VEHICLE LOGO RECOGNITION USING IMAGE PROCESSING METHODS

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ATILIM UNIVERSITY

by

SUMIA A.A ALBERA

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Approval of the Graduate School of Natural and Applied Sciences, Atılım University.

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I certify that this thesis satisfies all the requirements as a thesis for the degree of Master of Science.

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This is to certify that we have read the thesis "Vehicle Logo Recognition Using Image Processing Methods" submitted by "Sumia A.A Albera" and that in our opinion it is fully adequate, in scope and quality, as a thesis for the degree of Master of Science.

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ABSTRACT

VEHICLE LOGO RECOGNITION USING IMAGE PROCESSING METHODS

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Vehicle logo recognition is the ability to recognize and classify the vehicle logos in different conditions with high accuracy. This system plays significant role in monitoring systems, security and surveillance systems, such as the control system in government buildings and military camps. Vehicle logo recognition starts with reading the logo as an image, goes on analyzing and classifying of the logo. The goal of this study is to compare the performance of three methods used for vehicle logo recognition and determine the accuracy of each method in noisy environments and from images captured from different directions. The main methods used for vehicle logo recognition in this thesis are: SURF algorithm, LBP and GLCM. In addition, KNN is used as a classifier with LBP and GLCM features. These methods are tested on the data sets collected in two ways: gathering logo images from the website of the manufacturers and capturing logo images by a standard camera. Best result in this thesis for vehicle logo recognition was achieved by the SURF algorithm.

Keyword: Vehicle logo recognition, Vehicle logo classification, SURF algorithm, Local Binary recognition, Gray Level Co-occurrence Matrix.

ÖZ

GÖRÜNTÜ İŞLEME YÖNTEMLERI İLE ARAÇ LOGO TANIMA

Albera, Sumia

Yüksek Lisans, Yazılım Mühendisliği Bölümü

Tez Yöneticisi: Yrd. Doç. Dr. Gökhan Şengül

Ekim 2016, 75 sayfa

Araç logolarının tanımlanması, farkli çevre şartlarında araçların logolarının yüksek performans ile algılanması ve sınıflandırılması yeteneği olarak tanımlanabilir. Logo tanıma, devlet kurumları, askeri alanlar gibi kontrol gerektiren bölgelerde güvenlik ve gözetleme amacıyla kullanılmaktadır. Logo tanımlamada öncelikle logo görüntüleri okunur, analiz edilir ve logonun ait olduğu üretici belirlenir. Bu tez çalışmasının amacı, araç logolarının tanımlanması için kullanılan üç farklı yöntemin gürültülü ve gürültüsüz ortamlardaki başarımlarını araştırmak ve bu yöntemlerin karşılaştırmasını yapmaktır. Bu tez çalışmasında logo tanımlama için SURF, LBP ve GLCM yöntemleri denenmiştir. LBP ve GLCM yöntemleri için sınıflandırıcı olarak kNN kullanılmıştır. Önerilen yöntemler biri üreticilerin internet sitelerinden alınan görüntüler diğeri ise doğrudan araçların logoların fotoğraflarının çekilmesi ile elde edilen görüntüler olmak üzere iki farklı veri kümesinde test edilmiştir. Sonuç olarak en iyi başarım, SURF algoritması ile elde edilmiştir.

Anahtar Kelimeler: Araç logo tanıma, logo sınıflandırma, SURF, Local binary Pattern, Gray-Level Co-occurrence Matrix.

To My Parents,

My Husband and My Daughter

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LIST OF ABBREVIATION

BoW: Bag of Words

CNN: Convolutional Neural Network

GLCM: Gray Level Co-occurrence Matrix

HOG: Histogram Oriented Gradients

ITSs: Intelligent Transportation Systems

KNN: K Nearest Neighbors

KPCA: Kernel Principal Component Analysis

LBP: Local Binary pattern

M-SIFT: Merge- Scale Invariant Features Transforms

MFM: Multiple Feature Matching

MMD: Minimum Mean Distance

PCA: Principal Component Analysis

ROI: Regions of Interest

SFM: Single Feature Matching

SIFT: Scale Invariant Features Transforms

SURF: Speeded Up Robust Features

SVM: Support Vector Machin

CHAPTER 1

INTRODUCTION

Pattern Recognition is a branch of digital image processing and artificial intelligence. Researchers and technicians of this science aim to develop techniques that identify specific patterns or structures in the digital images. In daily life, there are many applications and technologies related to this science such as recognizing faces in the control systems, logos and geometric shapes.
The general idea of pattern recognition is all the processes that make the computers understand the patterns in the same way that is understood by the human and even more efficiently in some cases. As mentioned earlier about the wide usage and multiple applications of pattern recognition, in this thesis, we will focus on logo recognition.

Nowadays logos are important patterns because there is a significant dependency on logos and the existence of the logo obviates the name a lot of times. Also, the logos are used widely in various domains. For example, shops, productivity companies, humanitarian organizations and universities use the logos in advertising, documentation and transportation systems.
Logos can be written by characters, expressive drawn or both. Each logo has specific features including the color, the shape, and symbol. So most companies and organizations are seeking for a unique logo for them.

Generally, logo recognition is a part of pattern recognition which has an essential role in image processing. Many types of research and studies have worked on logo recognition and still take more attention in this time. Also, logo recognition is considered a wide field of research and innovation. At this time, the technological revolution and the dependence on devices and artificial intelligence techniques, require more studies and an expansion at this science.

Logo recognition science requires precision, concentration, and development depending on the areas evolution where it is used.

Logo recognition is a process of understanding and defining the logos automatically by the automated systems. Logo recognition works on avoiding the human mistakes in works which require great patience and accuracy.

One of the domains that use the logo recognition is the transportation system. Logo recognition in transportation system can use many modern technologies for monitoring and controlling of traffic. It can be used for vehicle logo recognition, vehicle model identification and license plate detection, and recognition, etc.

In this thesis, the focus is on vehicle logo recognition. It is an important science that captures the attention of researchers recently, as well as it is applied in the Intelligent Transportation Systems [ITSs]. Vehicle logo recognition starts with reading the logo as an image, and then analyzing and classifying of the logo. The recognition and the classification of vehicle logo is an important step in the automotive control systems, especially with the increasing number of cars in the cities. Due to this increase, an automated logo recognition system is needed to count the number of vehicles and theirs brands, where it is difficult, time consuming and error prone to be done by humans.

The areas that use vehicle logo recognition are wide. It is a very important system in the areas of security and surveillance systems, such as the control system in government buildings, military camps, at the traffic lights and crossroads, checkpoints in the city and its suburbs, as well as within the country's borders that are crossed by cars. Recognizing and distinguishing the logos are an easy task for human beings in normal conditions. But it can be very difficult in the crowded cities where there are large number of cars and humans and where numerous security breaches occur. So in order to detect and recognize the vehicle logos, automated systems with high precision are needed. Civilian and military government organizations can take advantage of this system when they use it with their own surveillance systems, where some

vehicle logo recognition systems can recognize the logos and distinguish them quickly and accurately in a high number of conditions such as bad light and its reflection, and when it rains and snows.

In general, vehicle logo recognition is helpful in other applications such as car tracking and security.

Vehicle logo recognition passes through several stages, but mainly depends on the specific features for each logo, these steps are as follow: After logo images are collected, they can place into groups and create their own database. As a second step we read the logo as an image, then analyzing these images to draw lines and measure how approximate these lines through mathematical functions, after that certain points are selected on the lines and consider them as attributes or features, this is called "Extract features". The third step is the "classification" of the data where it is classified according to its features and compatibility in a given space.

Finally, the results are obtained after classifying the logos according to the groups that present in the database.

Our work focuses on three methods for vehicle logo recognition. These methods are SURF algorithm, LBP (Local Binary Pattern) and GLCM (Gray-Level Co-Occurrence Matrix). In addition, KNN classifier is used for the classification of logos with LBP and GLCM features. These methods were utilized on a set of data "logo images". The logo images were collected by two different ways: first way, searching and collecting images from the website of logo manufacturers and the second way is taking the images by a standard camera. In the two cases, the focus was on logo images from different directions.

Thesis objective:

The main objective of this thesis is Vehicle Logo Recognition with high accuracy and efficiency. Three image processing methods were applied to achieve the main goal. These methods are SURF algorithm, LBP, and GLCM. In this work, the goal is to compare the performance of each method and get best results for vehicle logo recognition. Also, the parameters for the methods

were changed to show that the parameters can affect the results. Also, this thesis is provided to make the things easier for researchers and those interested in this field and guiding them to the best results obtained from these methods.

Thesis Outlines:

The beginning of this thesis was with a general idea about logo recognition and information about vehicle logo recognition and its application areas. The remaining of this thesis is organized as follows: Chapter 2 provides literature reviews and related works in this domain. Chapter 3 presents the materials and methods. First, we explain the data collection. Then, we review the methods that were applied in this work. In Chapter 4, the experimental results are explained and given in detail. The discussion of the results was offered in Chapter 5. Finally, Chapter 6 includes the conclusion and the future plans.

CHAPTER 2

LITERATURE SURVEY

2.1. Pattern Recognition:

Pattern recognition is the science for observing the environment, learning to recognize patterns of interest from their background and making right decisions about the patterns or pattern classes. [1].

Pattern recognition definition has been introduced by [2] according to earlier studies. Duda and Hart (1973) defined the pattern recognition as a field which is concerned with machine recognition of meaning regularities in complex and noisy environment [3]. As well as, Pavlidis (1977) defined the pattern recognition in his book as the term pattern is derived from the same root as the term patron and in its original use; it means something that is set up as an optimal example to be imitated. Gonzalez and Thomas (1978) defined the pattern recognition as classifications of input data by extracting the features which have importance from a lot of noisy data [5]. Watanabe (1985) stated that pattern recognition can be imaginable as the classifications problem, structure analysis, inductive process, discrimination approach and so on [6]. Fukunaga (1990) stated that pattern recognition is "A problem of assessing density functions in a high- dimensional space and separating the space to regions of classifications of classes" [7]. Schalkoff (1992) defined the pattern recognition as "The science that deals with the classification or description of the measurements" [8].

Srihari, Govindaraju (1993) defined the pattern recognition as the discipline that learn some theories and approaches in order to design machines which have the ability to identify the patterns in noisy data and complex environment [9]. Ripley (1996) defined the pattern recognition in his book as "Given some examples of complex signals and the correct decisions for them, make decisions automatically for a stream of future examples" [10]. Robert P.W.

Duin (2002) stated that the pattern recognition is an engineering approach and its (pattern recognition) final goal is designing machine that can solve the existed gap between the application and the theory [11]. Sergios Theodoridis (2003) defined the pattern recognition as a scientific discipline and its aim is to classify the object into many categories of classes [12].

