quick and Simple	Time-consuming
Less accurate	More accurate
Does not distinguish small differences in therapeutic response	Distinguishes small differences in therapeutic response
Effect of treatment on individual lesions cannot be estimated.	Effect of treatment on individual lesions can be estimated.
Used in offices and clinical settings	Used in clinical trials

2.2.1 The Global Acne Grading System

For an example of grading system, “The Global Acne Grading System” developed by Doshi et al. [25] is one of the most comprehensive acne grading criteria [24], as shown in Table 2.2.

Table 2.2 The global acne grading system

Location	Factor (F)	Severity (S)	Local Score (F x S)
Forehead	2	0: Nail	Mild: 1-18
Right cheek	2	1: Comedone	Moderate: 19-30
Left check	2	2: Papules	Severe: 31-38
Nose	1	3. Pustule	Very Severe > 39
Chin	1	4. Nodule	
Chest and upper back	3		

Assessment of the acne vulgaris severity continues to be a challenge for dermatologists, because there is no universal grading system that has been accepted. But to evaluate image processing system performance for acne quantification, the most accepted method is Confusion matrix and Sensitivity, Precision and Accuracy analysis.

2.2.2 Confusion Matrix

A confusion matrix (or error matrix) is a table designed to visualize the performance of a supervised learning algorithm. Because the accuracy only cannot determine real performance of a classifier if the data set is unbalanced. It is a contingency table which has *actual* and *predicted* dimensions [26]. To test classification function the conditions of confusion matrix is shown in Table 2.3 and the interpretation of each condition is shown in Table 2.4.

Table 2.3 Confusion matrix

		Predicted condition	
True condition	Total population	Prediction positive	Prediction negative
	Condition positive	**True Positive (TP)**	**False Negative (FN) (type II error)**
	Condition negative	**False Positive (FP) (type I error)**	**True Negative (TN)**

Table 2.4 Condition and interpretation of confusion matrix

Condition	**Interpretation**
True positive (TP):	Acne that is correctly detected as acne.
False positive (FP):	Scar and normal skin which are incorrectly detected as acne.
True negative (TN):	Scar and normal skin which are correctly detected as scar and normal skin.
False negative (FN):	Acne that is incorrectly detected as scar and normal skin.

Therefore, conditions can be calculated as the followings:

Sensitivity = TP/(TP+FN),

Precision = TP/(TP+FP),

Accuracy = (TP+TN)/(TP+TN+FP+FN).

Chapter 3
Acne Detection Using Adaptive Thresholding

3.1 Thresholding

Thresholding is one of the most simple image segmentation method. The thresholding process separates object from background by selecting threshold T that separates these modes. Any point (x, y) for which f(x, y) >T is an object point, otherwise, it is a background point [6]. Single level (or Binary Thresholding) thresholding only has one threshold T but for multilevel thresholding, the system has two or more T, for example T1 and T2. The point is object class if f(x, y) >T2, and it is background class if f(x, y) <= T1. Multilevel thresholding is less reliable than single thresholding because of difficulty of finding multiple threshold points that are effectively separate regions of interest from background [6].

Binary thresholding, also called "Simple Global Thresholding", is the most simple thresholding techniques. Binary thresholding partitions the image histogram by separating the object from the background with a single thresholding T. The segmentation process starts by scanning through each pixel and labels them as object or background depending on their gray levels of that pixel which is greater or less than the value of T. The gray level range is from 0 to 255. In practice, binary thresholding can be expected to be successful in highly controlled environments. Chantharaphaichit et al. [1] achieved fair accuracy by using binary thresholding to detect acne vulgaris. The main drawback of binary thresholding was single thresholding value if not optimal, it reduced accuracy of the system, as shown in Figure 3.1.

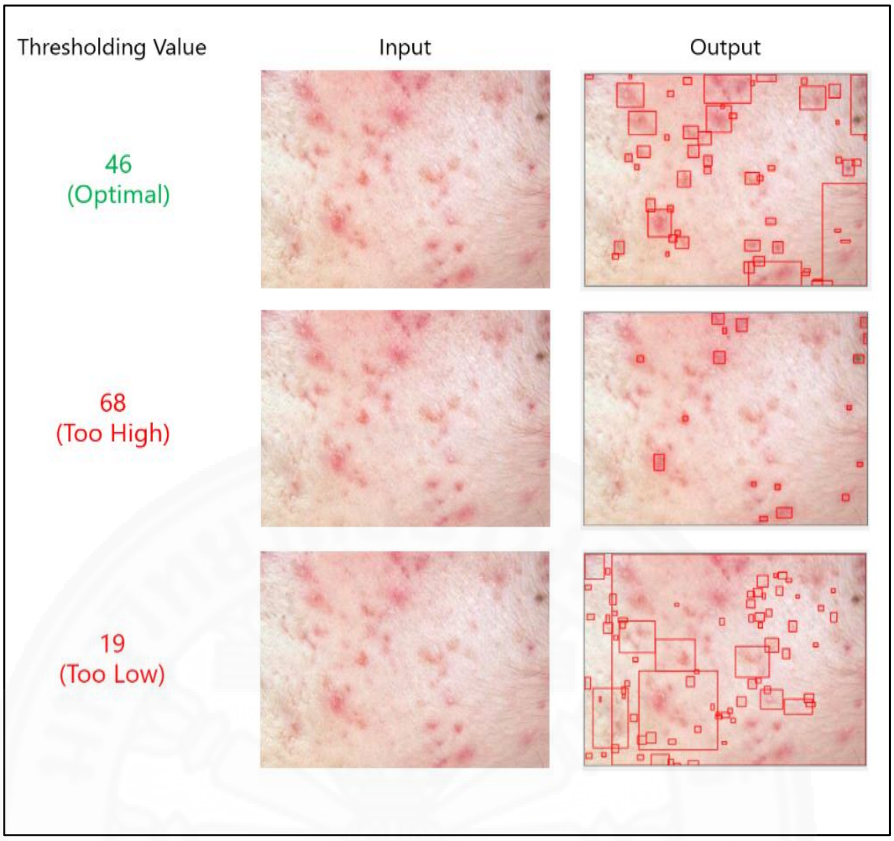


Figure 3.1 Thresholding value comparison

Thresholding approach has main drawback that the result is subjective to image illumination. Generally, when the histogram of an image with no illumination noise is seen, there will be two valleys that separate foreground from background. But when the image has illumination noise, the noise will eliminate each valley boundaries from other, making segmentation by single threshold impossible.

Regarding Adaptive thresholding, unlike binary thresholding, the thresholding value of each pixel location depends on the neighboring pixel intensities [27]. This approach assumes that smaller image regions tend to have uniform illumination, thus it is more suitable for thresholding. Adaptive thresholding gives better results for an image with varying illumination. The comparison of Binary Thresholding and Adaptive Thresholding is shown in Figure 3.2.

