2023

Bolt classification system for motorcycle retail shop

Monchai Angkapiyasiri
Faculty of Science

BOLT CLASSIFICATION SYSTEM FOR MOTORCYCLE RETAIL SHOP

Mr. Monchai Angkapiyasiri

A Thesis Submitted in Partial Fulfillment of the Requirements
for the Degree of Master of Science in Computer Science and Information Technology
Department of Mathematics and Computer Science
Faculty Of Science
Chulalongkorn University
Academic Year 2023

ระบบการจำแนกสลักเกลียวสำหรับร้านค้าปลีกจักรยานยนต์

นายมนต์ชัย อังคปิยะศิริ

วิทยานิพนธ์นี้เป็นส่วนหนึ่งของการศึกษาตามหลักสูตรปริญญาวิทยาศาสตรมหาบัณฑิต
สาขาวิชาวิทยาการคอมพิวเตอร์และเทคโนโลยีสารสนเทศ ภาควิชาคณิตศาสตร์และวิทยาการคอมพิวเตอร์
คณะวิทยาศาสตร์ จุฬาลงกรณ์มหาวิทยาลัย
ปีการศึกษา 2566

Thesis Title	BOLT CLASSIFICATION SYSTEM FOR MOTORCYCLE RETAIL SHOP
By	Mr. Monchai Angkapiyasiri
Field of Study	Computer Science and Information Technology
Thesis Advisor	Associate Professor SUPHAKANT PHIMOLTARES, Ph.D.

Accepted by the FACULTY OF SCIENCE, Chulalongkorn University in Partial Fulfillment of the Requirement for the Master of Science

.... Dean of the FACULTY OF SCIENCE
(Professor PRANUT POTIYARAJ, Ph.D.)

THESIS COMMITTEE

.... Chairman
(Professor CHIDCHANOK LURSINSAP, Ph.D.)

.... Thesis Advisor
(Associate Professor SUPHAKANT PHIMOLTARES, Ph.D.)

.... External Examiner
(Prem Junsawang, Ph.D.)

มนต์ชัย อังคปิยะศิริ : ระบบการจำแนกสลักเกลียวสำหรับร้านค้าปลีกจักรยานยนต์. (BOLT CLASSIFICATION SYSTEM FOR MOTORCYCLE RETAIL SHOP) อ.ที่ปรึกษาหลัก : รศ. ดร.ศุภกานต์ พิมลธเรศ

สถานการณ์โควิด-19 ในประเทศไทยนำไปสู่การเพิ่มขึ้นของคำสั่งซื้อออนไลน์ ส่งผลให้ความต้องการใช้รถจักรยานยนต์สำหรับการส่งสินค้าเพิ่มมากขึ้น ซึ่งเพิ่มความต้องการสำหรับส่วนประกอบที่จำเป็นด้วย โดยเฉพาะอย่างยิ่งสลักเกลียวที่ทนทานและสวยงาม เพื่อเพิ่มโอกาสทางธุรกิจสลักเกลียว 19 ประเภทถูกรวบรวมจากร้านค้ารถจักรยานยนต์เพื่อสร้างกระบวนงานการจำแนกประเภทสลักเกลียวอย่างเป็นระบบที่ประกอบด้วยระยะการสกัดลักษณะและระยะการจำแนกประเภท การสกัดลักษณะกำหนดขึ้นจากการใช้หลายขั้นตอนได้แก่ การลบพื้นหลัง การสกัดเส้นรอบขอบ การหมุนภาพ การตัดส่วนภาพ การวิเคราะห์เชิงโครงสร้าง การวิเคราะห์สีเด่น การตรวจหารู และการคำนวณอัตราส่วนความยาวหัวต่อทั้งหมด ต่อจากนั้นตัวแบบการจำแนกประเภทห้าแบบ ซึ่งประกอบด้วยเพอร์เซปตรอนแบบหลายชั้น ป่าสุ่ม ต้นไม้ตัดสินใจ ซัปพอร์ตเวกเตอร์แมชชีน และการถดถอยลอจิสติกถูกนำมาใช้เพื่อระบุประเภทที่เหมาะสมสำหรับสลักเกลียวแต่ละตัว ผลบ่งชี้ว่าเพอร์เซปตรอนแบบหลายชั้นมีความโดดเด่นในฐานะตัวแบบการจำแนกประเภทที่มีประสิทธิภาพมากที่สุดต่อลักษณะที่เสนอ

สาขาวิชา	วิทยาการคอมพิวเตอร์และเทคโนโลยีสารสนเทศ	ลายมือชื่อนิสิต ....
ปีการศึกษา	2566	ลายมือชื่อ อ.ที่ปรึกษาหลัก ....

6278508423 : MAJOR COMPUTER SCIENCE AND INFORMATION TECHNOLOGY
KEYWORD: motorcycle bolt, multi-layer perceptron, principal component analysis, median cut algorithm, circular Hough transform

Monchai Angkapiyasiri : BOLT CLASSIFICATION SYSTEM FOR MOTORCYCLE RETAIL SHOP. Advisor: Assoc. Prof. SUPHAKANT PHIMOLTARES, Ph.D.

The COVID-19 situation in Thailand has led to a rise in online purchase orders, resulting in a higher demand for using motorcycles for shipment, which has also increased the demand for essential components, notably durable and aesthetically pleasing bolts. To enrich their business opportunities, bolts of 19 classes are gathered from a motorcycle shop to establish a systematic bolt classification procedure containing feature extraction stage and classification stage. A feature extraction is formulated from utilization of steps, which are background removal, contour extraction, image rotation, cropping, structural analysis, dominant color analysis, hole detection, and calculating head-to-whole length ratio. Subsequently, five classification models, comprising multi-layer perceptron, random forest, decision tree, support vector machine, and logistic regression, are employed to identify the appropriate class for each bolt. The results indicate that the multi-layer perceptron stands out as the most effective classification model with the proposed features.

Field of Study:	Computer Science and Information Technology	Student's Signature ....
Academic Year:	2023	Advisor's Signature ....

ACKNOWLEDGEMENTS

In this section, I extend my sincere gratitude to those who have provided assistance, support, and understanding, enabling me to successfully complete this thesis.

I sincerely appreciate and wish to express my gratitude to my family for their unwavering support and motivation during my research on this thesis of great interest.

Indispensable to the success of my research and thesis, I would like to extend my heartfelt gratitude to Associate Professor Dr. Suphakant Phimoltares, my advisor, for their invaluable guidance in research and the essential skills I have acquired during this study.

Also, I wish to express my gratitude to the committee members, Professor Chidchanok Lursinsap and Dr. Prem Junsawang for their valuable time and constructive comments.

Furthermore, I wish to extend my heartfelt gratitude to my friends for their unwavering support and understanding.

Finally, I would like to express my appreciation to myself for dedicating attention to researching this thesis of great interest.