The design of a pattern recognition system essentially involves the following phases, one is data building; the other two are pattern analysis and pattern classification. Data building transforms original information into vector which can be processed by computer. Pattern analysis task is to process the data (vector), such as feature selection, feature extraction, data- dimension compress and so on. The goal of pattern classification is to use the information obtained from pattern analysis to discipline the computer in order to accomplish the classification [2].

Pattern recognition can be used in any area which uses the observations structures. Currently, pattern recognition is commonly used in numerous applications related to military, healthcare and manufacturing industry, such as face recognition, character recognition, computer vision, and speech recognition, recognizing fingerprints, recognition of automobile type personal identification systems, fault diagnosis for vehicle system, and enhance the automobile safety performance [2].

2.2. Image Processing:

Image Processing is a method to transform an image into digital form and implement some operations on it, in order to get an enhanced image or to extract some useful features from it. It is a type of signal release in which input is image, like video frame or photograph and output may be image or characteristics associated with that image. Usually Image Processing system includes handling images as two dimensional signals while applying already set signal processing methods to them [13], [14].

The purpose of image processing is separated into five groups:

1. Visualization – To observe the invisible objects.

2. Image sharpening and restoration - To generate a better image.

3. Image retrieval – To seek for the image of interest.

4. Pattern measurement– To measure several objects in the image.

5. Image Recognition – To differentiate the objects in the image.

Some of the Image Processing applications are given below:

1. Intelligent Transportation Systems – This method is used in Automatic number plate recognition, Traffic sign recognition and Vehicle logo recognition.

2. Remote Sensing – For this application, sensors capture the pictures of the earth's surface in remote sensing satellites or multi – spectral scanner which is mounted on an aircraft. These images are processed in the Earth station. Techniques applied to interpret the objects and regions are used in flood control, city planning, resource mobilization, agricultural production monitoring, etc.

3. Moving object tracking – This application allows to measure motion parameters and acquire visual record of the moving object. The different types of approach to track an object are: Motion based tracking and Recognition based tracking.

4. Defense surveillance – Aerial surveillance approaches are used to constantly keep an eye on the oceans and land. As well as, this application is used to discover the types and formation of naval vessels of the ocean surface. The important duty is to split the several objects present in the water body part of the image. The different parameters such as length, breadth, area, perimeter, compactness are set up to classify each of divided objects. It is important to realize the distribution of these objects in different directions that are east, west, north, south, northeast, northwest, southeast and south west to explain all possible formations of the vessels. The entire oceanic scenario can be interpreted from the spatial distribution of these objects.

5. Biomedical Imaging techniques – This application is used in medical diagnosis, different types of imaging tools such as X- ray, Ultrasound,

computer aided tomography (CT) etc. Some of the Biomedical imaging applications are as follows:

- Heart disease identification: The size of the heart and its shape are examples of the important diagnostic features that are required to know in order to classify the heart diseases. To improve the diagnosis of heart diseases, image analysis techniques are employed to radiographic images.

- Lung disease identification – In X- rays, the regions that appear dark contain air while region that seems lighter are solid tissues. Bones are more radio opaque than tissues. The ribs, the heart, thoracic spine, and the diaphragm that separates the chest cavity from the abdominal cavity are clearly seen on the X-ray film.

6 Automatic Visual Inspection System – This application recovers the excellence and efficiency of the product in the industries. Such as:

- Automatic surface inspection systems – In metal industries it is a major step to detect the defects on the surfaces. Image processing techniques such as texture identification, edge detection, fractal analysis are used for the detection.

- Faulty component identification – This application characterizes the faulty components in electronic or electromechanical systems. The faulty components can be identified by analyzing the Infra-red images [14].

2.3. Image Classification:

Image classification denotes to divide the image into a number of predefined categories. The simple classification system comprises of a high resolution camera that is fixed above the interested region which capture and process the image consequently. The classification process involves image pre-processing, object segmentation, feature extraction, object detection and object classification. As well as, the classification system must include a database which comprises predefined patterns that compares with detected object to categorize into a proper classification. Image classification process is

considered a significant and interesting task in numerous application domains such as biometry, video surveillance, industrial visual inspection, biomedical imaging, robot navigation, vehicle navigation and remote sensing. The classification process comprises the following phases:

A. Pre-processing: Atmospheric correction, noise removal, image transformation, analysis of the main component etc.

B. Detection and extraction of an object: Detection involves detection the position and other properties of moving object in the image from camera and in extraction, from the sensed object assessing the trajectory of the object in the image plane.

C. Training: Selecting a specific characteristic which best defines the pattern.

D. Classification of the object: Object classification step classifies the detected objects into a set of predefined classes through the use of appropriate technique that matches the image patterns with the target patterns [15].

2.4. Vehicle Logo Recognition:

There are numerous techniques available in the literatures which are used to recognize and classify the logos of vehicles. Psyllos et al. [16] suggested a new algorithm which is used for the purpose of recognition and classification of vehicles logos based on enhanced Scale Invariant Feature Transform (Merge-SIFT or M-SIFT). The algorithm has been evaluated through a set of vehicles logos which includes 1500 logo images that belong to 10 different vehicles manufacturers. In this study an accuracy of 94.6% is obtained.

Pan et al. [17] presented a technique for a vehicle logo recognition using CNN (Convolutional Neural Network). The technique introduces photos with a height of 140 pixels and width of 100 pixels. The sample included 26 classes that belong to 16 different brands, are: (Wu Ling 1, Peugeot, VW 1, Buick 1, Buick 2, Citroen, Skoda, KIA 2, Ford, Nissan 1, Honda 1, Hyundai 1, VW 2, KIA 1, Audi, Hyundai 2, Chery, Toyota 2, Toyota, Hyundai 3, Honda 1, DongFeng, Wu Ling 2, Honda 2, Nissan 2, and Nissan 3). The experimental results show that CNN has a good evaluation in order to detect the vehicles

logos where the percentage accuracy rate achieved is 99.23%.

Lipikorn et al. [18] presented an approach for the purpose of vehicle logo recognition made from the front view image by using SIFTS descriptor of interior structure and back-propagation neural network. The training set includes 18 images for 6 different logos while the testing set includes 220 images of automobiles. Whereas, the accuracy ratio obtained using this approach were over 50%.

Llorca et al. [19] have presented a new technique for the purpose of vehicles logos recognition by using Histograms of Oriented Gradients (HOG) and Support Vector Machines (SVM). This algorithm has been evaluated by capturing 3.579 images by two traffic cameras. These images belong to 27 types of vehicles. The accuracy of this algorithm for vehicle logos detection is 92.59% which can be used in the practical applications.

Psyllos et al. [20] suggested a new algorithm for the vehicle logo recognition depending on an improved scale-invariant feature transform (SIFT) -based feature-matching scheme. This technique has been tested on 1200 logos which belong to 10 types of vehicle manufacturers. The report of results showed that the accuracy of the algorithm is about 91% on Multiple Feature Matching (MFM) while the accuracy is 88% on Single Feature Matching (SFM) system.

Farajzadeh et al. [21] presented cars logo recognition system automatically for moving cars based on histogram doctrinaire. At this technique, after identifying the area where the logo locates, the matching method and textural characteristics are used distinctly for the purpose of logo recognition. The experimental results show that these methods have the capability of recognizing four types of cars which are Mazda, Renault, Peugeot and Samand with a performance of 96% for the image matching and 90% for the textural features extraction.

Sulehria et al. [22] introduced a technique for cars logo recognition through the images of cars using the mathematical morphology technique. This technique is

based on four processes including image enhancement, morphing transformations, filtering the resulting images and finally, extracting the logo from objects. The technique is characterized by identifying the logo area from the vehicle image rapidly with accuracy about 96%.

Sam et al. [23] introduced a solution for the recognition of vehicle logo by using Modest AdaBoost combined with radial Tchebichef moments. This technique has been tested on the images that are captured by Macau University of Science and Technology for vehicles which crossing the borders in the outdoor circumstances. The experimental results of this technique showed that the average of precision and efficiency of this technique is 92%.

Zhang Nan [24] presented a technique for vehicle logo recognition by relating numerous classifiers. In order to extract the characteristics, they have used two techniques that are Kernel Principal Component Analysis (KPCA) and Principal Component Analysis (PCA). The chosen methods applied on a database called VLD-SPU (1.0) which includes 8 subjects, each one of them has 10 images. The experimental results show that PCA has better performance with a ratio of 98%.

Dai et al. [25] adopted that Tchebichef moment invariants and support vector machine (SVM) in order to identify the logo of the vehicles. The process works by capturing 6 invariant moments from the vehicle and then detecting the logo of the vehicle by using Support Vector Machine (SVM). The experimental results showed that the accuracy rate is 92% in the noisy environment and be 100% in a noise-free environment.

Wang et al. [26] introduced a system in order to recognize the logo of the vehicle using CNN (Convolutional Neural Network) and the method has been applied to 20 classes of vehicle logo. Each class comprises on 1000 samples of training and 100 test samples. The experimental results showed that the accuracy of the technique to recognize the vehicle logo is about 97%.

Yu et al. [27] introduced a system for vehicle logo recognition based on Bag-of-Words (BoW). At this system, they have used dense-SIFT in order to extract

characteristics, quantize characteristics by ‘Soft assignment' and calculate the histogram with spatial information. This technique has been estimated on a dataset containing 840 segmented vehicle logo images. The accuracy rate of this system is 97.3%.

A vehicle logo recognition system has been introduced in the paper [28] which is based on the use of a Moment Invariant in order to extract the characteristics. Minimum-Mean Distance (MMD) has been used to take the classifier role and Tchebichef and Legendre moment invariants have also been used to recognize the logo of the vehicles. These techniques have been applied on 240 dataset images that belong to 6 different types of vehicles logos. The performance of this technique is 88.3%.

In paper [29], a vehicle logo recognition system has been introduced depending on a Weighted Spatial Pyramid Framework. In order to recognize the area of interest, the AdaBoost-based detector has been used. SIFT descriptors were extracted from the ROIs for the robust description of the image and (SVM) classifier was functional to categorize the logos based on max pooling of confined descriptors. This system has been applied on 1791 images belonging to 15 branches of vehicle logos. The experimental results showed that the accuracy of this technique is about 98%.

Paper [30] presented vehicle logo recognition by multi-class support vector machine ensembles of weighted depending on the features of sharpness histogram. This technique recognizes the logos of vehicle in real time via constructing the weighted multi-class support vector machine (SVM) ensemble model to categorize the vehicle logos depending on sharpness histogram features. This technique has been tested on 800 different logos which belong to 8 branches of vehicles and its accuracy is 82%.

Previous studies can be summarized in Table 2.1 which contains the name of the methods, their performance, the number of samples that used in tests, and the advantage and disadvantage for the methods.