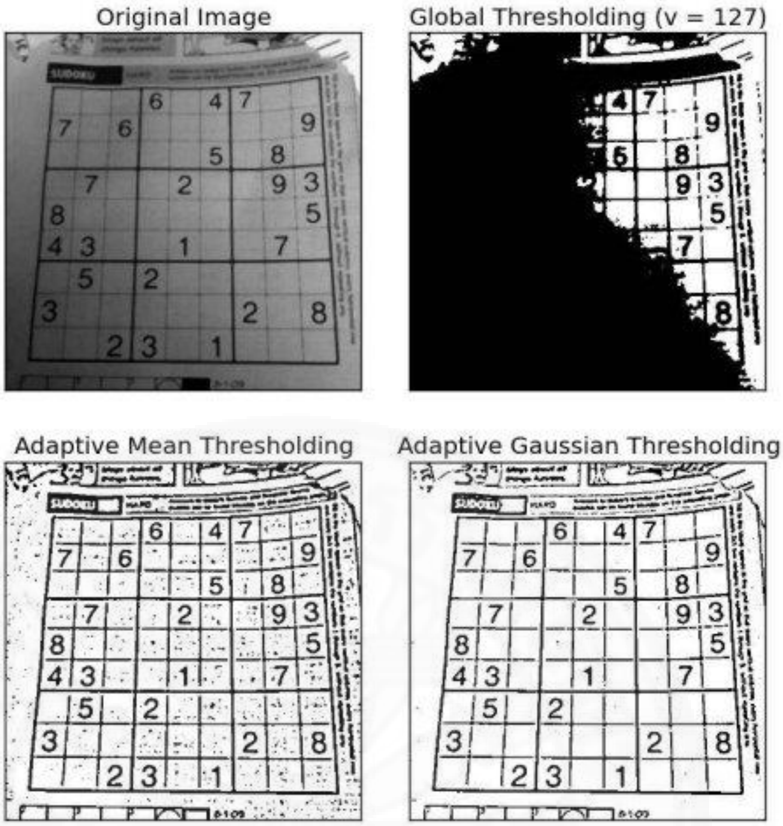


Figure 3.2 Comparison of Binary Thresholding and Adaptive Thresholding

3.2 Adaptive Thresholding Implementation

The Adaptive Thresholding Flow Chart is shown in Figure 3.3. The system starts from pre-processing by applying Smooth Gaussian filter with smooth value=3. The system extracts only green channel from RGB color space, because in green channel, acne exhibits more contrast but red and green channels tend to contain more noise [28].

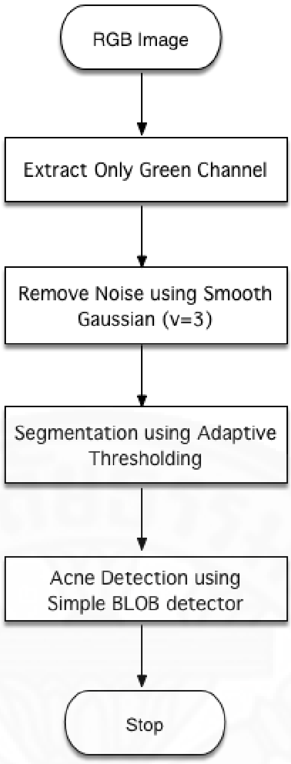


Figure 3.3 Adaptive Thresholding Flow Chart

In adaptive thresholding, there are two adaptive methods:

1. Adaptive Thresholding Mean C: threshold value is the mean of neighborhood area.
2. Adaptive Thresholding Gaussian C: threshold value is calculated from the weighted sum (Gaussian window) of neighborhood values.

In this implementation, method 1: Adaptive Thresholding Mean C will be used because this method gives more persistent results in the giving data set. The block size parameter = 699, C=1, the thresholding segmentation results are presented in Figure 3.4 to Figure 3.9.