Monchai Angkapiyasiri

TABLE OF CONTENTS

Page

ABSTRACT (THAI) ... iii

ABSTRACT (ENGLISH) ... iv

ACKNOWLEDGEMENTS ... v

TABLE OF CONTENTS ... vi

CHAPTER I ... 1

INTRODUCTION ... 1

1.1 Background and Rationale ... 1

1.2 Research Objectives ... 7

1.3 Scope of work ... 7

1.4 Expected Outcomes ... 8

CHAPTER II ... 9

LITERATURE REVIEW ... 9

CHAPTER III ... 18

PROPOSED METHOD ... 18

3.1 Dataset ... 19

3.2 Feature Extraction ... 22

3.2.1 Background Removal ... 22

3.2.2 Contour extraction ... 23

3.2.3 Image rotation ... 24

3.2.4 Cropping ... 26

3.2.5 Structural analysis ... 27

3.2.6 Dominant color analysis 28
3.2.7 Hole detection 29
3.2.8 Calculating head-to-whole length ratio. 30
3.3 Classification Models 31
3.3.1 Multi-layer perceptron 31
3.3.2 Random Forest 31
3.3.3 Decision tree 32
3.3.4 Support vector machine 33
3.3.5 Logistic regression 33
3.4 Building each model in this study 34
3.4.1 Splitting a dataset 34
3.4.2 Defining parameters of a model 35
3.4.3 Creating a model 36
3.4.4 Evaluating model performance 37
CHAPTER IV 38
EXPERIMENTAL RESULTS 38
4.1 Experimental setup 38
4.1.1 Multi-layer perceptron 38
4.1.2 Random forest and decision tree 39
4.1.3 Support vector machine 39
4.1.4 Logistic regression 39
4.2 Experimental results 40
4.2.1 True positive, false positive, true negative, and false negative 40
4.2.2 Recall 41

4.2.3 Precision.. 41

4.2.4 Results of models.. 41

4.3 Model analysis 44

4.4 Misclassification 45

CHAPTER V 46

CONCLUSION 46

5.1 Discussion and conclusion 46

5.2 Future work 47

REFERENCES 48

VITA... 50

CHAPTER I
INTRODUCTION

1.1 Background and Rationale

Currently, the global epidermic situation has forced many people to self-isolate at home to prevent the spread of the epidemic, leading to more time spent at home. So, they increase their home maintenance and cleaning efforts. Additionally, there is an increased demand for products and food from habitats. They reside in various locations. Therefore, food delivery companies require fast, flexible, and economical vehicles, such as motorcycles, that possess all the mentioned characteristics.

Typically, using heavy motorcycles increases maintenance, resulting in the demand of numerous motorcycle spare parts. A motorcycle part store was visited to gather and research the available motorcycle spare parts from various brands and models. There are over 2000 classes. Selling spare parts typically requires personal expertise, including collecting experience and training prior to making sales. It takes at least 1-2 months to learn about motorcycle spare parts. Becoming a specialist which takes over 6 months consumes a significant amount of time and money. The research reveals that both best-selling and smaller spare parts face challenges in classification, necessitating careful and precise categorization of the bolts, which amount to over 200 different classes.

The survey of the motorcycle parts store classifies bolts into three main categories: standard bolts, stainless bolts, and special stainless bolts.

The first category is the standard bolt made from steel, which lacks anti-rust properties and is prone to rusting. However, this category is inexpensive and widely available as shown in figure 1.1.

Figure 1.1 The standard bolt category.

The second category is the stainless bolt, which is typically more expensive than the standard bolt because of its rust-resistant stainless steel material. Most of the bolts are small and not particularly decorative as shown in figure 1.2.

Figure 1.2 The stainless bolt category.

The special stainless category consists of the stainless bolts designed to prevent rust. Additionally, they are varied with color, length, and head style. Installing bolts in a motorcycle adds distinctiveness and uniqueness.

There are various head styles available, including square, drill, round, and even umbrella heads. Most customers want to customize their motorcycles significantly. The example displays the various bolt head styles available at the motorcycle parts store as shown in figure 1.3.

Figure 1.3 The bolt head styles within the special stainless category.

The special stainless bolts come in different lengths as shown in figure 1.4.

Figure 1.4 The bolt lengths within the special stainless category.

Various colors, including blue, gold, and silver color are available. The colorful bolts enhance the prominence of the motorcycles as shown in figure 1.5.

Figure 1.5 The bolt colors within the special stainless category.

The thread styles include fully threaded and non-fully threaded. However, the fully threaded option is more popular than the non-fully threaded one. As shown in figure 1.6.

Figure 1.6 The bolt threads within the special stainless bolts.

The bolt classification applies not only to physical stores but also to online platforms, as technological advancements create new business opportunities. Typically, the bolt classification demands the specialists to memorize all types, but current technology falls short in automating the process. Therefore, a new method is proposed to incentivize classification, reduce costs, and capitalize on new business opportunities.

Bolt classification has significant challenges caused by distance from the lens to the bolts, the perspective view, rotation of the bolt, illumination and shadow, image conditions including their quality of the images with a mobile phone.

In this study, there are 18 classes, including best-selling, expensive, and closely similar bolts, to be considered. While these classes present significant challenges for classification, class 19 is used to assist in the bolt classification for the bolts that do not belong to one of 18 classes.

Although we have researched numerous nut and bolt papers, none of them effectively classify the motorcycle bolt images. Therefore, both of feature extraction and classification techniques are proposed for the motorcycle bolt image classification. The feature extraction process involves utilizing principal component analysis to calculate an angle between bolt and horizontal axis, the median cut algorithm to extract the dominant colors of bolts, and structural analysis to effectively extract relevant features. Afterwards, the feature vector extracted from a bolt image is classified by using the random forest model, multi-layer perceptron, decision tree, support vector machine, and logistic regression. The multi-layer perceptron yields excellent results, while further details will be provided in the next section.

1.2 Research Objectives

To develop a model to classify bolts of motorcycle to their classes with high accuracy.

1.3 Scope of work

There are five issues to be considered about this research.

1. The classification result is impacted on the complicated background. Thus, the background must be eliminated to focus on the performance of bolt classification.
2. The bolt image is independent of image variations, which are image scaling, rotation, and translation.
3. Bolt color, head style, and size are three main factors to define 18 different classes in this study. Moreover, the reject class (class 19) is also reserved for images, not belonging to any pre-defined class.
4. The bolt image is captured in top-view and daylight condition due to practical use in retail shop during the office hours.
5. Only single bolt is considered at a time, resulting in one bolt in each image.

1.4 Expected Outcomes

This research aims to build a classification model that can classify the bolts of motorcycle with real-world image conditions into one of 19 classes with high accurate rate.

CHAPTER II
LITERATURE REVIEW

Numerous scholarly papers have been dedicated to solving the bolt and nut problems, with a comprehensive focus on their evaluation, encompassing up to seven pertinent sources. The complex findings are elaborated upon in the following sections.

For the first source, Abdel Belaid presented a prototype version of an image processing system designed for nut quality control using diameter and length [1]. The system was proved to be accurate. The performance was determined by the quality of the original nut image. To find edges more precisely, they use the gradient and Laplacian methods, and then Pythagoras' theorem is applied to calculate the length.

The second source is 'Design and Performance Analysis of a Moveable Groove-tracking Milling Machine for Repairing Thread of Marine Steering Gear Nuts'. After prolonged usage, nearly all ships operate at high pressure and for extended durations. This situation leads to the failure of the nut threads, both between the tiller and rudderstock and between the propeller and stern shaft. Typically, the technique used to repair the failed nut thread is 'groove-tracking machining.' Nevertheless, the technique faces challenges when dealing with nuts of large diameters, typically ranging from 300 to 1,500 mm.

Guiping Lu et al. aim to solve this issue, and to achieve this, they have developed a moveable groove-tracking milling machine that was designed for easy assembly and disassembly [2]. Furthermore, the machine is fixed within the nut's threads to facilitate the repair process. Finite element analysis, kinematics simulation analysis, and dynamics analysis were performed using UG NX software on the main components, providing essential data and a theoretical foundation for the production process.

The development of the moveable groove-tracking milling machine design stemmed from investigations into technological repair for large nut threads in shipyards. The paper presents the collection, calculation, and analysis of the cutting force exerted by the spindle cutter in groove-tracking milling for threads. Advanced simulation of NX is applied to analyze the finite element (FEA) of main components and motion movement for all machine components, thereby facilitating the analysis of potential design possibilities. Lastly, the proposed solution is effective in repairing large nuts, which can reduce maintenance costs for essential components.