Table 2.1: Summary of the previous studies:

#Ref	Method	Accuracy	Number of Samples	Advantage	Disadvantage
16	M-SIFT	94.6%	1500 logo images belonging to10 vehicle manufacturers	-The recognition speed is fast (~1 Sec), so this method is suitable for real-time applications. - Suitable in different conditions such as: cloudy weather, reflection and low lighting etc.	Not mentioned
17	A vehicle logo recognition method based on CNN (Convolutional Neural Network)	99.23%	26 classes derived from 16 l vehicle brands	This method has a chance to apply widely in city traffic video surveillance system	Not mentioned
18	Vehicle Logo Recognition Based on Interior Structure Using SIFT Descriptor and Neural Network	Over 50%	Training set contains 18 image belonging to 6 logo manufacturers and test set contains 220 images	This method robust in recognizing logos whose interior shape is complex	The problem with SIFT descriptor is sensitive to lighting condition
19	Vehicle logo recognition in traffic images using HOG features and SVM	92.59%	3.579 vehicle images belonging to 27 vehicle manufacturers	- This system is successful in dealing with images that were captured by traffic cameras with low resolution. - The increasing number of training set helped in	Not mentioned

				increasing the performance	
20	Vehicle Logo Recognition Using a SIFT-Based Enhanced Matching Scheme	91%	1200 logo images belonging to 10 logo manufacturers	It is an appropriate system in real time applications because its speed is fast	Not mentioned
21	Vehicle Logo Recognition using Image Matching and Textural Features	96% for image matching. 90% for textural features	210 logo images that belonging to 4 vehicle manufacturers	The results of these methods don't depend on the color of the logos.	The methods are limited which are able to recognize four types of logo (Peugeot, Renault, Samand and Mazda)
22	Vehicle Logo Recognition Using Mathematical Morphology	96%	50 color logo images	- This method is effective in any environment because it provides high accuracy Regardless of the size, location, angles and colors of the logos. - It is applied on two kinds of vehicles (van and cars)	- This method is less effective in real time applications. - It is just suitable to extract logos and plates that they include English text and numerals.
23	Vehicle Logo Recognition Using Modest AdaBoost and Radial Tchebichef Moments	92%	200 vehicle images	- This method is effective and highly accurate when it is applied on logo images that are taken from different views and outdoor conditions. - It is succeed in overcoming	Not mentioned

				on the issues of views variation and non-symmetrical frontal license plate location	
24	Vehicle-logo Recognition Based on Classifier Combinations	98%	80 logo images belonging to 8 vehicle manufacturers	This method is used with classifier combinations and gets better result than one classifier.	Not mentioned
25	Vehicle-logo Recognition Method Based on Tchebichef Moment Invariants and SVM	in noise-free is 100%, in noisy images is 92%	200 logo images	It is robust and it works best with high potential and the impact of better recognition.	Not mentioned
26	Vehicle-logo Recognition Algorithm Based on Convolutional Neural Network	97%	1000 training samples and 100 test samples	This system improves the vehicle logo recognition rate effectively.	Not mentioned
27	Vehicle Logo Recognition Based on Bag-of-Words	97.3%	840 logo images	It is fast and reliable which it provides high accuracy with less processing time	Not mentioned
28	Pattern Recognition of Vehicle Logo Using Tchebichef and Legendre Moment	88.3%	240 logo images of six type vehicle manufacturers	Effective in recognize the fine segmented vehicle logos and this is suitable for real applications	Not mentioned

29	Vehicle Logo Recognition Based on a Weighted Spatial Pyramid Framework	98%	1791images belonging to 15 classes of vehicle logos	Through the images that were taken from the surveillance cameras showed that this technique will be suitable to be applied in real work applications.	Not mentioned
30	Vehicle Logo Recognition By Weighted Multi-Class Support Vector Machine Ensembles Based On Sharpness Histogram Features	82%	800 logo images belonging to 8 classes of vehicles	- It can recognize the vehicle logos in real time. -It can avoid the burden of choosing the appropriate kernel function and parameters comparing with multi-class SVM model.	Not mentioned

CHAPTER 3

MATERIALS AND METHODS

In this chapter, the materials and methods followed in this thesis are given. First of all the data used in this work is summarized in Section 3.1, and then the methods are explained later in Section 3.2.

3.1. Data collection:

At the beginning, 10 logo manufacturers (Audi, BMW, Fiat, Honda, Mazda, Mercedes, Nissan, Renault, Toyota and Volkswagen) were selected to test the logo recognition methods. The original logo images were collected from the websites of the manufacturers. 100 logo images were collected for each manufacturer from the websites without focusing on their sizes or their types. A total of 1000 original logo images were collected as a result of this procedure. Figure 3.1 shows samples of the original logo images.

Figure 3.1: Samples of original logo images

In the second approach the logo images were collected using a standard camera in real condition from different directions and without any effect. In this approach 20 logo images were captured for each manufacturer. A total of 200 logo images were collected in this approach.

The camera which was used to collect the logo images has a 16 megapixel sensor, its resolution is (5312× 2988 pixel) and f/2.2 lens with an equivalent focal length of 31mm.
Figure 3.2 shows samples of logo images that were captured by standard camera.

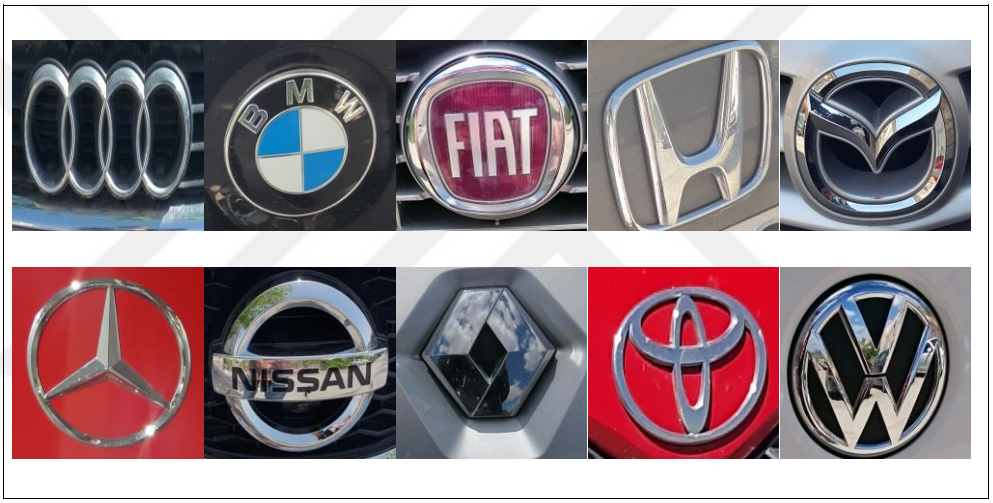

Figure 3.2: Samples of logo images by standard camera

3.2 Pre-Processing:

Before applying the methods for vehicle logo recognition, the logo images should be pre-processed. The logo images were collected in various sizes and dimensions. In order to the goal of this study which focuses on the recognition and is not for detection, the images were cropped according to the logo space only. Second step in this stage is converting the color images to grayscale images to be suitable to test the methods. Finally, the logo images were resized by 100× 100 pixel, which decreased the size of the collected images. This process helps to decrease the classification time.

The two databases are ready that will be used as training set and test set in the two different test cases. The first test case 1000 original logo images will be used as training set and 200 natural logo images will be used as test set. In the second case, 200 natural logo images will be divided into training set and test set. The test cases will be explained in Chapter 4 in detail.

In the next section, the methods followed in this thesis will be presented. The methods followed are: SURF algorithm, Local Binary Pattern (LBP) and Gray Level Co-occurrence Matrices (GLCM). K Nearest Neighbors (KNN) is used for the classification with LBP and GLCM. KNN will be introduced in next section too.

3.3. The Methods:

3.3.1 SURF Algorithm:

This algorithm has been suggested by Bay, H., Tuytelaars, T. and Van Gool, L, in the paper [31] and published in 2006. SURF algorithm is short for Speeded Up Robust Features. Also, SURF considers a modern version of SIFT (Scale-Invariant Feature Transform) algorithm and it is faster than SIFT. As well as, SURF is rotation- invariant interest point detector and descriptor. SURF is used in many areas as proposed in [32], [33] and [34]. The SURF algorithm has several features which include repeatability, robustness and fast if compared with SIFT algorithm [31, 35]. SURF depends on the integral images using a Hessian matrix-based measure for the detector, and a distribution-based descriptor [35]. The processes of SURF may be clarified in three steps:

- Detection
- Description.
- Matching.
-

Detection: in order to find the interest points, SURF uses Hessian matrix. The points of interest are the extrema points within 8 neighbors in the existing level and its 2×9 neighbors in the above and below level [36].

Due to the high performance of Hessian matrix in SURF, it will depend on it. The Hessian matrix H(x, σ) in x at scale σ for a given point is defined as:

$$H(x,\sigma) = \begin{bmatrix} L_{xx}(x,\sigma) & L_{xy}(x,\sigma) \\ L_{xy}(x,\sigma) & L_{yy}(x,\sigma) \end{bmatrix} \quad (1)$$

Where

$$L_{xx}(x,\sigma) = I(x) * \left(\frac{\partial^2}{\partial x^2}\right) g(\sigma) \quad (2)$$

$$L_{xy}(x,\sigma) = I(x) * \left(\frac{\partial^2}{\partial xy}\right) g(\sigma) \quad (3)$$

The L_{xx} (x, σ) in Equation 2 represents the image convolution with Gaussian second derivatives. The non-maximal-suppression of the determinants of the Hessian matrices represents the SURF detection heart. It is so costly to calculate the convolution and it is estimated and speeded-up by using the integral images and approximated kernels.

The integral image I(x) represents the image where each point $x=(x, y)^T$ stores the sum of the whole pixels in the rectangular area between the origin and x.

$$I(x) = \sum_{i=0}^{i \le x} \sum_{j=0}^{j \le y} I(x,y) \quad (4)$$

The integral images are used to compute the response in the rectangular area with arbitrary size using 4 look-ups as clarified in Figure 3.3.

The second order of the Gaussian kernels $\frac{\partial^2}{\partial y^2} g(\sigma)$ which is used for the hessian matrix must be discretized and cropped before we can relate them; a 9×9 kernel is clarified in Figure 3.3. The SURF algorithm estimates these kernels with rectangular boxes and box filters. In the gray area clarification which relates to 0 in the kernel whereas black is negative and white is positive.

At this way, it may compute the approximated convolution efficiently for subjectively sized kernel using the integral image.