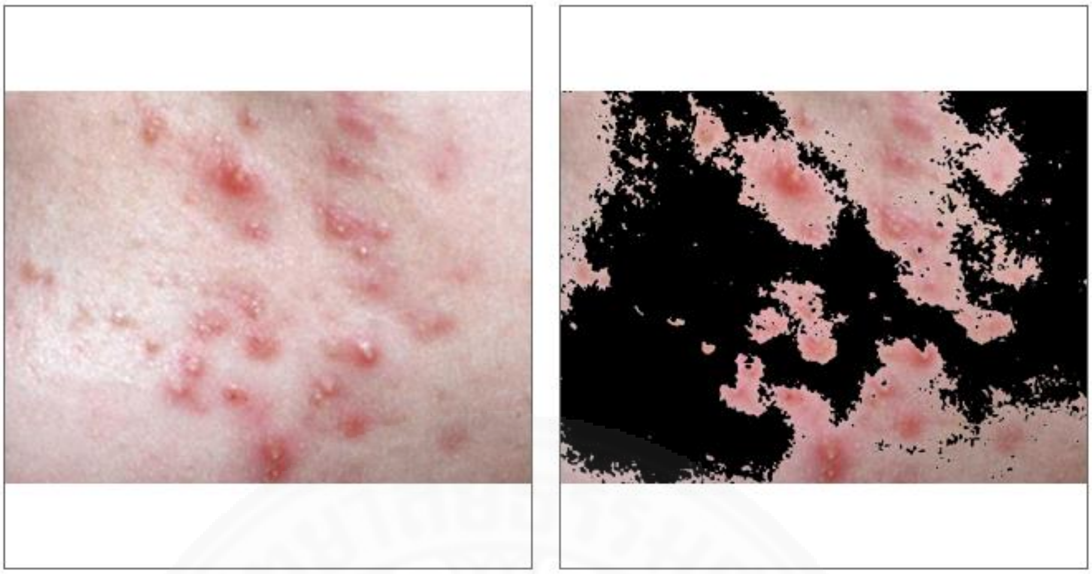


Figure 3.4 Result 1 of Adaptive Thresholding Segmentation

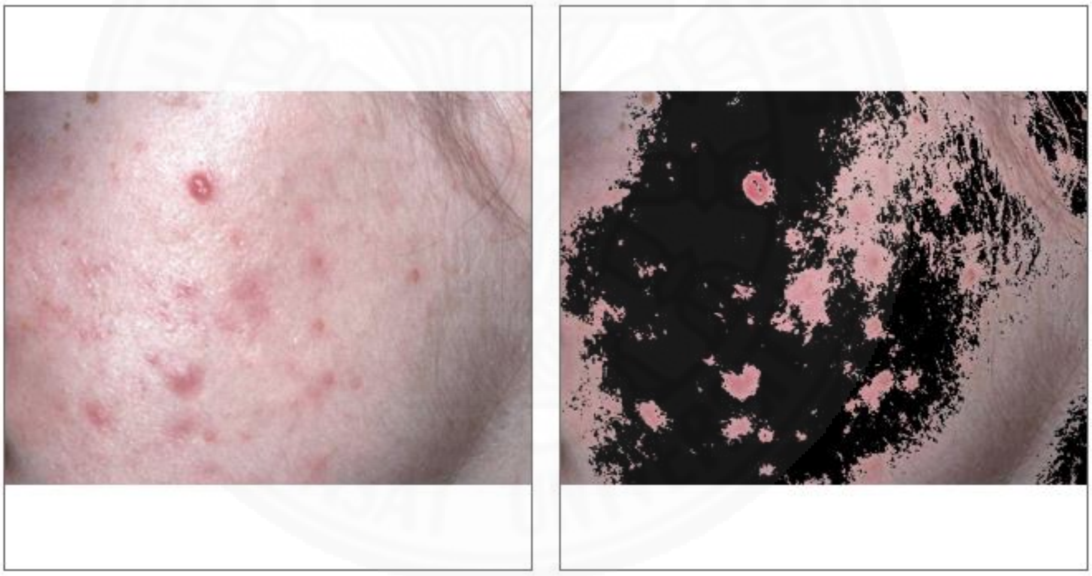


Figure 3.5 Result 2 of Adaptive Thresholding Segmentation

Figure 3.6 Result 3 of Adaptive Thresholding Segmentation

Figure 3.7 Result 4 of Adaptive Thresholding Segmentation

Figure 3.8 Result 5 of Adaptive Thresholding Segmentation

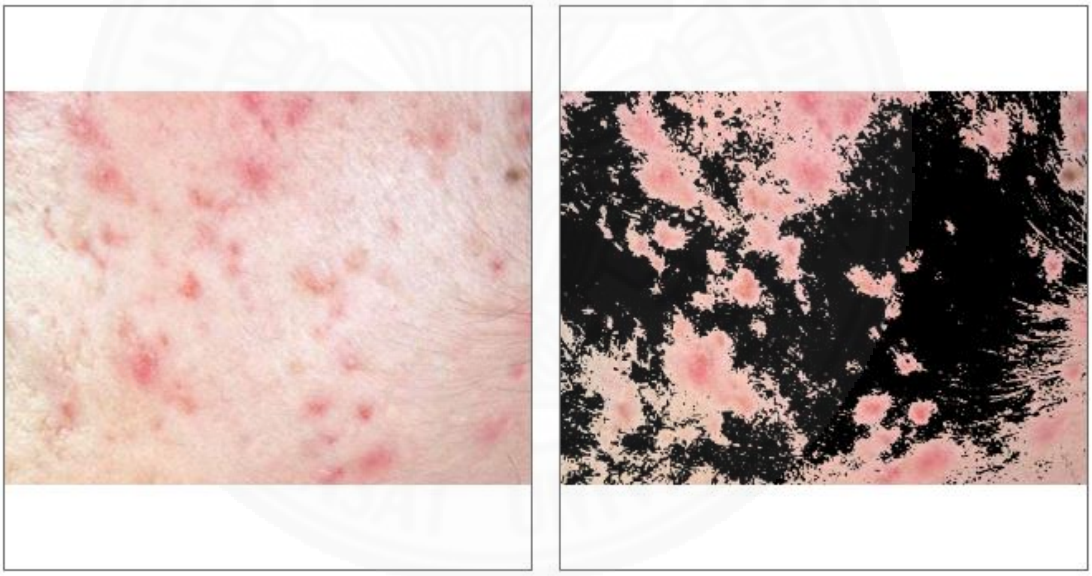


Figure 3.9 Result 6 of Adaptive Thresholding Segmentation

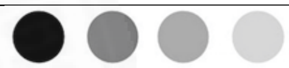
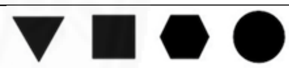
After the segmentation process, the system will do BLOB detection which is Simple BLOB Detector which implements an algorithm for extracting blobs [29]:

1. The binary images convert from the source image by applying several thresholding values between minThreshold to maxThreshold with gradually increased thresholdStep.

2. FindCountours are used to extract connected components from all binary images and then calculate their centers.
3. Several binary images are used to calculate centers coordinates: centers that are close to others from one group that transforms to one blob. The parameter that controls grouping process is minDistBetweenBlobs.
4. The estimated centers and radiuses of detected blobs are calculated from the groups. Locations and sizes of key points are returned.

This Simple BLOB Detector has filtration parameters as shown in Table 3.1. User can adjust these filters to improve BLOB detection accuracy.

Table 3.1 Parameters of simple BLOB detector

Parameter	**Detail**	**Value Visualization (0-1)**
Color	The color of BLOB from dark to light.	
Area	The size (width x height) of the blob between min and max values.	
Circularity	The circularity value can be calculated from $f_{\mathrm{circ}} = \frac{4\pi A}{P^2}$ Where A=Area, P=Perimeter The circularity is limited between min and max Circularity value.	
Inertia	Extracted blobs have their Inertia ratio between min Inertia ratio and max Inertia ratio.	
Convexity	The convexity is calculated from (area / area of blob convex hull). The limit is between min and max convexity.	

Simple BLOB detector demonstrates average acne's candidate detection results, as shown in Figure 3.10 to Figure 3.12.