The third source is ‘Real-time Pitch Diameter Measurement of Internal Thread for Nut using Laser Triangulation’. Typically, conventional approaches, such as utilizing contact methods and thread plug gauges, are applied for measuring the pitch diameter. However, these methods are limited in terms of both accuracy and real-time measurement. Alternative methods, such as non-contact methods like reflected light methods and laser triangulation, have been devised to address specific objects, driven by differences in appearance and reflective properties.

Chun-Fu Lin et al. proposed a real-time method for measuring the pitch diameter of a nut using laser triangulation [3]. The process involves sending the image of a nut with laser projection through an image processing procedure for appearance extraction and distortion correction. Subsequently, the preprocessed image is then directed into the proposed measurement algorithm to quantify the pitch diameter of the nut's internal thread as shown in figure 2.1.

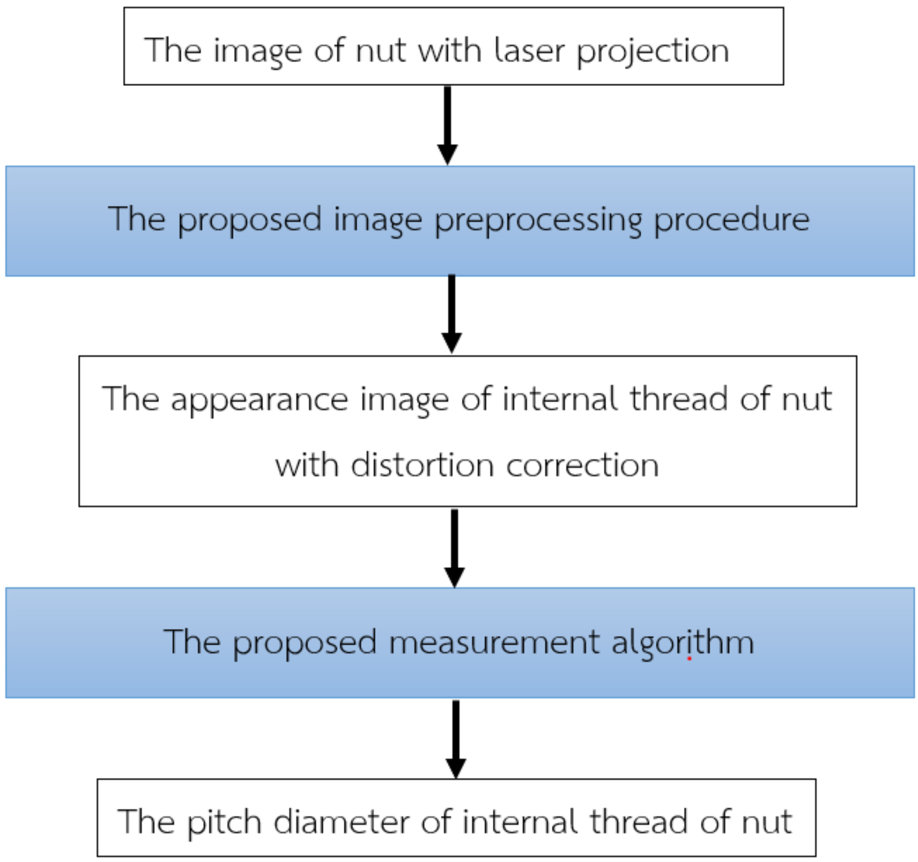


Figure 2.1 The method for measuring the pitch diameter.

The effectiveness of the proposed method is evaluated by analyzing over 100 test images, revealing that the variation between individual pitch diameter measurements obtained through the proposed method does not exceed 100 μm.

The fourth source is 'The Development of Adaptive Gray Level Mapping Combined Partical Swarm Optimization for Measuring the Dimeter Size of Automotive Nut'. Typically, the inspection process for automotive nuts within the TSC industry involves the manual utilization of vernier calipers. This situation is influenced by multiple factors that can contribute to errors. Therefore, the implementation of image processing techniques is required to facilitate the transition to automated inspection, thereby enhancing accuracy and mitigating potential errors associated with human involvement.

Wichai Pondech et al. proposed a method that combines Adaptive Gray Level Mapping (AGLM) with Particle Swarm Optimization (PSO) to improve image quality and achieve precise measurement of the radius or diameter of a nut utilizing the Circular Hough Transform (CHT) technique [4]. Furthermore, AGLM's BETA is modulated by PSO (Particle Enhancement), and 50% nut data is used to validate its validity. The objective function of PSO with AGLM applied is derived through a four-step process: Step 1 involves measuring the diameter of 100 nuts using a vernier caliper. In Step 2, nut images are collected. Step 3 entails dividing the set of images into two distinct sample and validate sets. Finally, in Step 4, the beta value of the AGLM algorithm is determined utilizing the Particle Swarm Optimization technique to create the objective function.

The effectiveness of the proposed method was evaluated through the mean square error between the reference data measured by the Circular Hough Transform using the proposed method and the measurements obtained with a vernier caliper. The results confirmed the effectiveness of the proposed measuring method better than the conventional threshold method in real-world scenarios as shown in table 2.1.

Method	RMS Error (mm)	Standard Deviation (mm)	Min Error (mm)	Max Error (mm)
Proposed PSO combined AGLM	0.0110	0.0149	0.001	0.02
Threshold technique	0.0799	0.0339	0.003	0.078

Table 2.1 The error results.

The fifth source is 'Measuring Diameter of Non-threaded Hex Bolts Based on Hough Transform'. During the manufacturing process, the measurement of the diameter of non-threaded hexagon-head bolts according to specifications is carried out through manual operator-based methods, which presents several inherent weaknesses, including elevated labor costs and diminished efficiency. The absence of prompt identification of substandard bolts can result in structural impairment, which serves as the impetus for the research presented in the subsequent section.

Zhou Zhifeng proposed a vision measurement method for measuring the diameter of a non-threaded bolt presented [5]. The methodology employs vision detection to augment the quality control process, achieving this by transforming the raw grayscale original image into a binary image through the utilization of the Canny edge detector. The detector identifies circles within a binary image and estimates the center and radius coordinates utilizing the Hough transform. This transition from manual to automated detection significantly enhances overall detection efficiency and methodology.

The effectiveness of the proposed method was evaluated through the utilization of a meticulously measured movable calibration bolt. This ensures that the accuracy of the bolt was confirmed and in accordance with production specifications. Furthermore, the proposed approach entails an automated measurement of the diameter of non-threaded hexagon-head bolts, replacing manual labor-intensive processes.

The sixth source is ‘Recognition of Bolt Quality Base on Elman Neural Network by Ant Colony Optimization Algorithm’. It can be inferred that a significant portion of construction projects necessitate the utilization of bolts as essential components. Hence, the structural integrity and operational condition of bolts exert a profound influence on safety. The proposed objective is to ensure the effectiveness of bolts within the context of support system engineering, with the aim of preventing potential disasters.

Wei-Guo Di et al. proposed Ant colony algorithms to optimize the Elman neural network to recognize the bolt quality [6]. The features of bolt anchoring stress waves are extracted based on wavelet packets. They optimize the weights and thresholds in Elman neural network with ant colony algorithm (ACO-Elman) and they also optimize the Elman neural network with a genetic algorithm (GA-Elman).

The effectiveness of the proposed method was evaluated through the metrics of correct recognition rate and Mean Absolute Error. Upon comparison with the standard ant colony algorithm and the Elman neural network optimized by genetic algorithms, the results indicate superior performance of the ant colony-optimized Elman neural network.