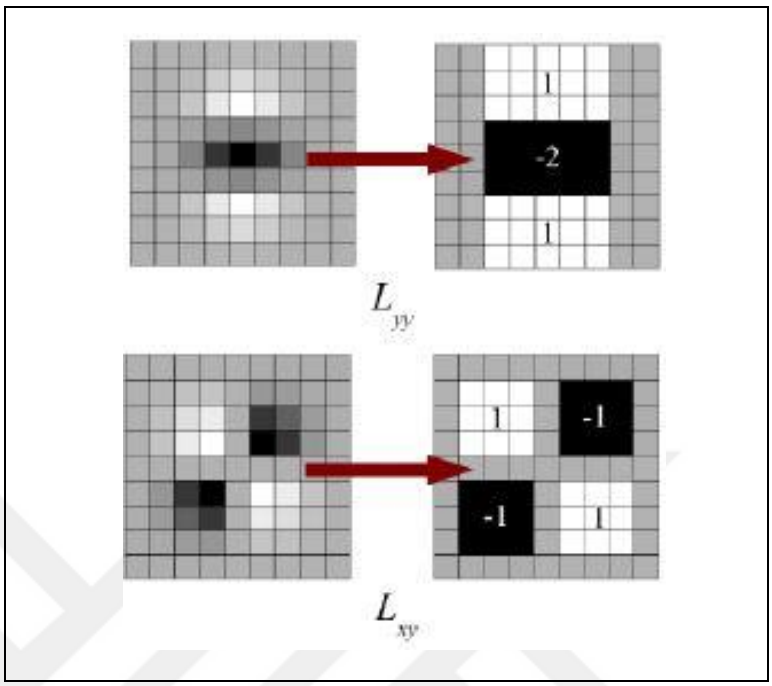

Figure 3.3: $L_{yy}(x, \sigma)$ and $L_{xy}(x, \sigma)$ discretized Gaussians and the approximations D_{yy} and D_{xy} [37]

Many levels and octaves must be examined in order to recognize the features across a scale. When finding extrema at one of the higher octaves, the area covered by the filter is rather big and this presents a major error for the position of the interesting point.

In order to reform this, the precise location of the interesting point is interpolated by fitting a 3D quadratic in scale space. The point of interest locates in the scale space by (x, y, s). Wherever, x, y are relative coordinates (x, $y \in [0, 1]$) and s is the scale. The SURF detection has been used in this thesis in order to find the blob features in the grayscale input images. (See Figure 3.4).

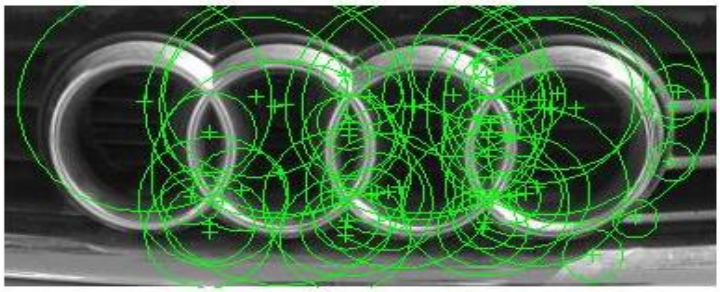

Figure 3.4: Detection the Features in Vehicle Logo using SURF algorithm

Description: The descriptor can be generated through the region surrounding the point of interest and one of its advantages is to work on providing a single and vigorous description of a feature. The descriptor of SURF depends on Haar wavelet responses and can be computed effectively with the integral images.

The rotational invariance can be achieved through the determination of the unique orientation for the interesting point. The area of interest which surrounds the interesting point is rotated to its direction before calculating the descriptor. The SURF descriptor characterizes the area of interest with size 20s. The values of a wavelet response in the *x* and *y* directions characterize the area of interest which is divided to 4 × 4 subareas.

The wavelet response in the *x* and *y* direction is indicated to dx and dy correspondingly. Figure 3.5 clarifies the wavelets which are used to compute the response. [38].

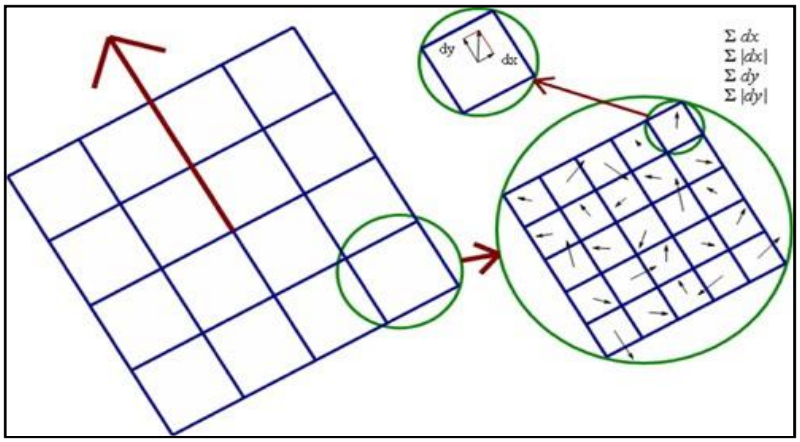

Figure 3.5: The description in SURF, the areas is divided into 4×4 subareas that are sampled 5×5 times to get the wavelet response. [38]

The area of interest is weighted with a Gaussian centered at the point of interest in order to give some strength for translations and deformations.

$$v = \left\{ \sum dx, \sum |dx|, \sum dy, \sum |dy| \right\} \tag{5}$$

For each subarea, a vector v (Equation 5) is calculated, based on 5×5 samples. The number of vectors for a descriptor in the point of interest is 16 vectors for the concatenated subareas.

Lastly, the descriptor is normalized, to accomplish invariance to contrast variations that will characterize themselves as a linear scaling of the descriptor. Many schemes have been tested which are different in wavelet function, size, and samples number. This setup has been experimentally found as a standard which takes into consideration the accuracy and precision. After the descriptor has been calculated, finding match between two descriptors is a matter of testing if the distance between the two vectors is adequately small.

Matching: In the matching phase, the features will be compared, if they have the same contrast type. This least information permits the faster of matching without reducing the performance of the descriptor [37]. Figure 3.6 shows the matching in Vehicle logo recognition using SURF.

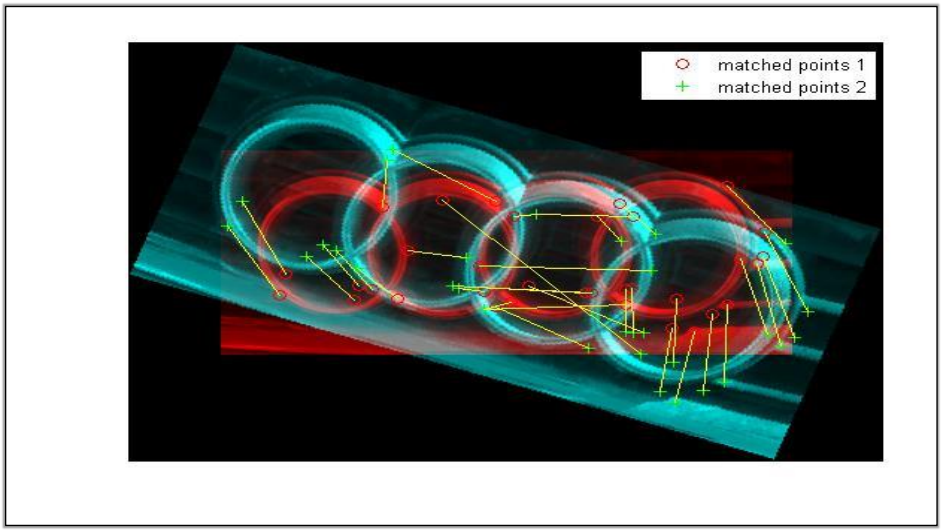

Figure 3.6: The matching in Vehicle logo using SURF

Figure 3.6 shows the corresponding points between two images are discovered by SURF detector. The images were rotated and scaled with estimated to each other. The matching points are displayed with (+) and (o), and the matched features or the properties are shown (e.g feature (o) in one image is matched to feature (+) in the rotation images where both have the same properties).

Advantages of SURF algorithm:

SURF does not need to long and boring training and it is a fast interest point detector and descriptor. In addition, it is characterized by preserving the performance comparing with other detectors. Also, it can find the same interest points in different viewing situations.

3.3.2 Local Binary Pattern (LBP):

LBP was introduced by Timo Ojala. et. al in (2002) and it is a gray-scale and rotation invariant texture classifier [39]. The most important characteristics of LBP are the simplicity and efficiency and it is used in many applications such as the image processing and pattern recognition [40], face and facial expression recognition [41], [42], [43], remote sensing [44], [45], visual inspection [46], [47], motion analysis [48], [49] and gender prediction [50].

In order to clarify the implementation of LBP operator, an example is presented

in Figure 3.7. The operator puts a label to each pixel of image by thresholding the 3×3 neighborhood with the center pixel value, where the center pixel's value is greater than the neighbor's value, write "0". Otherwise, write "1".

Then, the results of 0 and 1 are considered as binary number. Through reading the values clockwise, the binary results will be gotten. In the final code, the top left pixel in the neighborhood is convoluted as the most important bit (see Figure 3.7).

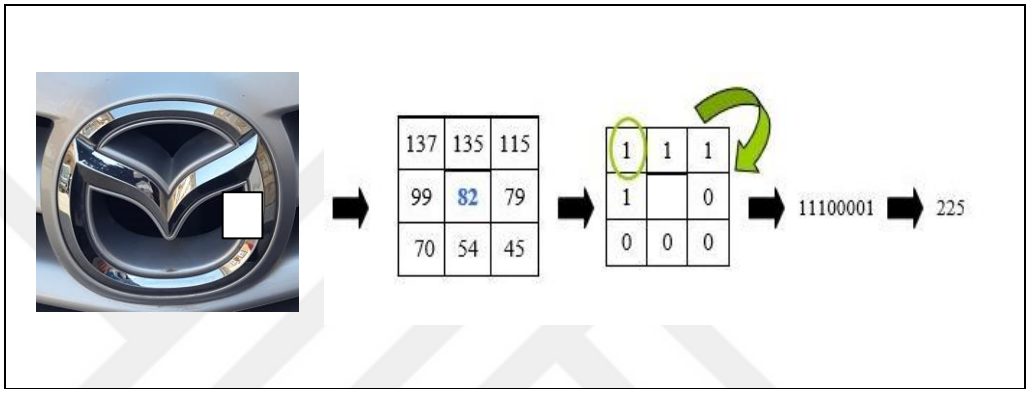

Figure 3.7: The implementation of LBP

This provides a decimal label value of the 8-bit consistent with intensity pixel between the center pixel and its neighbors [40], [51]. LBP result represents the feature of the vector. In general, LBP of a given pixel position (x_c, y_c), can be calculated as follows:

$$LBP(x_c, y_c) = \sum_{n=0}^{7} s(l_n - l_c)2^n \tag{6}$$

Where l_c corresponds to the gray value of the center pixel (x_c, y_c), l_n to the gray values of the 8 surrounding pixels, and function s(k) is defined as [51]:

$$s(xk) = \begin{cases} 1, & k \geq 0 \\ 0, & k < 0 \end{cases} \tag{7}$$

An example of the LBP code computation from the 3×3 of the central pixel is shown in Figure 3.7. Each pixel, starting from the upper-left corner (137 in the example) is compared with the central pixel (82) and yield 1 because its value

is larger than a center pixel, else, any pixel less than the center value, such as (79 < 82) is equal, 0. The result is an 8-bit binary code (11100001) which is converted to a decimal value (225). An example of applying the LBP in vehicle logo recognition is given in (Figure 3.8).