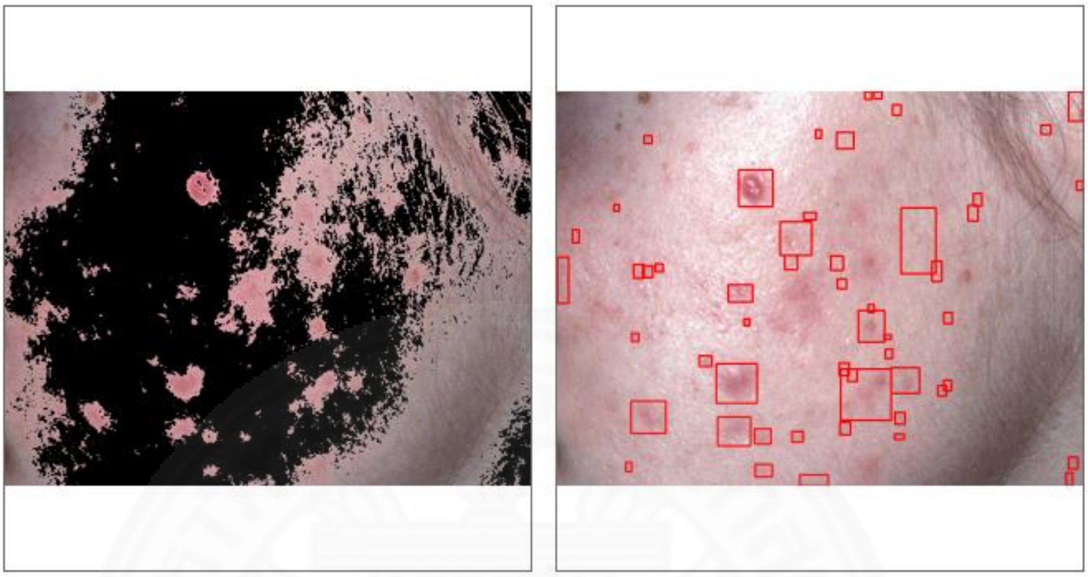


Figure 3.10 BLOB detection Result 1 of Adaptive Thresholding Segmentation

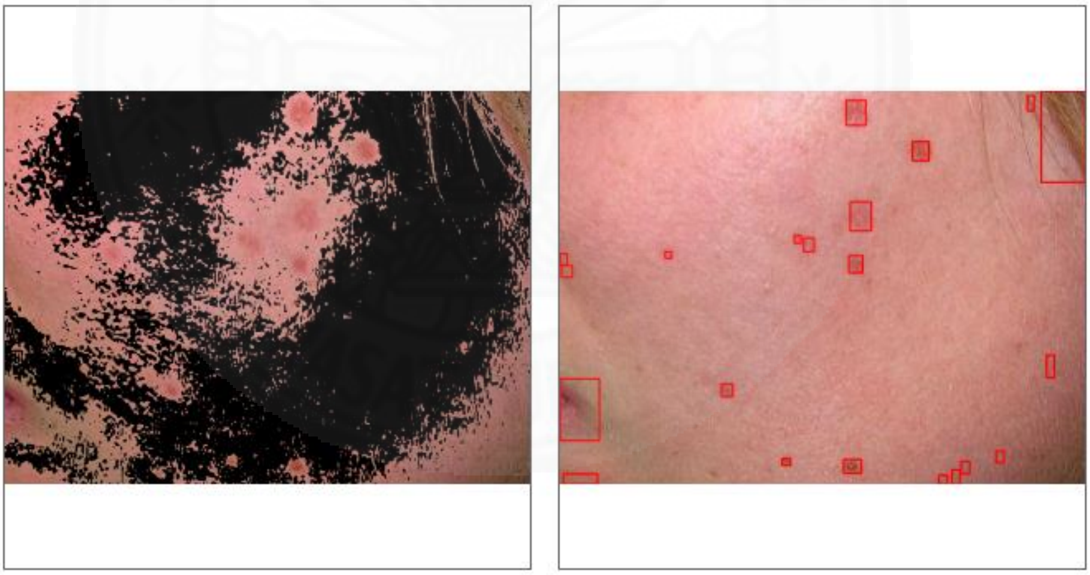


Figure 3.11 BLOB detection Result 2 of Adaptive Thresholding Segmentation

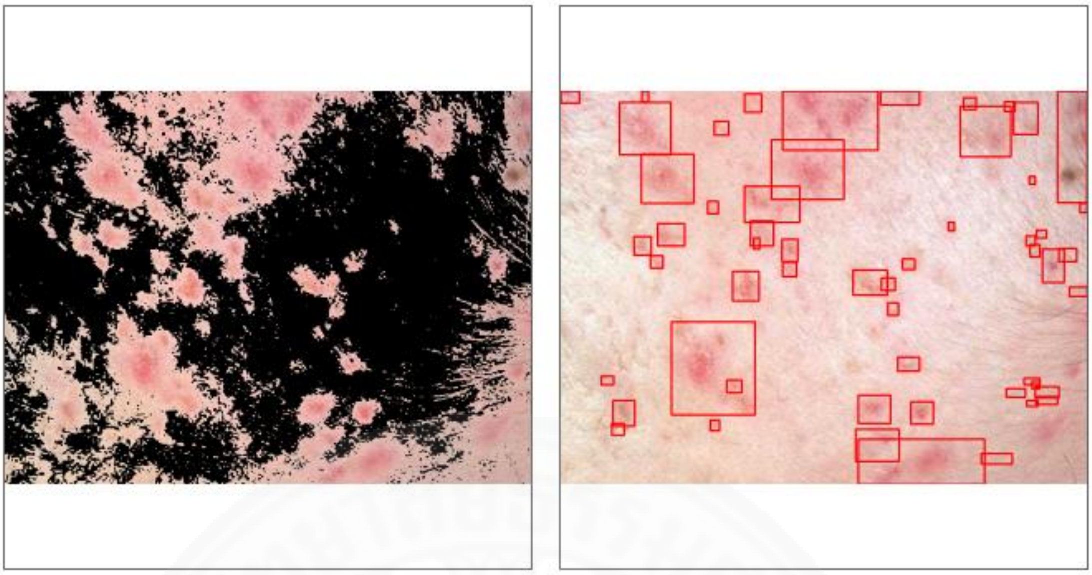


Figure 3.12 BLOB detection Result 3 of Adaptive Thresholding Segmentation

In Conclusion, adaptive thresholding method is good for acne segmentation but the BLOB detection process, which implements Simple BLOB detector, needs more advance method to detect acne which will be explained in the next chapter.

Chapter 4
Acne Detection Using Speeded Up Robust Feature and Quantification Using K-Nearest Neighbors Algorithm

In previous chapter, an algorithm for acne detection was proposed using Adaptive Thresholding segmentation method and Simple BLOB detector. However, adaptive thresholding technique still have flaw due to illumination and constant Block Size parameter, furthermore, Simple BLOB detector requires user to specify some filtration parameter to improve its performance and filter value can differ through images. So, in this chapter more robust acne detection method is proposed. The method applied Speeded Up Robust Features (SURF) and more advance feature extraction and classification.

4.1 Pre-Processing

The system starts by pre-processing the image by extracting only green channel, then removes noise with Gaussian Blur with Smooth value = 3. In this implementation, the color spaces that will be used are RGB color space and Hue Saturation Value (HSV) color space.

HSV color space represent points in an RGB color model in the cylindrical-coordinate representations. HSV rearranges the geometry of RGB in more intuitive and perceptually relevant way which gives benefits over the Cartesian representation.

HSV decouples intensity value from color, with hue and saturation corresponding to human perception. Image processing algorithms can be developed from this representation easily [31].

4.2 Speeded Up Robust Feature (SURF)

SURF is a scale- and rotation-invariant interest point (key point) detector and descriptor. It is partly inspired by the scale-invariant feature transform (SIFT) descriptor and faster than SIFT [30]. Han and Uyyanonvara [31] did Biomedical image BLOB detection survey and found that SURF, which implemented Determinant of Hessian (DOH) blob detector, was suitable for real-time key point detection. Moreover, detection speed was independent from blob's size parameter and it could detect several common geometrical structures.

The SURF algorithm has three main processes: first, interest point detection, second, local neighborhood description, and third, matching. For the first process, interest point detection: SURF applies square-shaped filter as Gaussian smoothing approximation on integral image as eq. 4.1.

$$S(x, y) = \sum_{i=0}^{x} \sum_{j=0}^{y} I(i, j) \tag{4.1}$$

Then, Hessian matrix blob detector was used to find key points in eq. 4.2 as done by Lindeberg [32]. Given a point p=(x, y) in an image, the Hessian matrix H (p, σ) can be calculated at point p and scale σ, where $L_{xx}(p, \sigma)$ etc. are the second-order derivatives of the grayscale image. The determinant of Hessian matrix measures local change around the point. The candidate point will be the key point if the determinant is maximal.

$$H(p, \sigma) = \begin{pmatrix} L_{xx}(p, \sigma) & L_{xy}(p, \sigma) \\ L_{yx}(p, \sigma) & L_{yy}(p, \sigma) \end{pmatrix} \tag{4.2}$$

Key points can be found at various scales by up-scaling the filter size. The scale space is analyzed. The output of the above 9×9 filter is considered as the initial scale layer at scale s=1.2 wit Gaussian derivatives at σ=1.2. The gradually bigger masks filter is applied to the image to get the following layers. Brown's method is used to find the maxima of the determinant of the Hessian matrix, which is interpolated in scale and image space [33].

For local neighborhood description, the descriptor objective is to provide a unique and robust description of image feature. SURF descriptor can withstand rotational invariance by introducing The Haar wavelet responses in X and Y direction within a circular neighborhood of radius *6s* around the interested points which are computed, where *s*, the scale value at the interested point, is detected. The Gaussian function is weighted at the center of the key point, then the system plots the point with the horizontal response in the abscissa and the vertical response in the ordinate (2 dimensions). The sliding orientation window of size π/3 is used to calculated dominant orientation by calculating the sum of all responses from the window. The horizontal and vertical responses within the window are summed. The local orientation vector is yielded from the two summed. The longest vector determines the orientation of the key point. To achieve good balance between robustness and angular resolution, the sliding windows size parameter need to be optimal.

The square window size of *20s* around the point is extracted with the selected orientation. This process is applied to describe the interested region.

The interested region is divided into smaller 4x4 square sub-regions, Haar wavelet responses are extracted at spaced sample points with the size of 5x5 for each one. The Gaussian is used to weight responses to give the system more robustness.

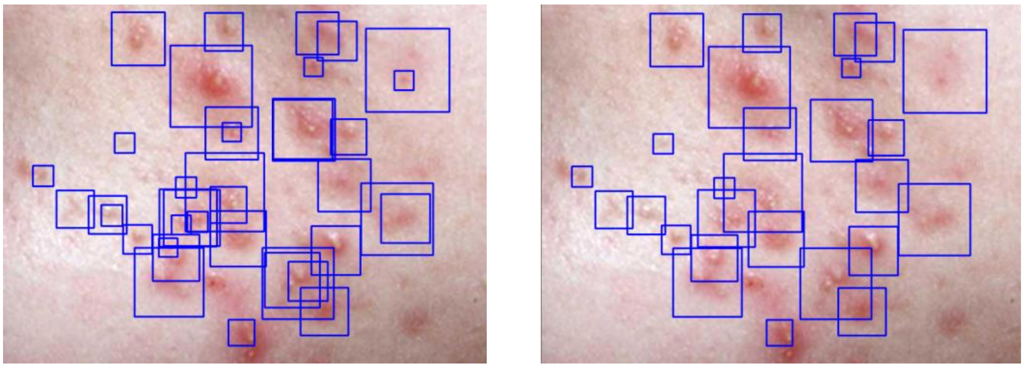
Lastly, Matching, SURF main objective is to match the descriptors obtained from different images to find matching pairs and do the image recognition process. But for this thesis SURF algorithm was used up to BLOB detection part only.

The system store all detected key points in the Vector of Key Points. In the experiment SURF demonstrated high performance with calculation time less than 10 seconds for each image.

4.3 Feature Extraction

The key points detected from SURF algorithm may overlap on each other, there are two types of overlap: 1. Whole overlap: the whole smaller BLOB is inside the larger BLOB, 2. Part overlap: two BLOB intersect on each other. The discard overlapped key points process is shown in Figure 4.1 Overlapping problem can be solved by two steps:

1. Sort key points from large to small, in this implementation, author used Bubble sort technique.
2. Iterate over each key point, check if small one is overlapped with large one more than ¼ of an area of small one, then discard small one.



A B

Figure 4.1 Discard Overlapped Key points

After that, the system will iterate over key points that size is greater than 30 x 30px which is the smallest size of acne. Then, the system applies Otsu Thresholding that will extract foreground object (acne) from background (skin).

Otsu thresholding is the thresholding technique that maximizes the likelihood that the threshold is chosen so as to split the image between foreground and background [34]. Otsu thresholding method selects a threshold point that best separate two classes automatically.

Otsu thresholding may result in unwanted result because some detected skin BLOB do not have foreground object, therefore the system will filter out these detected skin BLOB by this algorithm:

1. Assume that the foreground object will be in the center, the system sampling the center pixel to check whether it has value or not.
2. The system scales up to 5x5 square to check if any pixel has value or not. If there are not any pixels that has value>0, then discard this BLOB.