The seventh source is ‘Bolt positioning method based on active binocular vision’ Typically, power equipment encounters malfunctions or security issues, which can pose risks to the smart grid and result in power accidents. Due to the nature of traditional maintenance methods, the approach is not only inefficient but also poses safety risks for workers. The proposed method has been developed to ensure the safe and stable operation of the power system.

Xu Jian et al. proposed the method for measuring the posture of bolts using active binocular vision [7]. Following a systematic procedure, the initial step involves obtaining an RGB image and a depth image, followed by bolt recognition. Subsequently, the depth of the bolts is determined, and a binocular camera model is employed to accurately establish the 3D coordinates of the bolts. The angle of the fitting plane is derived by applying the least square method based on the point cloud to obtain the position and posture of bolts as shown in figure 2.3.

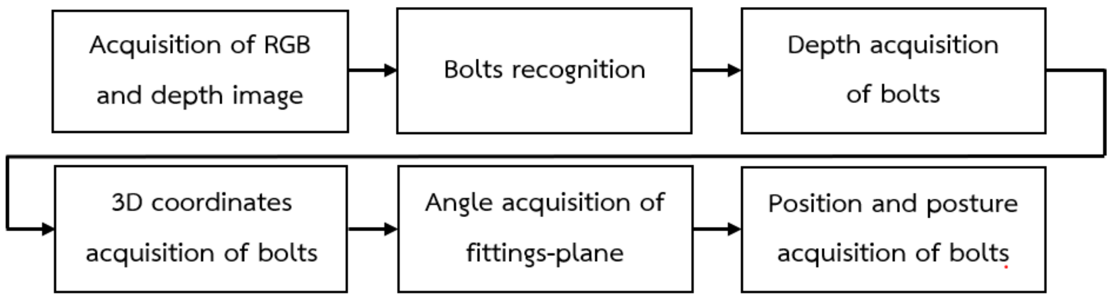


Figure 2.3 The proposed method for bolt localization.

The effectiveness of the proposed method was evaluated by achieving a position measurement error for bolts within substation fittings of less than 0.8% within a 500 mm measurement range, coupled with an angle measurement error for the fitting plane that remains under 1 degree. Therefore, the proposed technique holds significance in the realm of robotic maintenance for substation fittings.

As mentioned above, each of relevant studies holds inherent interest. Nevertheless, existing research has not fully resolved the problem stated in this thesis. Hence, this thesis proposes the utilization of images captured from mobile phones to address the classification challenges. Despite the multitude of bolt classes and varying image environments during acquisition, Multi-layer Perceptron demonstrates superior performance. In addition, multiple models are employed to classify the bolt images by using the features that are extracted in the feature extraction step. The details for developing the models will be proposed in the next section.

CHAPTER III
PROPOSED METHOD

Within this chapter, the overall procedure of the proposed method for classifying bolt images is elucidated in the subsequent section as shown in figure 3.1.

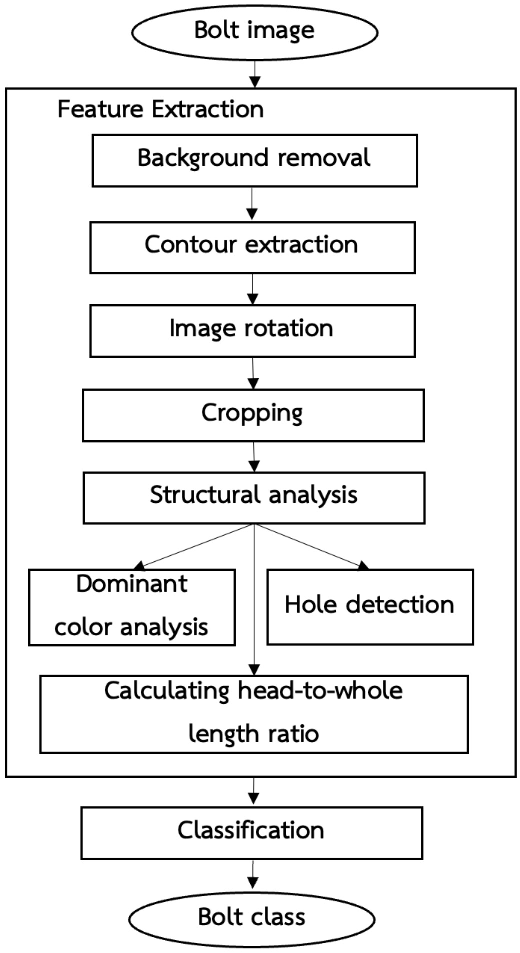


Figure 3.1. Procedure Overview of the Proposed Method.

The overall procedure can be subdivided into two primary segments. The initial major segment encompasses feature extraction, comprising a sequence of eight distinct steps. Subsequently, the second principal segment involves classification, wherein a series of classifiers are employed to process the bolt images and determine their corresponding bolt class. Elaboration on these aspects will be provided in the ensuing subsections.

3.1 Dataset

A total of 619 motorcycle bolt images, each with dimensions of 3024x4032 pixels, were meticulously collected under various environmental conditions. The bolts encompass a total of 19 distinct classes, as shown in Table 3.1. Subsequently, the compilation of bolt images was partitioned into training and test sets, maintaining an 75/25 ratio. The training set comprises 464 images, while the test set encompasses 155 images. However, the various environments are captured, as shown in Table 3.2.

Table 3.1. Details of bolt collection employed in this study.

Class	Head type	Hole existence	Thread length (mm)	Color
1	Square	No	15	Blue
2	Square	No	20	Blue
3	Square	No	25	Blue
4	Square	No	30	Blue
5	Square	Yes	15	Gold
6	Square	Yes	20	Gold
7	Square	Yes	25	Gold
8	Square	Yes	30	Gold
9	Square	Yes	35	Gold
10	Square	Yes	40	Gold
11	Square	No	15	Silver
12	Square	No	20	Silver
13	Square	No	25	Silver
14	Square	No	30	Silver
15	Circle	No	15	Gold
16	Circle	No	20	Gold
17	Circle	No	25	Gold
18	Circle	No	30	Gold
19	Square	Yes	45	Gold/ Silver

Table 3.2. Factors involving the environment when capturing an image.

Background Colors	dim and bright
Distance	100 – 400 mm.
Bolt rotation	0° – 360°
Parts of the day	morning, afternoon, evening, and night
Shadow type	dark and fade

Figure. 3.2. Sample images captured in different environments.

3.2 Feature Extraction

As a preprocessing step, prior to undergoing the feature extraction process, an image is converted into a binary image. Subsequently, the initial step involves feature extraction, where a set of features is extracted from a bolt image to facilitate the classification of bolts.

Upon collection and observation of the dataset, it became evident that the bolts encompass a multitude of intriguing features. In the study, the assessment of significant features is divided into three distinct features, namely dominant color, hole existence, and a head-to-whole length ratio. The steps involved in extracting significant features can be described in the following section.

3.2.1 Background Removal

In this step, a bolt image is background removed using the U2-Net model [8]. Prior to forwarding the image to the subsequent step, the existing bolt represents the most visually distinct entity within the image as shown in figure 3.3.