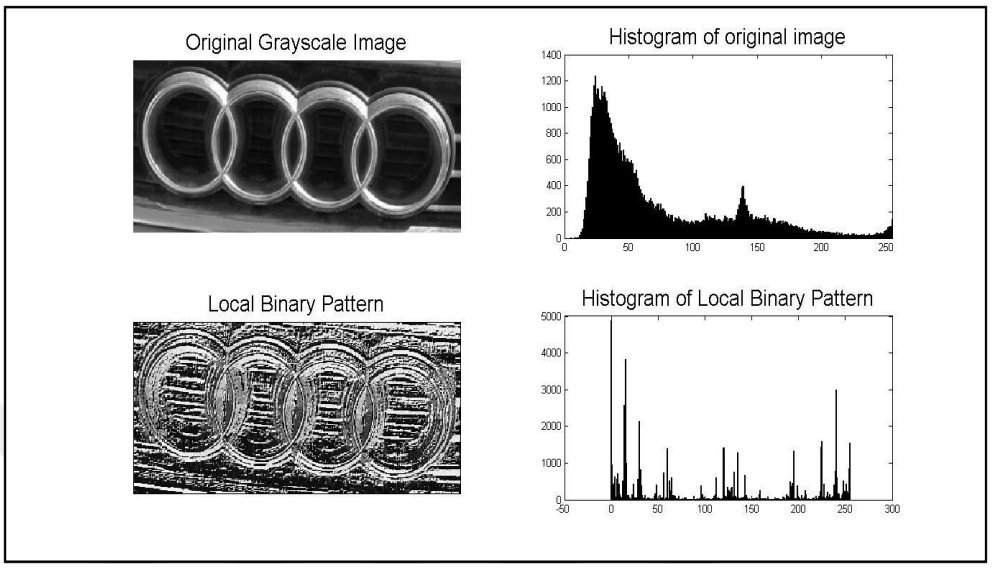

Figure 3.8: An example of applying LBP in vehicle logo recognition

Advantages of Local Binary Pattern:

LBP is very robust in condition of gray scale variations and it is calculated by computational simplicity.

3.3.3 Gray Level Co-occurrence Matrices (GLCM):

Grey Level Co-occurrence Matrix (GLCM) is a technique which is first introduced by Haralick et.al [52] in 1973 and comprises information about the pixels' places which have comparable gray level values. The purpose of this technique is to extract the features of texture. GLCM is not popular in vehicle logo recognition applications but it has been used in many domains for texture analysis, which characterizes texture [53], number of presented quantitative measures of texture [39] [54] [55] [56], 3D co-occurrence matrices were used in CBIR applications [57], special multidimensional co-occurrence matrices were applied for object recognition and matching [58], multi-dimensional

texture analysis, which is used in clustering techniques [59] and classification of parasite egg cells [60].

The features of texture in the statistical analysis are calculated from the statistical distribution of intensive observation combinations in specific locations relative to each other in the image. The statistics are categorized into three groups which are first-order, second-order and higher-order statistics according to the intensity points (pixels) number [61]. Furthermore, GLCM is considered as a matrix and its rows and columns are equal to the gray level number in the image. The matrix element P (i, j | d, θ) is the proportional frequency with two pixels, which one with intensity i and the other with intensity j separated by distance d, and in the direction specified by the particular angle (θ).

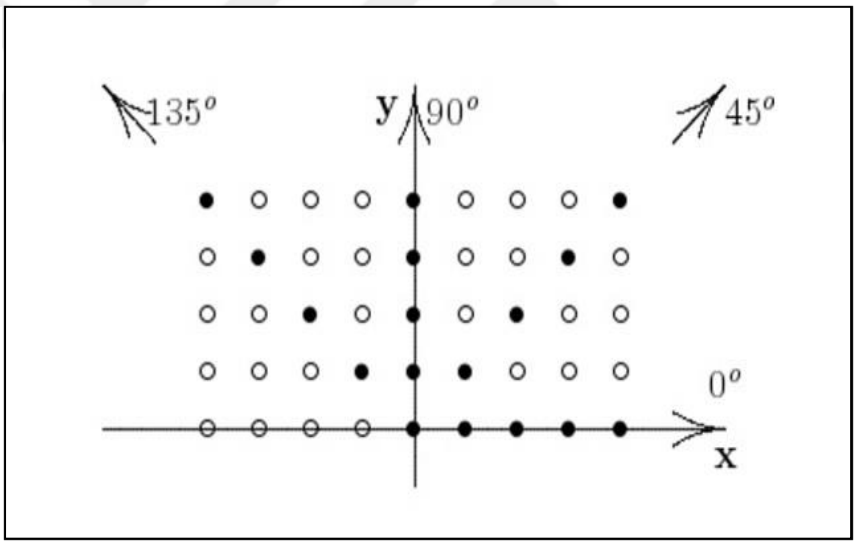

Figure 3.9: Geometry for measurement of gray level co-occurrence matrix for 4 distances d and 4 angles θ [62]

The algorithm of a basic GLCM is as follow:

1. Compute the whole pairs of pixels where the first pixel will be given I value and the matching pair of a pixel which is displaced from the first pixel by d has the j value.
2. The summation of this will be inserted in the i row and j column of the matrix P_d [i, j].

3. It is worth to be mentioned that [i, j] is not symmetric, when the number of pair of pixels which possess the gray levels [i, j] do not similar to the number of pair pixels having the gray levels [i, j].

4. Each entry will be divided by the total number of pairs of pixels that normalize the [i, j] elements.

5. The normalization of GLCM N [i, j] is defined by [62]:

$$N[i,j] = \frac{P_d[i,j]}{\sum_i \sum_j P_d[i,j]} \tag{8}$$

GLCM has three parameters and they are as follow: First one is a range used scaling input image into gray levels which is the value of minimum and maximum grayscale in the image as limit. Second parameter is the number of gray levels which determines the GLCM size. Last parameter specifies to the distance between the interest and its neighbor based on the angle value.

Figure 3.10 shows example of applying GLCM in default properties [63].

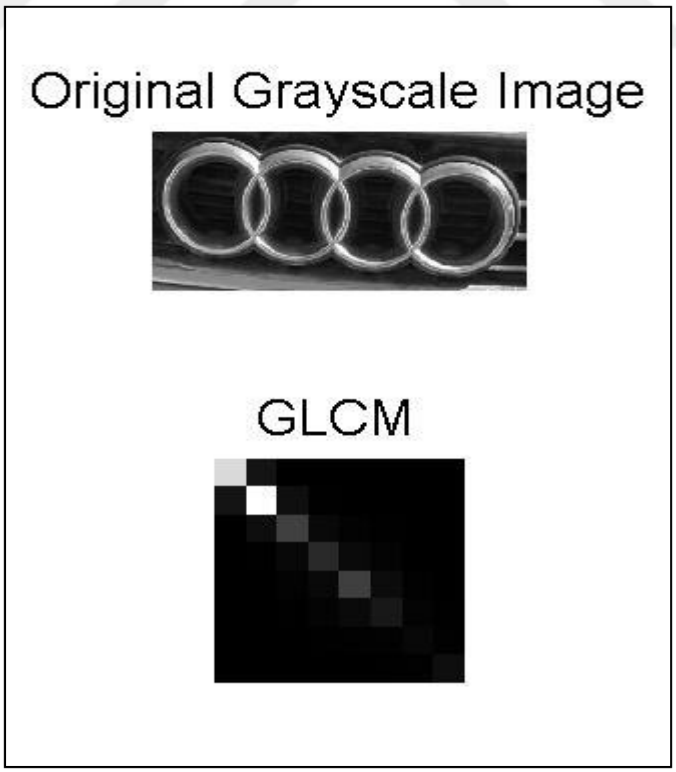

Figure3.10: Example of extract the features from vehicle logo using GLCM

Figure 3.10 shows the use of GLCM to extract the features of vehicle logo and GLCM is in the default case with angle 0. It explains that high values in the co-occurrence matrix are concentrated in the upper location.

3. 3.4. KNN classifier:

K nearest neighbors is considered a simple algorithm which stocks the whole attainable cases and classifies new cases depending on the measure of similarity. Thus, the classification of KNN has been developed from the need to execute discriminate analysis when the dependable parametric assessments of possibility densities are unidentified or problematic to conclude [64].

Through the training stage the algorithm basically stores the data points and their class labels while the entire calculations are delayed until the classification process. Thus, the KNN is based on the principle which its instances are in close proximity to another that has related characteristics.

Therefore, in order to categorize the new unclassified instances, one should take a look at their k-nearest neighbors, to configure the label of classifications as illustrated in Figure 3.11. The membership of the class may be defined by a major of k closest neighbors or the neighbors can be ranked and weighted consistent with their distance to the new instance. A common weighting scheme involves giving each neighbor a weight of 1/d, where d represents the distance to the neighbor.

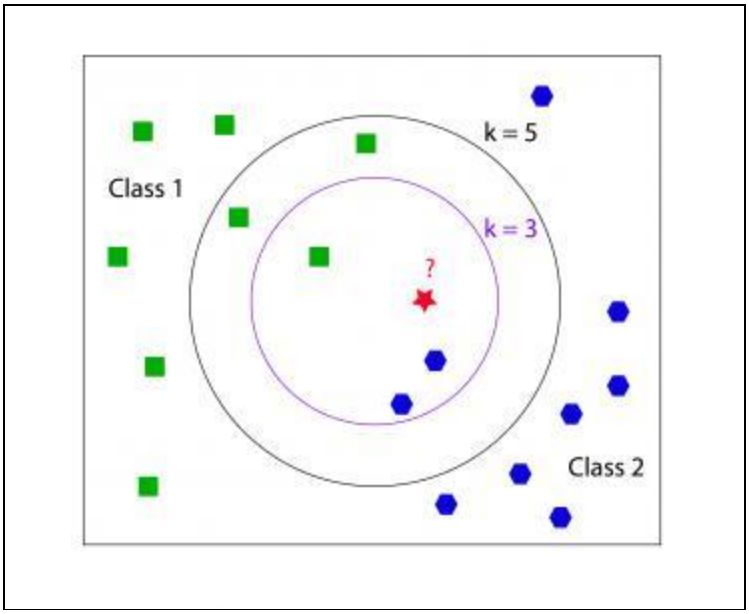

Figure 3.11: Example of classifying a new item using KNN. [65]

Using a majority vote of the k nearest neighbors, the defined k can change the assigned class of the red star (test object). If k = 3 (purple circle) the star resembles the blue polygon class, since the three closest neighbors comprise two blue polygons and one green rectangle. While, if k = 5 (black circle) the star is assigned to the green class because the five closest neighbors comprise more green rectangles than blue polygons (three green rectangles vs. two blue polygons [65]. The KNN is used in many different classification problems such as: Classification of parasite egg cells as proposed in [60] and estimation of polypropylene concentration of modified bitumen images [66].