Features of each acne will be calculated. Initial designed features are:

4.3.1 Redness: calculated from number of pixel in EMGUCV's Hue range between (0-8 and 172-255) which is red color.

4.3.2 Hue Mean: average hue of every pixels.

4.3.3 Standard Deviation (SD) of Red.

4.3.4 Standard Deviation (SD) of Green.

4.3.5 Standard Deviation (SD) of Blue.

4.3.6 Circularity: the system find contour of detected candidate and calculate area (A) and perimeter (P) to obtain circularity which is calculated from eq. 4.3 if the circularity is close to 1. Therefore, the detected candidate is circular shape.

$$f_{\mathrm{circ}} = \frac{4\pi A}{P^2} \tag{4.3}$$

4.3.7 Entropy: Shannon Entropy of detected image.

4.3.8 Saturation Mean.

4.3.9 Standard Deviation (SD) of Saturation.

4.4 Training and Testing

For the training process: the system was trained with a total of 9 images, 865 training data which were 129 positive samples and 736 negative samples. User has to decide whether the detected candidate is an acne or not, based on ground truth image obtained from dermatologist. Training data stored in Microsoft SQL Database (MSSQL) which provides important benefits over storing in text file or excel such as querying, reporting and better scalability, with C#, database interface implemented natively.

The training process requires trainer's excessive effort to manually observe the detection result then compare with the ground truth image, which may result in inaccuracy and time wasting, consequently the automatic training system is developed. User will choose training image and corresponding ground truth image. The ground truth image is the image with all acnes are marked by black circle (pixel value=0). The system will iterate over each detected key point (candidate) of training then masking them with ground truth image to identify that the detected key point is an acne or not, if masked result has number of black pixel more than threshold, the key point is considered an acne and green square will be drawn. If not, therefore it is a skin and red square will be drawn. The system will continue doing this process until all key points are classified. The automatic training system is presented in Figure 4.2.

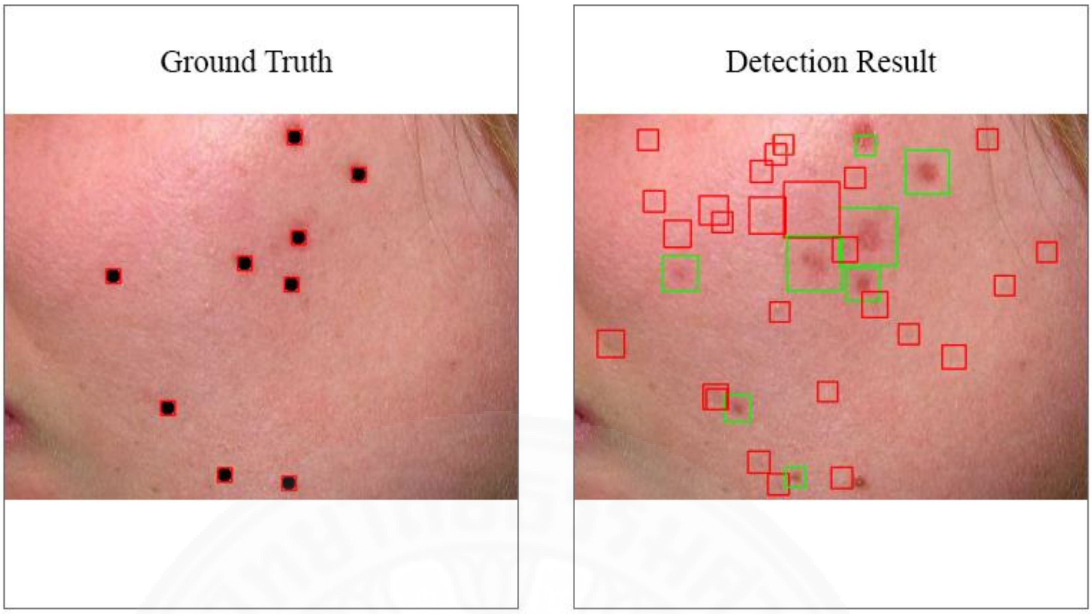


Figure 4.2 Automatic Training System

Six features were chosen that had the highest correlation values which were: SD of Green, SD of Red, Entropy, Saturation Average, SD of Blue and Circularity. More information of correlation values can be found in Chapter 5.

Testing. Cross-validation (rotation estimation) [35–37] is a model validation technique for assessing the relation of generalization of a statistical analysis result to an independent data set. 3-Fold cross validation is validated: all images are divided into 70% training data and 30% testing data (validation set). For each fold, the selection of training data is changed. The data tested in each fold are not included in testing data. The visualization of Cross Validation is shown in Figure 4.3.

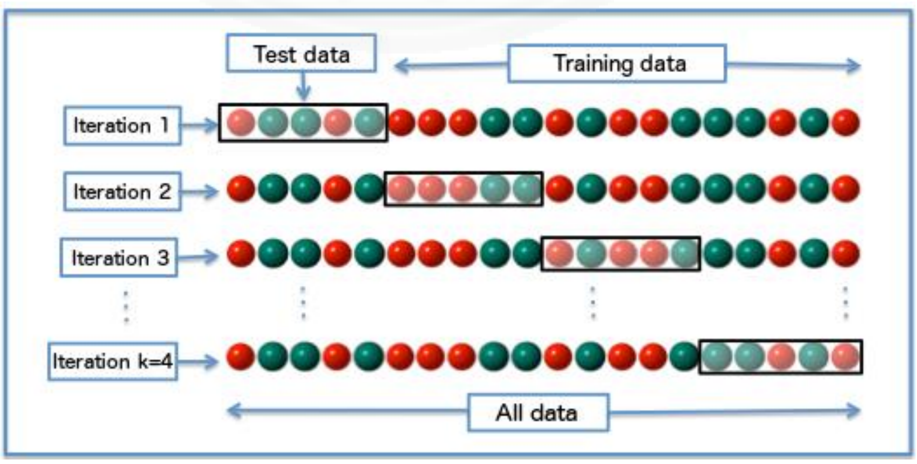


Figure 4.3 Cross Validation

4.5 K-Nearest Neighbor Classification

Supervised learning or supervised classification is the machine learning task of predicate a function from labeled training data. A set of training examples is provided in the training data. Each training example in supervised learning is a pair of an input object and a correct output value. There are two types of this approach: distribution free and statistical analysis. Distribution-free methods do not require any knowledge of probability distribution functions. The methods are based on reasoning and heuristics. In the other hand, statistical method is based on probability distribution model that requires prior knowledge which can be parametric or nonparametric.

K-Nearest Neighbors algorithm is a distribution-free classification [38] which used for classification and regression. In both cases, the input consists of the k closest training examples in the feature space. An object is classified by a majority vote of its neighbors. The object will be assigned to the class that is the most common class of neighbors among them.

The implementation of Acne Detection using Speeded Up Robust Feature and Quantification using K-Nearest Neighbors Algorithm is shown in Figure 4.4 and the results are shown in Figure 4.5 to Figure 4.8.

The experimental designs for each step of supervised learning to test this approach are shown in Table 4.1.