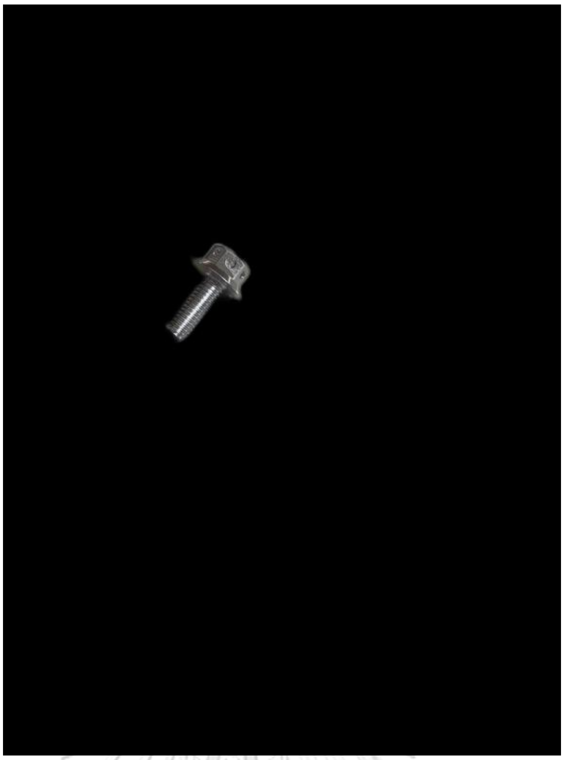


Figure. 3.3. Bolt image without background.

3.2.2 Contour extraction

A contour is defined as a sequence of points that are constructed and identified along the boundary of the bolt in the image. This contour is identified based on the intensity differences, encompassing both the horizontal and vertical directions, among the surrounding pixels of the bolt. In this step, the connected component corresponding to the contour of the bolt image is identified as shown in figure 3.4.

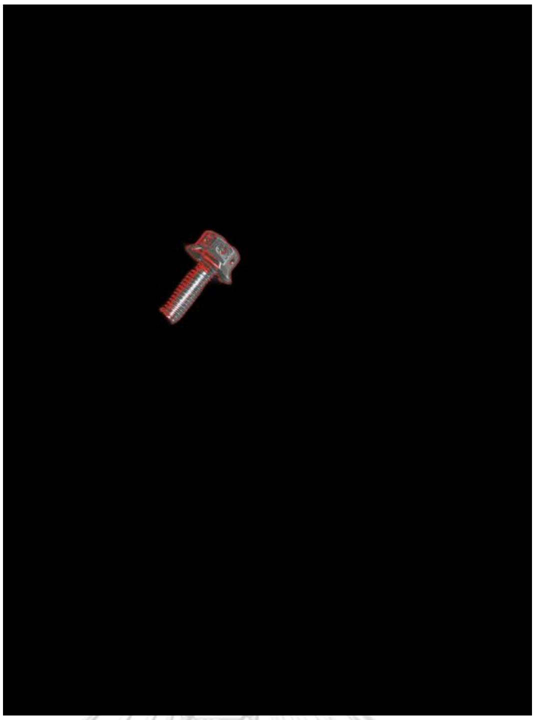
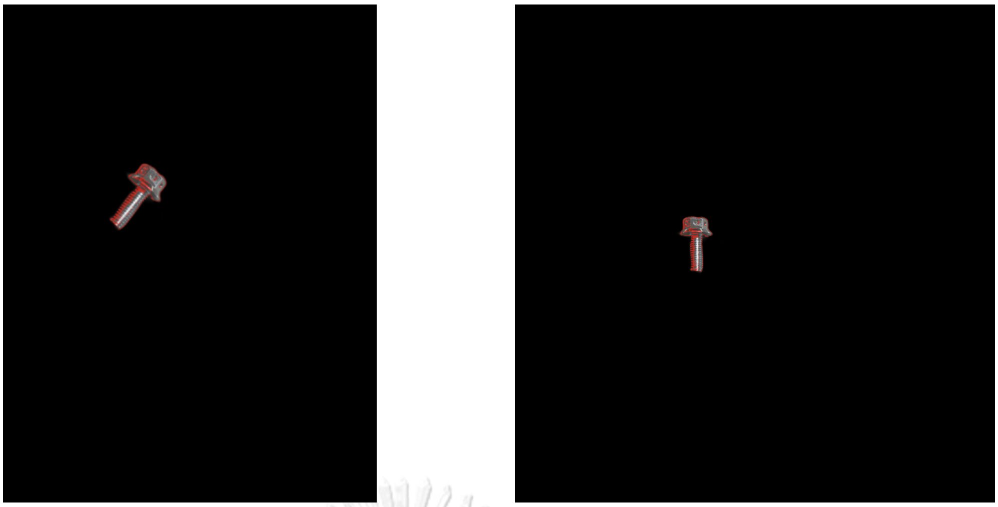


Figure. 3.4. Bolt contour.

3.2.3 Image rotation

In this step, Principal Component Analysis (PCA) is employed to compute the angle between a bolt and the horizontal axis, and subsequently, the bolt is rotated by that angle. Thus, the angle is 90° in relation to the horizontal axis as shown in figure 3.5. Utilizing PCA, the regions of all pixels in the bolt of an image are treated as data points. The first principal component provides the main angle of α of the bolt where the data points yield the most variance as shown in figure 3.6. Then, a bolt image will be rotated with $90° - \alpha$ in a clockwise direction.



(a) (b)

Figure. 3.5 Rotating the image to generate the rotated bolt, with a primary angle of 90° relative to the horizontal axis. (a) Bolt without background. (b) Bolt after rotation.

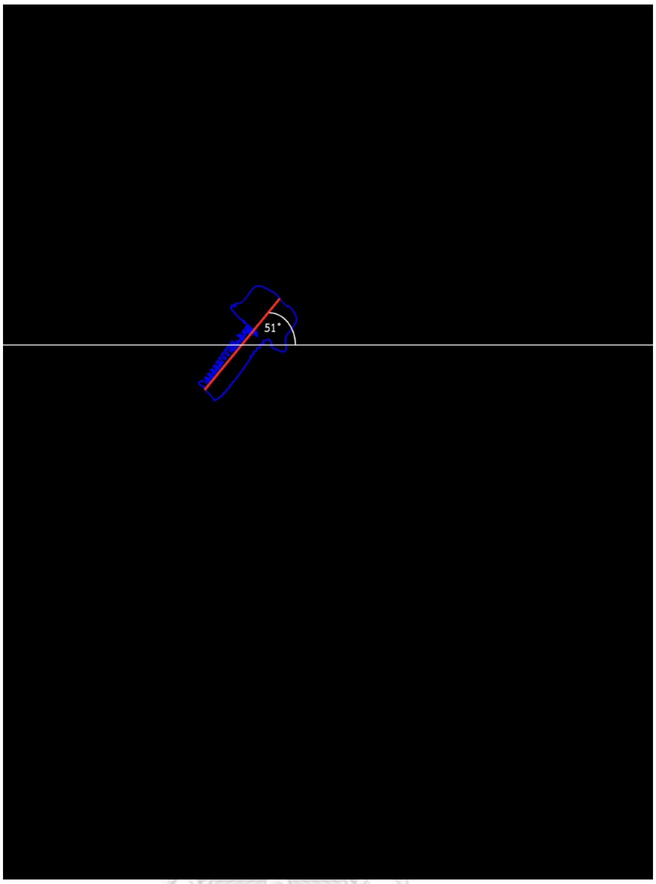


Figure. 3.6. The first principal component aligns with the data points of a bolt, forming an angle of 51° relative *to the horizontal axis.*

3.2.4 Cropping

In this step, cropping is employed to isolate the main region of the bolt, utilizing the contour of the rotated bolt outlined in the preceding section as a sequence of red points. They consist of the topmost, bottommost, leftmost, and rightmost points that can be employed to define the region for cropping, effectively encompassing the bolt as shown in figure 3.7.

(a) (b)

Figure. 3.7. Bolt image cropping. (a) Image featuring a rotated bolt (b) Image after cropping.

3.2.5 Structural analysis

In this step, a line is generated by connecting a leftmost point (x_L, y_L) and a rightmost point (x_R, y_R) using the contour obtained from the previous step. The line divides the cropped image into two sections: the bolt head and the bolt body. It is important to note that the height of the bolt body is at least twice that of the bolt head.