CHAPTER 4

EXPERIMENTS AND RESULTS

In this Chapter, the experimental test of this thesis and their results are presented. The main goal is comparing the results of each method and determining their performance according to a number of experiments.

4.1. The Experiments:

All the experiments were applied on the same 10 logo manufacturers (Audi, BMW, Fiat, Honda, Mazda, Mercedes, Nissan, Renault, Toyota and Volkswagen). These experiments were diverse and were utilized in two different cases, as explained below:

Case 1:

The training set contains 1000 logo images that belong to 10 logo manufacturers. The images were gathered from the websites of the manufacturers. In addition, testing set includes 200 logo images captured by standard camera that belong to 10 logo manufacturers.

In each experience, we test the matching between 20 logo images for each brand from testing set with 1000 logo images from the training set.

Case 2:

The case is based on the logo images captured by standard camera. In other words, the testing set in Case 1 only was used here and divided into two groups: training set and testing set. The training set contains 100 logo images for 10 logo manufactures and the testing set contain 10 logo images for each brand.

In each experiment, we match the 10 logo images from testing set with 100 logo images from the training set.
With regard to logo images collected from the websites of manufacturers, we do not care about if the images were processed or affected by any other affects. In addition, the size of all the images was specified by "100×100" in all the methods.

Both groups of images that were collected from the websites of manufacturers and the others which were taken by the standard camera are color images but they were converted to gray images in the experiments.

In the experiments, SURF algorithm does not need to the classifier. For the methods LBP and GLCM, they can extract the features and they need to the classifier. We use KNN for the classification with LBP and GLCM. In more details, the experiments start with SURF algorithm. Then, LBP with KNN is applied. After that, GLCM with KNN is utilized. Finally, we combine LBP and GLCM with KNN. Other experiments were provided by changing the parameters in GLCM to find how the changes in parameters affect the result. Furthermore, the value of K for the KNN is changed from k=1 to 20 when it is used with LBP to obtain the better result and high-performance.

4.2. The Results:

Here, the results that obtained along with all the experiments were illustrated using Confusion Matrix for performance evaluation. Confusion Matrix represents the evaluation of the performance for a model in cases of classification or prediction. It is performed by a matrix in which each column of the matrix represents the instances in a predicted class while each row represents the instances in an actual class [67]. See Figure (4.1).

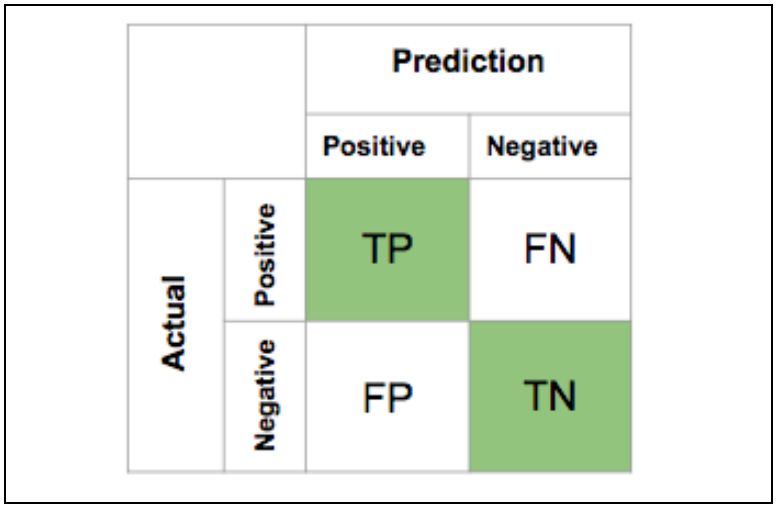

Figure 4.1: The Confusion Matrix [68]

In the Confusion Matrix, we Have Four outcomes are: True Positives (TP), False Positives (FP), False Negatives (FN) and True Negatives (TN). These are defined as:

. **True Positive (TP)**: is the proportion of positive cases that were correctly identified, (Correctly predicting a label).

. **False Positive (FP):** is the proportion of negatives cases that were incorrectly classified as positive, (Falsely predicting a label).

. **False Negative (FN):** is the proportion of positives cases that were incorrectly classified as negative, (Missing and incoming label).

. **True Negative (TN):** is defined as the proportion of negatives cases that were classified correctly, (Correctly predicting the other label) [48].

4.2.1. Experimental results of SURF algorithm:

The results of vehicle logo recognition based on SURF algorithms are exercised in the two cases (Case 1 and Case 2). Case 1 is employed 1000 logo images as training set and 200 logo images as testing set. In SURF algorithm experiment, a metric was applied to determine the number of features that will be used in the classification. The metric threshold of 600 was used in the two cases.

The result in Case 1 provides high accuracy (**99.5%**). **Table 4.1** shows the Confusion matrix for Case 1 and illustrates the performance rate for each logo.

Table 4.1: Confusion Matrix for SURF algorithm- Case 1

	Audi	BMW	Fiat	Honda	Mazda	Mercedes	Nissan	Renault	Toyota	VW	Undetected	Accuracy %
Audi	20											100%
BMW		20										100%
Fiat			20									100%
Honda				20								100%
Mazda					20							100%
Mercedes						20						100%
Nissan							20					100%
Renault								20				100%
Toyota					1				19			95%
VW										20		100%
Total accuracy rate = 99.5%												

To get clear view of our work, an overview for confusion matrix is presented. From Table 4.1, we can understand that all testing images (20 logo images) for Audi logo images were matched correctly, as well with other logo manufacturers' images which achieved correctly matching, except Toyota logo images, where 19 logo images were correctly classified to the training set but one logo image were incorrectly classified as Mazda logo image.

To evaluate the SURF algorithm in different way, the Case 2 includes logo images that were taken by a standard camera only. The training set is composed of 100 logo images and testing set contains 10 logo images for each brand. The accuracy rate in Case 2 is **59%**. **Table 4.2** illustrates the confusion matrix for Case 2.

In this case, Only Fiat's logo images got full correct matching with a performance rate 100%, where all the 10 testing set were coupled to the training set. Less performance rate belongs to Volkswagen logo images in which only one image was matched correctly.

Table 4.2: Confusion Matrix for SURF algorithm- Case 2

	Audi	BMW	Fiat	Honda	Mazda	Mercedes	Nissan	Renault	Toyota	VW	undetected	Accuracy %
Audi	7		1			2						70%
BMW		9							1			90%
Fiat			10									100%
Honda				6		1			3			60%
Mazda		1			3	2			3		1	30%
Mercedes		1	1			6			1	1		60%
Nissan			1			1	8					80%
Renault		1	1			1		5	2			50%
Toyota		1	1	3	1				4			40%
VW	1	4		2					1	1	1	10%
Total accuracy rate =59%												

4.2.2. Experimental results of LBP with KNN:

We used LBP to extract the features of the images in our dataset and KNN to classify these features. We applied these methods in the two cases which were followed in this thesis. **Case 1** Achieved a total correct rate **89.5 %** when **K=1** in KNN classifier as default value. The confusion matrix that was produced from experiments for LBP with KNN is illustrated in **Table 4.3.**

Table 4.3: Confusion Matrix for LBP + KNN- Case 1:

	Audi	BMW	Fiat	Honda	Mazda	Mercedes	Nissan	Renault	Toyota	VW	Accuracy %
Audi	20										100%
BMW	1	19									95%
Fiat		2	18								90%
Honda			3	17							85%
Mazda				3	17						85%
Mercedes					2	18					90%
Nissan						2	18				90%
Renault								16			80%
Toyota								2	18		90%
VW									2	18	90%
Total accuracy rate= 89%											

In Case 2, LBP performed a performance rate **72%**, when **K** value equaled to **1. Table 4.4** shows the Confusion Matrix for Case 2.

Table 4.4: Confusion Matrix for LBP+KNN- Case 2

	Audi	BMW	Fiat	Honda	Mazda	Mercedes	Nissan	Renault	Toyota	VW	Accuracy%
Audi	7									1	70%
BMW		9						1			90%
Fiat			4				1		1	4	40%
Honda				7						3	70%
Mazda		1			5	2	1				50%
Mercedes		1				7		2			70%
Nissan							10				100%
Renault								10			100%
Toyota								1	8	1	80%
VW		1				1		3		5	50%
Total accuracy rate = 72%											

The performance rate in the Case 2 is varied between 40% to 90% except for Nissan and Renault logo images that were matched with a rate of 100%.

4.2.3. Experimental results of LBP+KNN according to K value:

To increase the performance of LBP and get better result, KNN classifier was provided with different values of K, which K value is changed from 1 to 20. This changing gives various results. Best result for vehicle logo recognition using LBP with KNN is **91%**, where K value equal to 3.
Figure 4.2 appears the fluctuations in accuracy rate for LBP in vehicle logo recognition according to changes in K values.

In addition, these modifications were enforced in Case 2 as well. The result when K =1 and K= 2 is the same and it was best result **72%**.
Also, the deviations in Case 2 based on the variations values of K are illustrated in Figure 4.2.

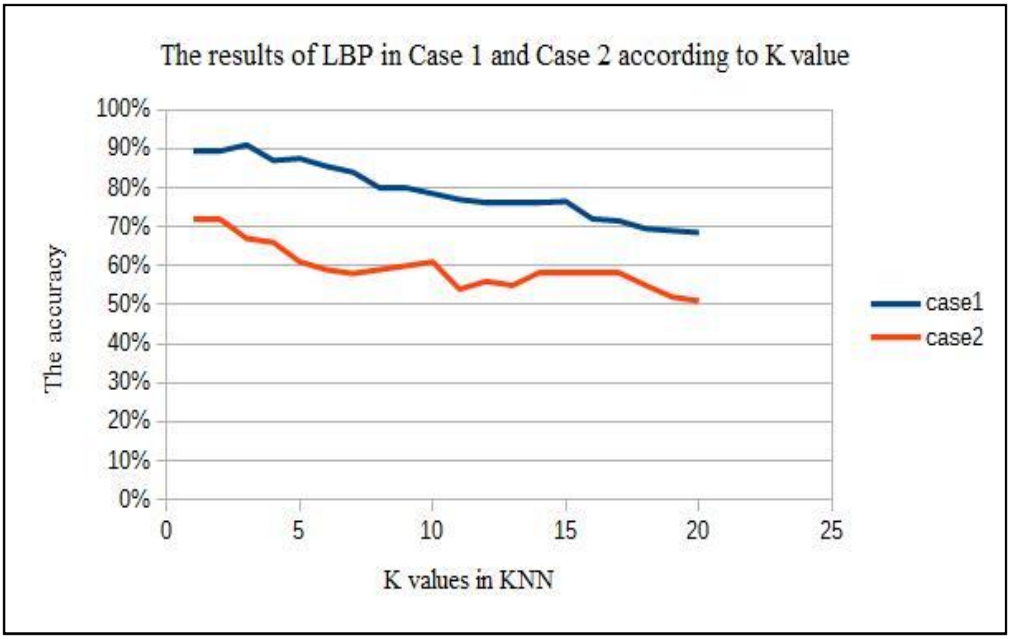

Figure 4.2: The results of LBP (Case 1 and Case 2) according to K value

4.2.4. Experimental results of GLCM with KNN:

By applying GLCM to extract the features of the input images and KNN as classifier for the features, we got accuracy rate 88.5% in Case 1 and Table 4.5 shows the confusion matrix for GLCM with KNN in Case 1.