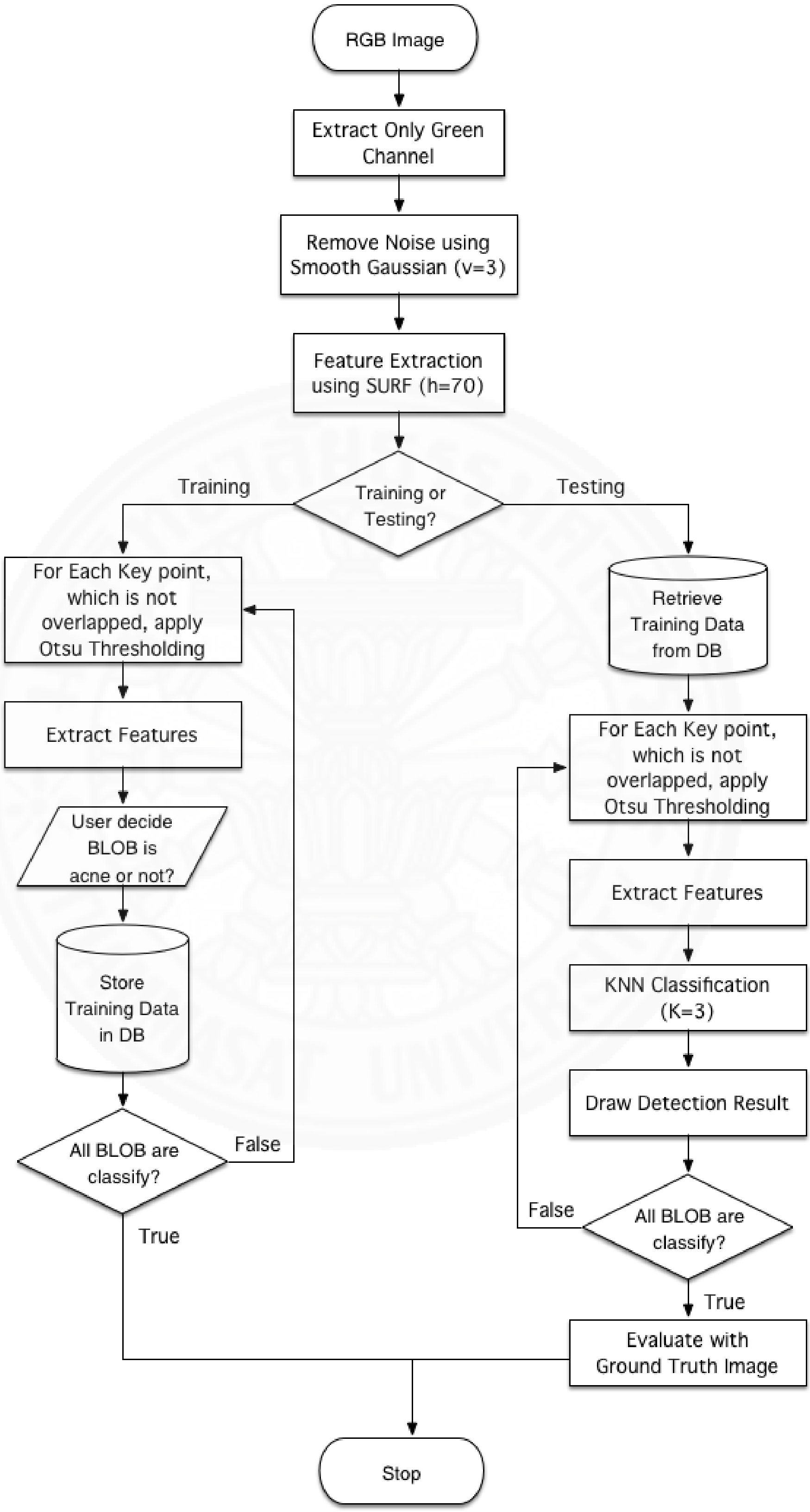


Figure 4.4 Acne Detection using Speeded Up Robust Feature and Quantification using K-Nearest Neighbors Algorithm Flow Chart

Figure 4.5 Result 1 of Acne Detection using Speeded Up Robust Feature and Quantification using K-Nearest Neighbors Algorithm

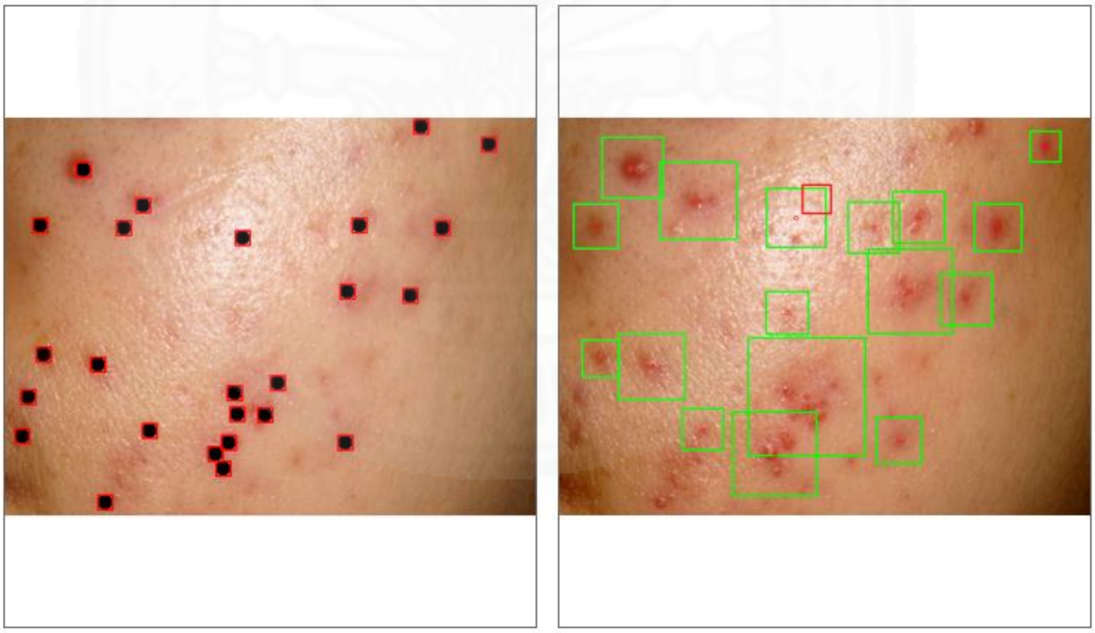


Figure 4.6 Result 2 of Acne Detection using Speeded Up Robust Feature and Quantification using K-Nearest Neighbors Algorithm

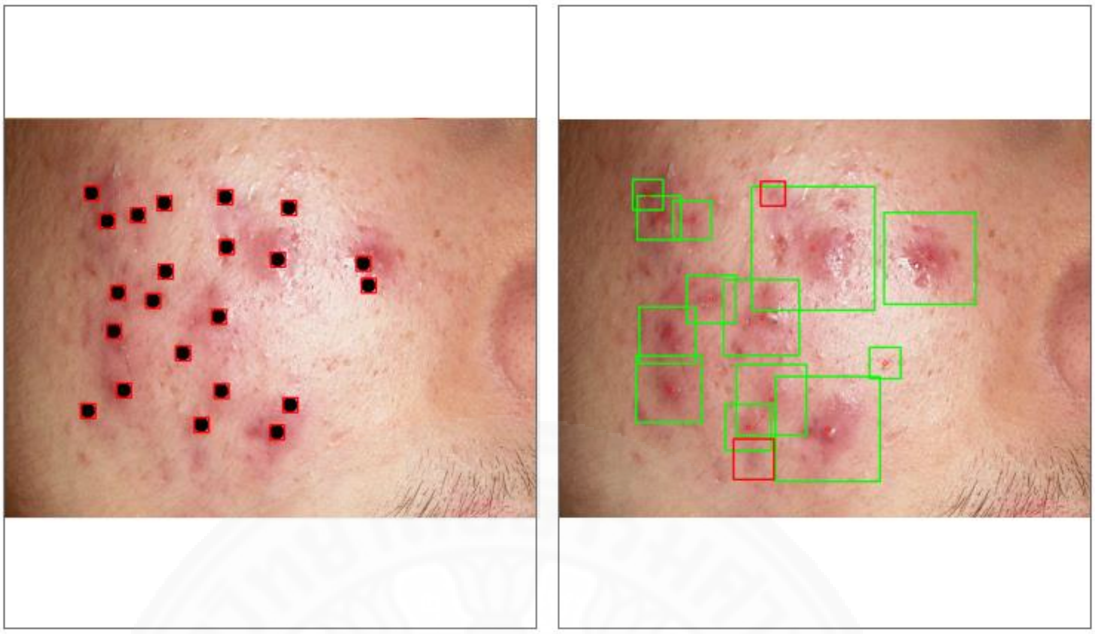


Figure 4.7 Result 3 of Acne Detection using Speeded Up Robust Feature and Quantification using K-Nearest Neighbors Algorithm