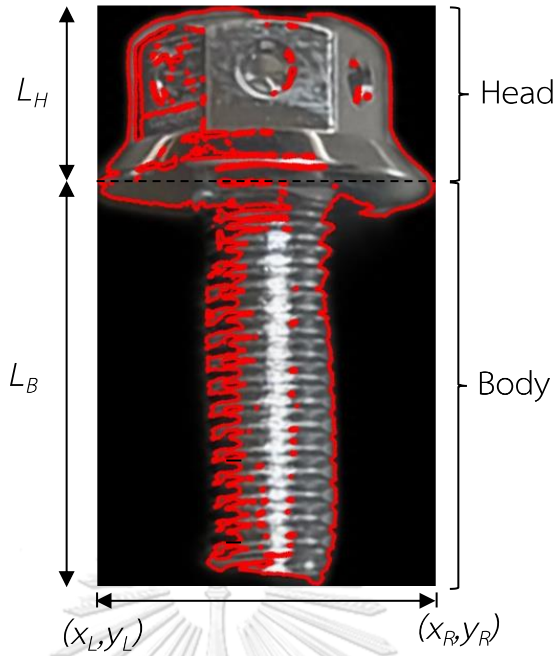


Figure. 3.8. Analyzing the bolt's structure.

3.2.6 Dominant color analysis

This section is dedicated to identifying the dominant color of the bolt. The original image in the bolt's head is analyzed in this step for this purpose. The assumption here is that the variance of color in the bolt's head is lower than that in the body. However, it's important to note that some pixels in the head might be influenced by shadows. To acquire the dominant color from the bolt's head image in the preceding step, it is transformed into a dataset of RGB color space, which is then subjected to the median cut algorithm. Within the algorithm, during the initial iteration, the RGB color space is partitioned into two sections utilizing the median of the color component exhibiting the broadest range. Subsequently, the process of division is iteratively repeated on these two segments until the total number of sections reaches 16. Following this, the median color is extracted from each of these sections, yielding a collection of 16 colors. The dominant color, $color_D$ is one color chosen from this set by (1) and (2).

$$color_D = (R_i, G_i, B_i) \tag{1}$$

and

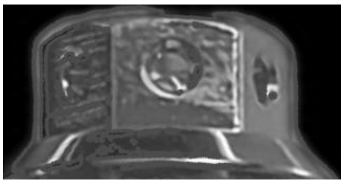
$$i = \underset{j}{argmin}\left(diff\left(color_j, color_{avr}\right)\right) \tag{2}$$

where $color_j$ is a color j in a set of 16 colors and $color_{avr}$ is an average color from a bolt head without including background. The dominant color of the bolt is determined by calculating the disparity between the color with the lowest value and the average color.

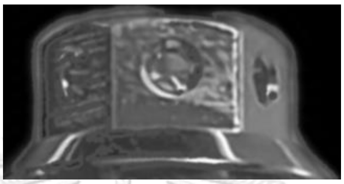
3.2.7 Hole detection

In this section, the Circular Hough Transform (CHT) is employed to identify a feature known as the existence of a round-shaped hole. Based on analyzing and observing of the dataset, the radius of the hole typically falls within a range of 11 to 20 percent of the head image's height. Iteratively, multiple circles with varying radii are drawn around the identified point head of bolt. Subsequently, the Hough space is examined and evaluated by comparing the positions against high values and the pre-defined threshold to determine the presence of a hole. It is important to highlight that in this section, only the bolt head is analyzed to expedite the process, and the blurring image using an averaging filter with a size of

3×3 is applied prior to using CHT, effectively reducing false positive artifacts on the bolt head as shown in figure 3.9.



(a)



(b)

(c)

Figure. 3.9. Detecting Hole in the bolt head image. (a) Grayscale image (b) Blurred image (c) Detected hole in image

3.2.8 Calculating head-to-whole length ratio.

Finally, as the last step of feature extraction, the calculating head-to-whole ratio is calculated to extract the significant feature before forwarding it to the classification model. The ratio is employed instead of actual lengths because of their dependence on camera distance and zoom feature. It can be calculated from $L_H/(L_H + L_B)$ where L_H is a vertical length of head and L_B is a vertical length of body as shown in figure 3.8.

Upon obtaining features from the feature extraction process, the dominant color, the existence of holes, and the head-to-whole length ratio serve as inputs for the classification model discussed in the subsequent classification model's section.

3.3 Classification Models

In the second part of the procedure, the classification models are implemented for comparative analysis. The proposed models include multi-layer perceptron, random forest, decision tree, support vector machine, and logistic regression.

3.3.1 Multi-layer perceptron

A multi-layer perceptron (MLP) is a kind of neural network with multiple layers of artificial neurons. In this approach, the data passes through the network in only one direction, moving from the input layer to the output layer to obtain the final output. The backpropagation algorithm is utilized to adjust the weights of the connections in the network, aiming to minimize the error. The backpropagation process is iterated until the error is reduced to an acceptable level.

3.3.2 Random Forest

Random forest is an ensemble of sub-decision trees that employs a majority vote mechanism to classify bolt images and produce the final results. In the process of creating the random forest, the dataset is partitioned into distinct subsets, and each of these subsets is utilized to construct a sub-decision tree. The random forest consists of 100 trees, with a predominant outcome of class 19 assigned to the given bolt. The architecture of random forest is shown in figure 3.10.

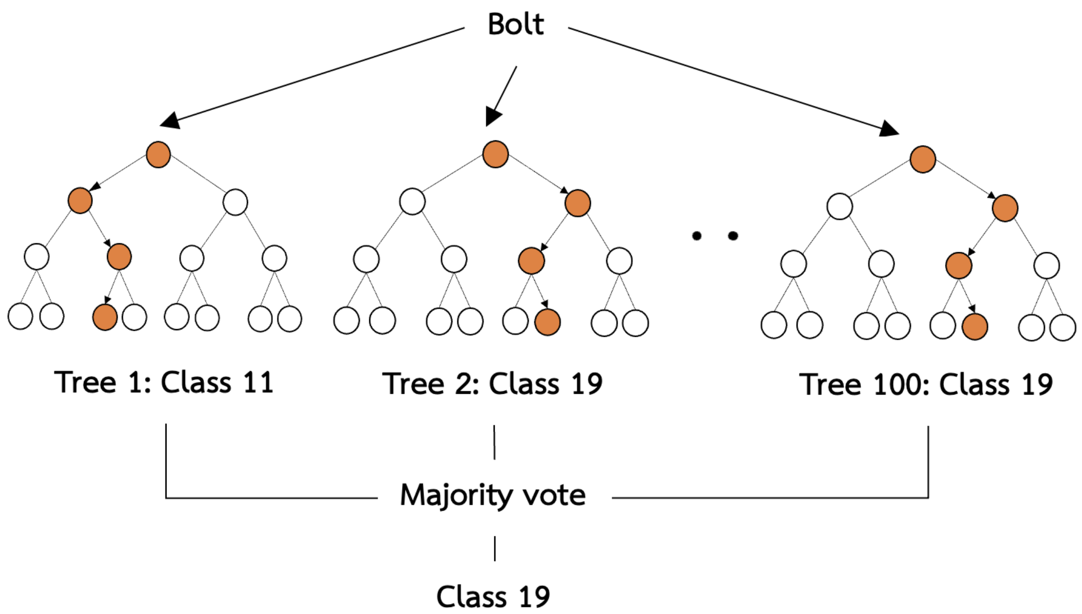


Figure. 3.10. Random forest structure comprising 100 sub-decision trees.