This experience was utilized GLCM in default parameters. This means, GLCM uses the minimum and maximum gray-scale values in the image as limits. As well it scales the values in the image so they are integers between 1 and 8 and the distance between the interest and its neighbor based on the value of the angle 0° in default case as well as K value in KNN equal to 1 that is default too.

Table 4.5: confusion matrix for GLCM with KNN- Case 1

	Audi	BMW	Fiat	Honda	Mazda	Mercedes	Nissan	Renault	Toyota	VW	Accuracy %
Audi	20										100%
BMW	1	19									95%
Fiat		2	18								90%
Honda			3	17							85%
Mazda				3	17						85%
Mercedes					2	17			1		85%
Nissan						2	18				90%
Renault							4	16			80%
Toyota					1			2	17		85%
VW									2	18	90%
Total accuracy rate= 88.5%											

By seeing the performance rate for each logo manufacturers, we found only Audi logo images has 100% accuracy rate but the other logos have variety percentage between 80% -95%, which perform well accuracy.

The experiments of GLCM with KNN in Case 2 performs accuracy rate = 54% for vehicle logo recognition. In Table 4.6, confusion matrix for GLCM with KNN in Case 2 is given. As a reminder, the size of training and test sets in Case 2 is smaller than the size in Case 1.

The result of this experiment shows the performance rates for all logos ranging between 20%- 80% and there is no optimal performance in this case. The lowest accuracy belongs to BMW logo image in which only 2 logo images were matched accurately to the training set. 80% refer to better result in this case and it is achieved by Audi, Fiat and Mazda. (See Table 4.6).

Table 4.6: confusion matrix for GLCM with KNN- Case 2

	Audi	BMW	Fiat	Honda	Mazda	Mercedes	Nissan	Renault	Toyota	VW	Accuracy%
Audi	8			1		1					80%
BMW	1	2	1		2	2			2		20%
Fiat			8					2			80%
Honda			1	5		1			2	1	50%
Mazda	2				8						80%
Mercedes	1	1				6			2		60%
Nissan		1		1		1	5	2			50%
Renault	1	1	1	1			1	5		1	50%
Toyota	1		2		2				4	2	40%
VW	3		1	2					1	3	30%
Total accuracy rate=54%											

4.2.5. Experimental results of GLCM +KNN with Changing GLCM parameters:

Here, the previous experiment was repeated but with changing the GLCM parameters, especially in the number of gray levels and the distance between the pixel of interest and its neighbor. The reason for this converting is to increase the performance rate for vehicle logo recognition using GLCM. Furthermore, another cause is to study the effect of the parameters values in the results and to measure which parameters give a higher rate.

In this experiment, we apply the minimum and maximum gray-scale values in logo images as limits in all the experiments.

But regarding to the parameter that indicates to the number of gray levels in an image, it is modified through these values (8, 16, 32, 64, 128 and 256) in each round. In addition, the distance between the pixel of interest and its neighbor is changed to these angles [0, 45, 90, and 135].

These varieties were employed in the two cases of GLCM and were provided different results that will be shown in Tables 4.7 and 4.8, which compare the accuracy rate for vehicle logo recognition in multiple experiments based on

changing parameters. Table 4.7 shows the result of changes the number of gray levels parameters.

Table 4.8 shows the performance rate for GLCM with changes in parameter the distance between the pixel of interest and its neighbor.

Table 4.7: Performance rate of GLCM with changes in the number of gray levels:

The number of gray levels	Case 1	Case 2
8	88.5%	54%
16	88%	49%
32	88%	48%
64	88.5%	47%
128	88%	42%
256	88%	39%

Table 4.8: Performance rate of GLCM with changes in the distance between the pixel of interest and its neighbor:

Angle	Case 1	Case 2
0	88.5%	54%
45	88.5%	53%
90	88%	54%
135	88.5%	54%

4.2.6. Experimental results of GLCM + KNN according to K value:

In this experiment, GLCM algorithm was applied with KNN classifier with different values of K value ranging between (1-20). This process checks the ability of K values in the result of GLCM. As expected, the accuracy rate varies when K is changed. Best result was achieved when K value equal to 1 and 2, which is 88.5% in Case 1 and 54% in Case 2. The performance rates in the other values (3-20) were disparate but not get better result than K=1 and

K=2. Figure 4.3 illustrates the performance rate of GLCM according to K value in Case 1 and Case 2.

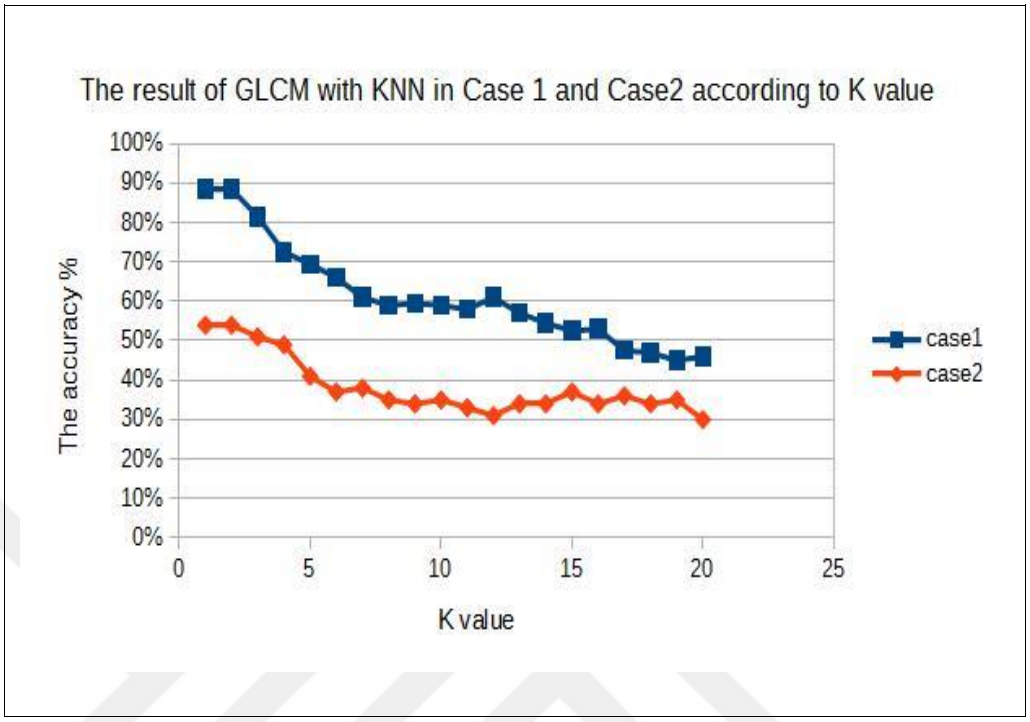

Figure 4.3: The result of GLCM +KNN (Case 1 and Case 2) according to K value

4.2.7. Experimental results of combined LBP and GLCM:

Other experiments were performed in order to increase the accuracy rate. Experiments on combining LBP and GLCM were applied in Case 1 and Case 2. In addition, the combination was exercised according to change the parameter ' number of gray levels, for GLCM features.

First, we provided the C**ase 1** with parameter 'number of gray levels' equal to 8, in the second round 'number of gray levels' equal to **64** and the accuracy rate was the same in this situation and it is **88.5%**.

According to C**ase 2**, its performance in the default for GLCM was equal to **51%** for vehicle logo recognition. As for changing in 'number of gray levels' to 64, the accuracy rate was **47%**. The results are not better when LBP and

GLCM are combined for vehicle logo recognition. We will discuss that in the next chapter.

The confusion matrix for each case was prepared separately. Tables 4.9, 4.10, 4.11 and 4.12 show the confusion matrices of combined LBP and GLCM.

Table 4.9: Case 1- Confusion Matrix of Combine LBP+GLCM when the number of gray levels =8

	Audi	BMW	Fiat	Honda	Mazda	Mercedes	Nissan	Renault	Toyota	VW	Accuracy %
Audi	20										100%
BMW	1	19									95%
Fiat		2	18								90%
Honda			3	17							85%
Mazda				3	17						85%
Mercedes					2	17			1		85%
Nissan						2	18				90%
Renault							4	16			80%
Toyota					1			2	17		85%
VW									2	18	90%
Total accuracy rate =88.5%											

Table 4.10: Case 2- Confusion Matrix of Combine LBP+GLCM when the number of gray levels =8

	Audi	BMW	Fiat	Honda	Mazda	Mercedes	Nissan	Renault	Toyota	VW	Accuracy %
Audi	**7**		1	1		1					70%
BMW	1	**2**	1		2	2			2		20%
Fiat			**8**					2			80%
Honda			1	**5**		1			2	1	50%
Mazda	2				**7**		1				70%
Mercedes	2	1				**5**			2		50%
Nissan		1		1		1	**5**	2			50%
Renault		1		1			1	**6**		1	60%
Toyota	1		2		2				**3**	2	30%
VW	3		1	2					1	**3**	30%
Total accuracy rate = 51%											

Table 4.11: Case 1- Confusion Matrix of Combine LBP+GLCM when the number of gray levels =64

	Audi	BMW	Fiat	Honda	Mazda	Mercedes	Nissan	Renault	Toyota	VW	Accuracy%
Audi	20										100%
BMW	1	19									95%
Fiat		2	18								90%
Honda			3	17							85%
Mazda				3	17						85%
Mercedes				1	2	17					85%
Nissan						2	18				90%
Renault							4	16			80%
Toyota			1					2	17		85%
VW									2	18	90%
Total accuracy rate = 88.5%											

Table 4.12: Case 2- Confusion Matrix of Combine LBP+GLCM when the number of gray levels =64

	Audi	BMW	Fiat	Honda	Mazda	Mercedes	Nissan	Renault	Toyota	VW	Accuracy %
Audi	5		1	1		1					50%
BMW	1	1	1		2	1	1		2	1	10%
Fiat			7					2			70%
Honda	1		1	6		1				1	60%
Mazda	1				6		1	2			60%
Mercedes			1	1		4	3	1			40%
Nissan	1				1		6	1	1		60%
Renault			1	2				4	1	2	40%
Toyota			1				1		7	1	70%
VW		2	2	5						1	10%
Total accuracy rate = 47%											

Table 4.13 shows the summary of the results obtained. It compares the accuracy rate of vehicle logo recognition in C**ase 1** and C**ase 2** when combined LBP and GLCM with changes in GLCM parameter 'number of gray levels' are

used.