Figure 4.8 Result 4 of Acne Detection using Speeded Up Robust Feature and Quantification using K-Nearest Neighbors Algorithm

Table 4.1 Supervised learning steps, detail and implementation

Supervised Learning Step	**Detail**	**Implementation**
1. Determine the type of training example.	Choose what kind of data is to be used as a training set.	Acnes images on part of the face, captured from dermatologist's clinic.
2. Gathering a training set.	Gathering real-world data from expert as a set of input objects and set of output objects.	Dermatologist create ground truth image.
3. Determine input feature representation.	The input feature representation will be represented in feature vector that contains corresponding features. The number of features will be limited due to the curse of dimensionality. But it should contain enough information to give the system good prediction accuracy.	Feature Vector with a total of 9 features.
4. Determine the structure of learned function.	Determine the learning function or algorithm such as Support Vector Machine, K-Nearest Neighbor, Decision tree, etc.	K-Nearest Neighbor Classification.
5. Complete the design.	Run the learning algorithm on the training set. Testing and determine certain control parameters.	Run the system, observe and fine-tune.

6. Evaluate	Evaluate the accuracy of the learned function. Do parameter adjustment to obtain optimal control parameter, after that, measure the performance of the learned function on a testing data set which is separate from training data set.	Evaluate by confusion matrix, 3-Folds Cross-Validation.

4.6 System Implementation on Whole Face Image

Acne detection and quantification device is a device consisting of web camera and Acne detection and quantification software. The software started from image acquisition process by capture a whole face image of patient with full high definition resolution of 1080x1920 pixels, the system drew an ellipse and mask the face area. The Heat-Mapping technique was applied on the green channel of the image, which acne's pixel had the highest contrast [28] to gray scale. The system created result image in HSV color space. Heat-Map image (C image in Figure 4.9 to Figure 4.12) was created from setting Saturation and Value of the image to 255 and used only original Hue value. The Heat-Map image provided explicit mark on acne. The patient could easily investigate and understood the acne on the Heat-Mapped image. The System then did the pre-processing process by Smooth Gaussian. The SURF parameter was adjusted to match the size of an image.

The first challenge is the SURF algorithm which detects the border between ellipse's mask and face to be candidates. So, the problem is solved by drawing smaller ellipse and checking whether detected candidate's area is overlapping with this area or not, if the detected candidate is in this area, then discard this candidate.

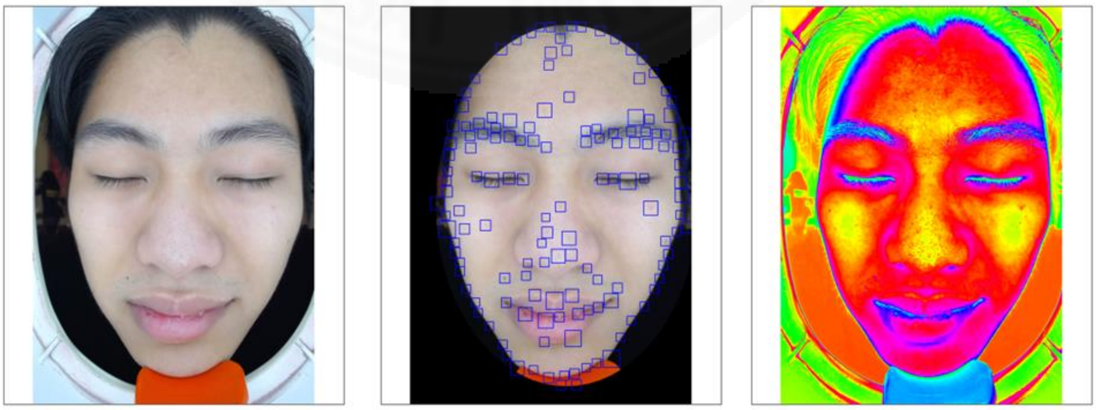
The next challenge is the system detecting candidates which are in eyebrows, eyes and mouth area. These candidates are discarded by using Haar-Cascade Classifier to detect eyes and mouth area and remove these areas from Region of Interest (ROI).

Viola and Jones [39] proposed an effective object detection method using Haar feature-based cascade. It is a machine learning approach of which the cascade function is trained with a lot of positive images and negative images. The function is used to detect objects in other testing images.

In the detection phase of the Viola–Jones object detection framework, a window of the target size is moved over the input image. Haar-like feature is calculated for each subsection of the image. This difference is then compared to a learned threshold that separates non-objects from objects. To improve accuracy in describing an object, a large number of Haar-like features are required to train this weak classifier. The stronger learner or classifier can be formed from the organization of the Haar-like features.

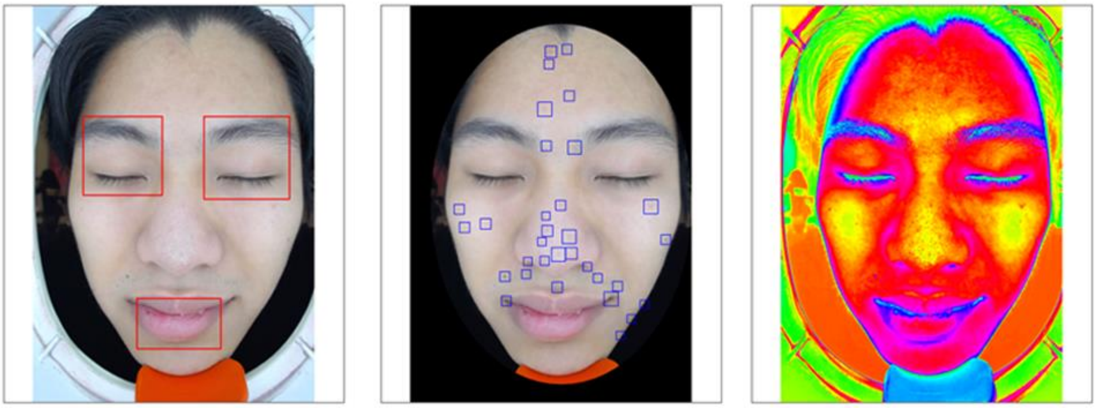
The Haar-like feature has key advantage of fast computation speed and the calculation time of any size object's Haar-like feature is a constant value.

The results of the system implementation on whole face images are shown in Figure 4.9 to Figure 4.12. Noted that these are only detected candidate which are not classified into acne or skin.