3.3.3 Decision tree

The decision tree model is structured as a tree, with input data being recursively divided into smaller subsets based on the significant features. The process involves traversing the tree to reach the leaf nodes, which ultimately define the bolt's class. At each step of the decision tree, the "if-then" conditions are employed to guide the data flow within the tree based on the features.

3.3.4 Support vector machine

A support vector machine is established to classify data into distinct classes using a hyperplane concept, aiming to maintain the maximum separation distance from the nearest points of each class. These pivotal points, referred to as support vectors, play a crucial role in determining the optimal positioning of the hyperplane within the data space.

3.3.5 Logistic regression

The logistic regression model is a commonly employed linear model for classification tasks. It calculates the probability of a given class by considering the significant features that contribute to the likelihood of belonging to one of the 19 classes. Subsequently, the output of each class is converted into a probability within the range of 0 to 1. A probability close to 1 indicates a higher likelihood of the input belonging to the class, whereas a probability approaching 0 suggests that the input is less likely to be a member of the class.

3.4 Building each model in this study

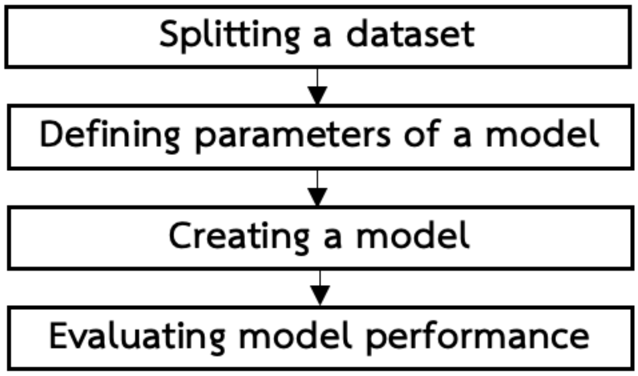


Figure 3.11. a model creating procedure.

In the forthcoming section, the utilization of specific methods within each model will be explained. These methods, denoted as splitting a dataset, defining parameters of a model, creating a model, and evaluating model performance, will be thoroughly examined and elucidated as Figure 3.11.

3.4.1 Splitting a dataset

In the experimental phase, the dataset is partitioned into distinct subsets, namely the training set comprising 75% or 464 images, and the test set encompassing 25% or 155 images. This division ensures a comprehensive evaluation of the model's performance, facilitating a rigorous analysis of its capabilities and accuracy.

3.4.2 Defining parameters of a model

There are twelve parameters used for five models as follows. First, the parameter architecture, which consists of multiple layers of interconnected artificial neurons, including an input layer, one or more hidden layers, and an output layer. Second, the parameter activation function, an operation employed to the output of each neuron in the network. The function introduces nonlinearity, allowing the model to learn and represent intricate relationships within the data. Third, the parameter L2 regularization parameter constitutes a regularization technique during training by introducing a penalty within the loss function. Fourth, the parameter learning rate determines the magnitude by which the model's weights are updated during training. Fifth, the parameter solver specifies the optimization algorithm employed to adjust weights during training, aiming to enhance the efficiency of the model. Note that the first five parameters are used for the multi-layer perceptron.

Sixth, the parameter impurity measure quantifies the extent of mixture or disorder within data subsets, providing guidance for decision tree splits by minimizing uncertainty. Seventh, the parameter maximum tree depth defines the upper limit of branching within individual decision trees and serves to regulate the potential for overfitting. Eighth, the parameter maximum feature parameter establishes the count of features that are selected randomly at each split point within the decision trees. This parameter is employed to mitigate overfitting by constraining the influence of individual features on the decisions made by the tree. Ninth, the parameter 'Minimum samples in leaf' establishes the minimum quantity of samples necessary within a leaf node of a decision tree. It is utilized to halt additional splitting if the sample count falls below the specified threshold. Tenth, the parameter 'Minimum samples of splitting' establishes the minimum required sample count within a node to warrant further consideration for splitting. The parameter is employed to curtail the development of excessively intricate models and govern the expansion of decision trees. Eleventh, the kernel function is a mathematical function employed to map input data into a higher-dimensional space, Twelfth, the regularization parameter is a technique used to prevent overfitting, ensuring the model performs well on new data by controlling its complexity. Subsequently, the parameters of each model will be explained in the following section.

3.4.3 Creating a model

The twelve parameters discussed in the preceding section are instrumental in configuring the five distinct models, denoted as multi-layer perceptron, random forest, decision tree, support vector machine, and logistic regression, respectively. These parameters play a role in shaping the intricate architecture and functionality of the models, contributing significantly to their overall performance and effectiveness in their designated tasks.

3.4.4 Evaluating model performance

The experiments are conducted through a rigorous process of training and testing, involving a total of 100 trials to attain stable and reliable results. The accuracy is calculated as the mean of these 100 trials, ensuring a comprehensive evaluation of the models under varying conditions. Subsequently, the test results obtained from the five models are analyzed, enabling the discernment of the superior model based on the accumulated data and meticulous assessment.

CHAPTER IV
EXPERIMENTAL RESULTS

4.1 Experimental setup

In this section, the experiment is conducted for a total of 100 trials. The dataset of 619 images consists of both the training set and the test set, with a ratio of 75/25, respectively. The accuracy of each model is calculated as the mean across 100 trials.

In continuation of the previous section, up to five models have been employed, each with distinct adjustable parameters. The adjustments made significantly influence the effectiveness of the classification process. Here, the sets of parameters can be presented as follows.

4.1.1 Multi-layer perceptron

- Architecture: Two hidden layers, each with 100 neurons
- Activation function: Hyperbolic tangent function
- L2 regularization parameter: 0.01
- Learning rate: Adaptive
- Solver: Limited-memory Broyden-Fletcher-Goldfarb-Shanno

4.1.2 Random forest and decision tree

- Impurity measure: Gini impurity
- Maximum tree depth: 10
- Maximum feature: 5
- Minimum samples in a leaf: 1
- Minimum samples for splitting: 2

4.1.3 Support vector machine

- Kernel function: Linear kernel
- Regularization parameter: 250

4.1.4 Logistic regression

- Regularization parameter: 1.0
- Solver: Limited-memory Broyden-Fletcher-Goldfarb-Shanno

4.2 Experimental results

Typically, experimental outcomes are evaluated not solely based on accuracy, but also through the incorporation of precision and recall metrics to assess the effectiveness of the experiment's performance. These metrics will be explained in the subsequent section.

4.2.1 True positive, false positive, true negative, and false negative

True positive occurs when the study context correctly identifies a bolt as class x, and the model also predicts the bolt to be class x.

False positive arises when, within the study context, a bolt that is not of x is incorrectly predicted as class x by the model.

True negative is observed when, within the study context, a bolt that is not of class x is correctly predicted as not belonging to class x by the model.

False negative occurs when, in the study context, a bolt of class x is incorrectly predicted as not belonging to class x by the model.

4.2.2 Recall

Recall is defined as the model's ability to identify all relevant cases within a given dataset. It is calculated as the ratio of the number of true positives to the sum of the number of true positives and the number of false negatives as shown in equation (4.1).

$$recall = \frac{true\ positive}{true\ positives + false\ negatives} \tag{4.1}$$

4.2.3 Precision

Precision represents the capacity of a classification model to accurately identify exclusively the pertinent data points. Precision is calculated as the ratio of the number of true positives to the sum of the number of true positives and the number of false positives as shown in equation (4.2).

$$precision = \frac{true\ positive}{true\ positives + false\ positives} \tag{4.2}$$

4.2.4 Results of models

Upon the conclusion of our experimentation encompassing the evaluation of five distinct models, the ensuing results establish the supremacy of the multi-layer perceptron model in terms of performance, showcasing an impressive achievement of up to 90.32% accuracy. Notably, the random forest model closely follows suit as the second most accurate, yielding an accuracy level of up to 89.83%. However, it is worth highlighting that the logistic regression model, while trailing behind in terms of performance, still manages to yield a relatively reasonable outcome of up to 83.36% accuracy. A comprehensive tabulation of these findings can be perused in the detailed presentation shown within Table 4.1.