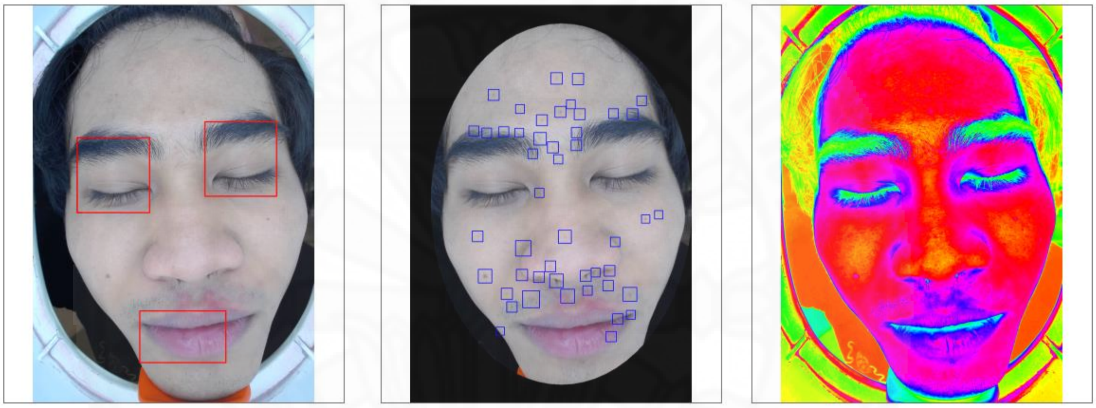
A B C

Figure 4.9 Result 1 of Acne Detection on whole face image



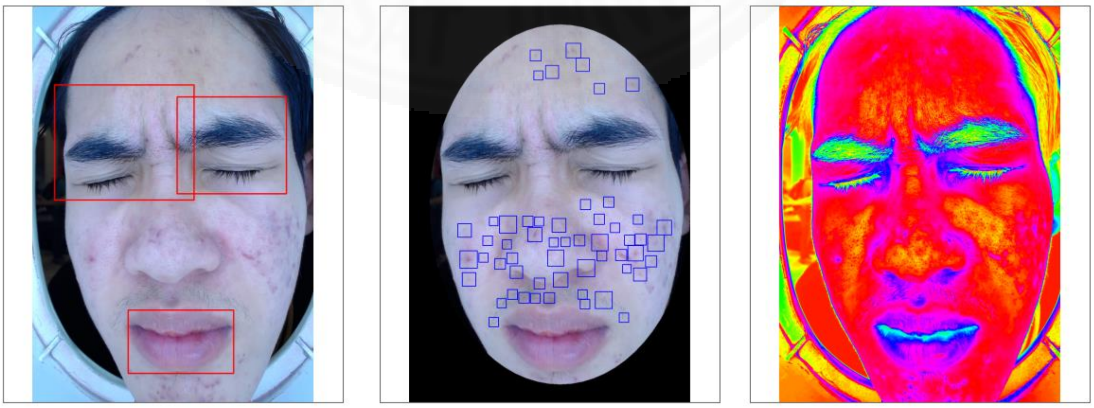
A B C

Figure 4.10 Result 2 of Acne Detection on whole face image



A B C

Figure 4.11 Result 3 of Acne Detection on whole face image



A B C

Figure 4.12 Result 4 of Acne Detection on whole face image

Chapter 5
Result and Discussion

The performance of acne detection using Speeded Up Robust Features and Quantification Using K-Nearest Neighbors algorithm is demonstrated in this chapter. The result was analyzed by comparing them with ground truth image which was obtained from dermatologist. There were 9 images which had a total of 129 acnes (mixed types). There were 865 training data including 129 positive samples and 736 negative samples. Lighting condition was not controlled. The image size was 800x600 px.

5.1 Features Evaluation

To evaluate features correlation with acne, the system was trained with training data, the correlation of 9 features is shown in Table 5.1.

Table 5.1 Correlation of 9 features

No.	Feature	Correlation
1	Redness	-0.074
2	Hue Mean	0.111
3	SD of Red	0.513
4	SD of Green	0.562
5	SD of Blue	0.158
6	Circularity	0.143
7	Entropy	0.425
8	Saturation Average	0.314
9	SD of Saturation	0.106

5.2 Detection and Quantification Algorithm Evaluation

3-Fold cross validation was validated: all images were divided into 70% training data and 30% testing data (validation set). For each time, the selection of training data was changed. The data that tested in each fold were not included in testing data. The number of Training and Testing data in each fold is shown in Table 5.2.

Table 5.2 Training and Testing data setting for the experiments

No.	K (Fold)	Total Training Data	Total Testing Data	Training Image Number	Testing Image Number
1	1	579	286	4,5,6,7,8,9	1,2,3
2	1	579	286	4,5,6,7,8,9	1,2,3
3	1	579	286	4,5,6,7,8,9	1,2,3
4	2	630	235	1,2,3,7,8,9	2,3,4
5	2	630	235	1,2,3,7,8,9	2,3,4
6	2	630	235	1,2,3,7,8,9	2,3,4
7	3	521	344	1,2,3,4,5,6	5,6,7
8	3	521	344	1,2,3,4,5,6	5,6,7
9	3	521	344	1,2,3,4,5,6	5,6,7

The confusion matrix was used to evaluate the performance of the algorithm. Six conditions were used to measure. Those were True positive (TP), False positive (FP), True negative (TN), False negative (FN), Sensitivity, Precision and Accuracy. The interpretation for each condition is shown in Table 5.3

Table 5.3 Conditions and interpretation of confusion matrix

Condition	Interpretation
True positive (TP):	Acne that is correctly detected as acne.
False positive (FP):	Scar and normal skin which are incorrectly detected as acne.
True negative (TN):	Scar and normal skin which are correctly detected as scar and normal skin.
False negative (FN):	Acne that is incorrectly detected as scar and normal skin.

Therefore, those conditions were calculated using the followings:

Sensitivity = TP/(TP+FN),

Precision = TP/(TP+FP),

Accuracy = (TP+TN)/(TP+TN+FP+FN).

Table 5.4 Acne Detection using Speeded Up Robust Feature and Quantification using K-Nearest Neighbors Algorithm

No.	TP	TN	FP	FN	Sensitivity	Precision	Accuracy
1	25	1	1	3	0.893	0.962	0.867
2	14	1	3	6	0.700	0.824	0.625
3	11	1	0	7	0.611	1.000	0.632
4	12	1	1	6	0.667	0.923	0.650
5	21	1	2	4	0.840	0.913	0.786
6	12	1	3	2	0.857	0.800	0.722
7	20	1	1	2	0.909	0.952	0.875
8	7	1	0	2	0.778	1.000	0.800
9	25	1	10	8	0.758	0.714	0.591
Average					**0.779**	**0.899**	**0.727**

By applying K-Nearest Neighbors classification with K=4, the performance was high with calculation time less than 10 seconds for each image. The average sensitivity was 78%, precision was 90% and accuracy was 73%.

Chapter 6
Conclusions and Recommendations

The main purpose of this study was to create novel acne detection and quantification method to help overcome doctor's excessive effort to manually quantify acne on patient's face. Acne segmentation method was introduced using adaptive thresholding, detection and quantification using Speeded Up Robust Features with feature extraction.

Adaptive thresholding segmentation is a good approach for acne image segmentation. It can create accurate segmentation to acnes image, the method does not require any manual adjustment.

A novel acne feature extraction and classification method was proposed. The method was first pre-processing with Smooth Gaussian technique. The system then did the BLOB detection and with Speeded Up Robust Feature (SURF) technique, iterated over detected key points, applied Otsu Thresholding extract, saved feature vectors and training results in the database. From the statistical analysis of correlation of 9 features that were introduced for acne quantification, the top 6 features that should be used for recognition were: SD of Green, SD of Red, Entropy, Saturation Average, SD of Blue and Circularity. Supervised learning with Train and Test were applied on the system. By training the system with 865 samples and testing the system with 129 acnes in 9 images, by applying K-Nearest Neighbors classification with (K=4), 3-Fold cross validation was validated and the results were analyzed on confusion matrix. The performance was high with calculation time for each image less than 10 seconds. The average sensitivity was 78%, precision was 90% and accuracy was 73%.

For future study, more acne images should be tested with the proposed algorithm by giving more training data and fine-tuning system, the accuracy would be improved. Acnes images should be made available online as Open-Database for accessing by other researchers. Implementation of the system with more advance pre-processing techniques such as advance brightness and contrast adjustment, histogram normalization and multi-scale smooth Gaussian can improve the accuracy. The controlled environment such as lighting, flash or non-flash photography can give the system more accuracy. Applying SURF on different color space such as YCbCr or CIELAB can tolerate different lighting conditions.

Furthermore, to implement acne detection system on whole face images. Ground truth images for acnes should be made and trained into automatic training system. For system implementation, patient's database with treatment record is one of an important software feature to record treatment progress and location of acnes. Lastly, implementation of the system with professional camera can improve the accuracy of the system.

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Appendices

Appendix A
List of Publications

1. Kittigul N., Uyyanonvara B. "Automatic acne detection system for medical treatment progress report”, *2016 7th International Conference of Information and Communication Technology for Embedded Systems (IC-ICTES)*, Bangkok, 2016, pp. 41–44.

2. Kittigul N., Uyyanonvara B. "Acne detection using Speeded Up Robust Features and quantification using K-Nearest Neighbor Algorithm”, *2017 6th International Conference on Bioinformatics and Biomedical Science (ICBBS 2017)*, Singapore, 2017, pp. 43–46.