Table 4.1 Accuracies of classification models.

Models	Accuracy (%)
Multi-layer perceptron	90.32
Random forest	89.83
Decision tree	89.68
Support vector machine	85.81
Logistic regression	83.36

Furthermore, the precision and recall metrics were assessed for both the multi-layer perceptron and random forest models. The results indicate that the models exhibited the highest performance for class 5 and class 14 of bolts, attributed to their distinctive characteristics. Class 14 stands out due to its distinctive silver color, while class 5 is identifiable by its short length and the presence of holes. In contrast, class 19, lacks a definitive definition like the other classes as shown in table 4.2.

Table 4.2 Precision and recall of each class obtained from each model.

Class	MLP		Random forest		Decision tree		Support vector machine		Logistic regression	
	Precision	Recall	Precision	Recall	Precision	Recall	Precision	Recall	Precision	Recall
1	1.00	0.67	1.00	0.78	1.00	0.89	0.75	0.67	1.00	0.56
2	0.67	0.67	0.86	0.67	0.88	0.78	0.75	0.67	0.60	0.67
3	0.91	0.91	0.82	0.82	0.83	0.91	0.82	0.82	0.89	0.73
4	1.00	0.88	0.88	0.88	0.88	0.88	0.54	0.88	0.54	0.88
5	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
6	1.00	1.00	0.82	1.00	0.80	0.89	1.00	1.00	1.00	1.00
7	0.86	1.00	0.67	0.33	0.57	0,67	0.86	1.00	0.67	0.67
8	1.00	0.70	0.78	0.70	1.00	0.70	1.00	0.80	0.86	0.60
9	1.00	0.80	1.00	0.80	1.00	0.80	0.83	1.00	1.00	0.80
10	0.78	1.00	0.78	1.00	0,78	1.00	0.60	0.86	0.55	0.86
11	1.00	1.00	0.89	1.00	1.00	1.00	0.78	0.88	0.73	1.00
12	0.64	1.00	0.88	1.00	0.88	1.00	0.86	0.86	0.67	0.57
13	0.86	0.86	0.78	1.00	1.00	1.00	0.67	0.86	0.70	1.00
14	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
15	0.93	1.00	0.88	1.00	0.93	1.00	0.93	1.00	0.82	1.00
16	1.00	1.00	1.00	0.86	1.00	0.86	1.00	1.00	1.00	0.86
17	0.90	0.90	1.00	0.90	1.00	0.90	1.00	0.90	0.75	0.90
18	1.00	0.92	1.00	0.92	1.00	0.92	0.91	0.83	0.80	0.67
19	0.67	0.80	0.57	0.80	0.57	0.80	1.00	0.60	1.00	0.60
Average	0.91	0.90	0.87	0.87	0.90	0.89	0.86	0.88	0.82	0.81

4.3 Model analysis

Upon completing the training of various models, the outcomes reveal that model multi-layer perceptron yields the most favorable results. However, it is noteworthy that the structural complexity of the multi-layer perceptron is significantly higher than the decision tree, which is characterized by a more straightforward and less intricate architecture. In addition, it is important to highlight that the reduction in accuracy observed in the decision tree is less than 1%. Furthermore, the Random Forest model has been configured with a maximum depth constraint of up to 10. This intentional limitation in depth is designed to effectively manage datasets characterized by intricate and challenging classification scenarios. The decision to restrict the depth is particularly relevant when dealing with data that exhibits high variability due to various environmental conditions. The aggregate count of support vectors across all classes in the Support Vector Machine does not exceed 278. Additionally, the formulation of the logistic regression model for classification results in 19 probability equations.

4.4 Misclassification

During the experiment, a collection of bolt images was gathered from diverse environments. In this section, the classification of the two images using the proposed method encounters a challenging task due to their capture from a considerable distance. This makes it difficult to identify the presence of holes and accurately determine the bolt's length. Despite expert assistance being employed for classification, these factors present inherent complexities. In other words, the extraction of features from these images poses significant challenges, leading to inaccurate classification as shown in figure 4.1.

Figure 4.1 Images with misclassification result.

CHAPTER V
CONCLUSION

5.1 Discussion and conclusion

This section focuses on the conclusion. Various features have been analyzed and categorized as primary features that produce favorable results in bolt image classification. These features can be categorized into three features: dominant color, head-to-whole length ratio, and the final feature, hole existence.

A range of techniques is employed during the feature extraction process from images, including principal component analysis for bolt image rotation, the median cut algorithm for dominant color computation, and the circular Hough transform for hole detection within the bolt images.

After acquiring three significant features, they are employed as inputs for five classification models, specifically denoted as models, multi-layer perceptron, random forest, decision tree, support vector machine, and logistic regression. These models are deployed to categorize images into eighteen distinct classes, with an additional class explicitly designated as the nineteenth class.

The results of the experiments involving the five models indicate that model multi-layer perceptron outperforms the others, achieving a performance improvement of up to 90.32%.

5.2 Future work

In the future, enhancing the proposed method should involve the incorporation of additional features, such as optimizing the number of bolt threads, to efficiently classify images. This improvement will not only benefit the business prospects of a retail motorcycle shop but also contribute to its overall growth and success.

REFERENCES

[1] Belaid, A. *Metrology in quality control of nuts*. in *[1990] Proceedings. 10th International Conference on Pattern Recognition*. 1990.

[2] Lu, G., et al. *Design and Performance Analysis of a Moveable Groove-tracking Milling Machine for Repairing Thread of Marine Steering Gear Nuts*. in *2020 International Conference on Sensing, Measurement & Data Analytics in the era of Artificial Intelligence (ICSMD)*. 2020.

[3] Lin, C.F., et al. *Real-time pitch diameter measurement of internal thread for nut using laser triangulation*. in *2017 IEEE International Instrumentation and Measurement Technology Conference (I2MTC)*. 2017.

[4] Pondech, W., A. Saenthon, and P. Konghuayrob. *The Development of Adaptive Gray Level Mapping Combined Partical Wwarm Optimization for Measuring the Dimeter Size of Automotive Nut*. in *2020 IEEE 7th International Conference on Industrial Engineering and Applications (ICIEA)*. 2020.

[5] Zhifeng, Z. *Measuring Diameter of Non-threaded Hex Bolts Based on Hough Transform*. in *2011 Third International Conference on Measuring Technology and Mechatronics Automation*. 2011.

[6] Di, W.G., et al. *Recognition Of Bolt Quality Base On Elman Neural Network By Ant Colony Optimization Algorithm*. in *2018 International Conference on Machine Learning and Cybernetics (ICMLC)*. 2018.

[7] Jian, X., et al. *Bolt positioning method based on active binocular vision*. in *2019 Chinese Control Conference (CCC)*. 2019.

[8] D. Gatis. Rembg. [Online]. Avaliable from: https://pypi.org/project/rembg. [2023, August 20].

VITA

NAME	Monchai Angkapiyasiri
DATE OF BIRTH	02 July 1997
PLACE OF BIRTH	Bangkok
INSTITUTIONS ATTENDED	B.Sc. in Computer Science, Department of Mathematics and Computer Science, Chulalongkorn University, 2018.
HOME ADDRESS	19 Soi. Rewadee 28 Tivanon Road Talat Khwan District Muang Nonthaburi 11000