Table 4.13: Comparing the results of combine LBP and GLCM according to number of gray levels

Number of gray levels	Case 1	Case 2
8	88.5%	51%
64	88.5%	47%

As a conclusion of this chapter, we provide an overview of the performance rate for each method (SURF, LBP and GLCM) in vehicle logo recognition. SURF algorithm achieved high accuracy rate 99.5% in Case 1 and 59% in Case 2. Regarding to LBP with KNN, they reached better performance rate 91% when K value is equal to 3 in Case 1. Moreover, LBP with KNN gets accuracy rate 72%, which is the highest result in Case 2.

In addition, GLCM with KNN in Case 1 accomplished performance rate 88.5% which was better accuracy rate during all the experiments of changing GLCM parameters. GLCM with KNN attained **54%** as highest performance rate for Case 2 when distance between the interest and its neighbor is refer to angles 90 and 135.

The experiments that conducted on to combine LBP with GLCM to vehicle logo recognition provided a performance rate 88.5% in Case 1 and 51% in Case 2 when parameter of number of gray levels equal to 8. As for LBP +GLCM when number of gray levels= 64 the performance rate was 88.5% for Case 1 and 47% for Case 2.

Figure 4.4 illustrates overview of the results from the proposed methods in Case 1 which is achieved best result. Also, Figure 4.5 shows overview of the results from the proposed methods in Case 2.

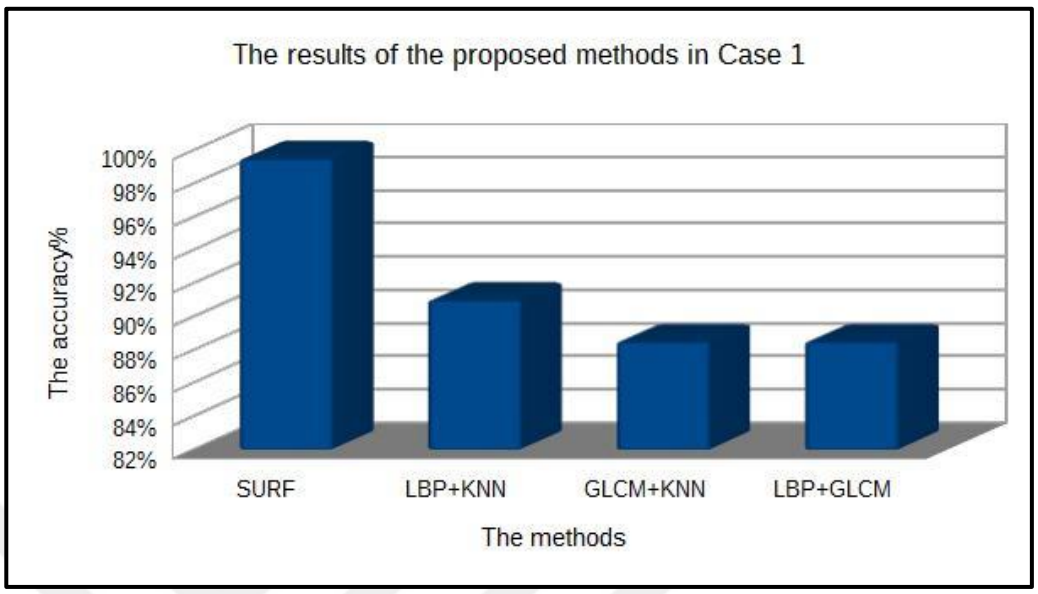

Figure 4.4: Overview of the result from the proposed methods for Case 1

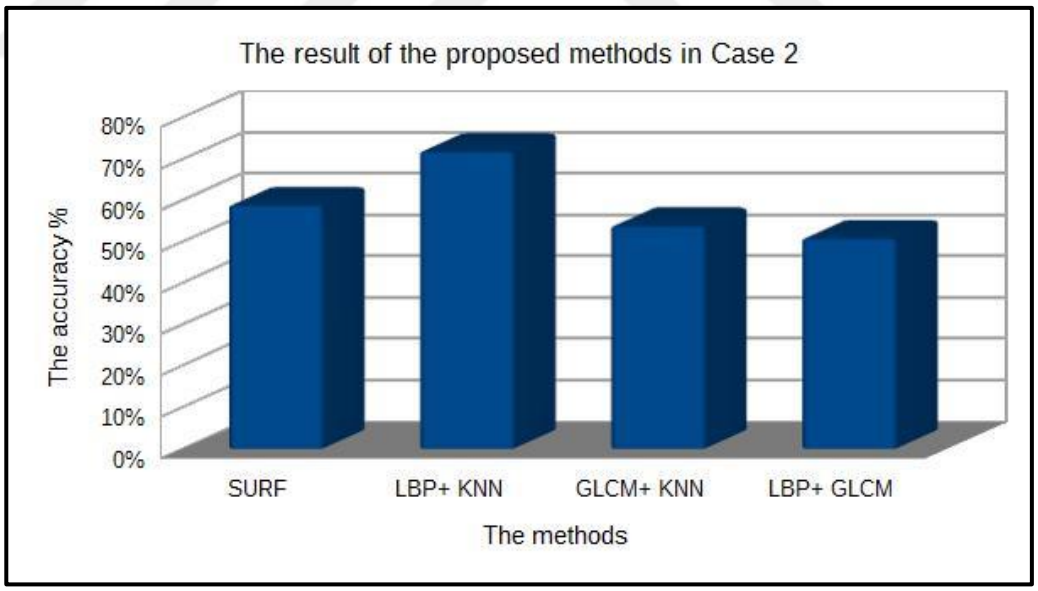

Figure 4.5: Overview of the result from the proposed methods for Case 2

Table 4.14 provides overview of the results of applying SURF algorithm, LBP and GLCM for vehicle logo recognition.

Table 4.14: Results of applying the main methods in this thesis

Methods	Case 1	Case 2
SURF	99.5%	59%
LBP+KNN	91%	72%
GLCM+KNN	88.5%	54%
LBP+GLCM	88.5%	51%

CHAPTER 5

DISCUSSIONS

5.1. Discussions:

This thesis implements vehicle logo recognition using image processing methods. The methods followed are SURF algorithm, LBP and GLCM. In addition, KNN is used for the classification with LBP and GLCM.
These methods were applied in two cases. The cases are named as Case 1 and Case 2 which were differed in the number of and the kind of the images. Both groups of logo images are not from the same side but they are from different directions to test the power of methods in recognizing the logos from different sides.

The logo images can be classified to noisy and noise free images. The logo images from the websites of manufacturers are noise free, as for logo images that are captured by standard camera are noisy images which were taken in different lighting conditions and have reflection of other backgrounds.

The results obtained by applying the three methods (SURF, LBP and GLCM) for vehicle logo recognition will be discussed in this chapter.
Best result was achieved by SURF algorithm when accuracy rate is 99.5% in Case 1. Then LBP+KNN with 91% and GLCM+KNN are 88.5%. Combined LBP method with GLCM provide accuracy rate of 88.5% in vehicle logo recognition. These results in Case 1 indicate that using a big number of images for the logos in the training set helps us to get better result.

Case 2 contains less number of images comparing with Case 1 and it is more affected by changing the parameters in GLCM. The result of GLCM in Case 2

is varied more than Case 1 when the parameters of GLCM were changed.

From the previous studies in vehicle logo recognition, we note that LBP and GLCM methods are not used widely in this field.
The results that were acquired from the proposed methods in this thesis are discussed and compared with the results of the previous studies and researched in vehicle logo recognition.

Psyllos et al. in paper [1] used M-SIFT (Merge- SIFT) that achieved accuracy rate 94.6%. This result is lower than the result obtained by the proposed SURF algorithm. In this thesis we obtained 99.5% accuracy rate of vehicle logo recognition.

The lowest accuracy rate in the previous studies was over 50% and it was achieved by paper [3] entitled Vehicle Logo Recognition Based on Interior Structure Using SIFT Descriptor and Neural Network. This experiment was employed on small numbers of logo images as a training set which includes 18 logo images, and it is tested on a set containing 220 logo images. Also, this method was sensitive to light conditions. The proposed SURF algorithm was attained better result than the methods in paper [5], which applied vehicle Logo Recognition Using a SIFT-Based Enhanced Matching Scheme and its performance rate is 91%.

In the previous studies that were explained in Chapter 2, one study is provided vehicle logo recognition using image matching and textural features [6]. This method used GLCM to textural features extraction and its accuracy rate is 90%, while two methods were used to extract the features in this thesis, are LBP and GLCM. Our proposed methods are reached accuracy rate 91 % using LBP and 88.5% using GLCM. The method in [6] was employed on 210 logo images and it is limited to recognize four types of logos and not able to other kinds of logo manufacturers.

Table 5.1 shows comparison between the proposed methods in this thesis and

the previous studies presented in Chapter 2.

Table 5.1: Comparison between the proposed methods and other studies

Methods	**Performance**
Vehicle Logo Recognition using M-SIFT [1]	94.6%
Vehicle Logo Recognition method based on CNN (Convolutional Neural Network) [2]	99.23%
Vehicle Logo Recognition Based on Interior Structure Using SIFT Descriptor and Neural Network [3]	Over 50%
Vehicle logo recognition in traffic images using HOG features and SVM [4]	92.59%
Vehicle Logo Recognition Using a SIFT-Based Enhanced Matching Scheme [5]	91%
Vehicle Logo Recognition using Image Matching and Textural Features [6]	96%for image matching and 90% for textural features
Vehicle Logo Recognition Using Mathematical Morphology [7]	96%
Vehicle Logo Recognition Using Modest AdaBoost and Radial Tchebichef Moments [8]	92%
Vehicle-logo Recognition Based on Classifier Combinations [9]	98%
Vehicle-logo Recognition Method Based on Tchebichef Moment Invariants and SVM [10]	noise-free is 100%, noisy environment is 92%
Vehicle-logo Recognition Algorithm Based on Convolutional Neural Network [11]	97%
Vehicle Logo Recognition Based on Bag-of-Words [12]	97.3%
Pattern Recognition of Vehicle Logo Using Tchebichef and	88.3%

Legendre Moment [13]	
Vehicle Logo Recognition Based on a Weighted Spatial Pyramid Framework [14]	98%
Vehicle Logo Recognition By Weighted Multi-Class Support Vector Machine Ensembles Based On Sharpness Histogram Features [15]	82%
Vehicle Logo Recognition Based on SURF algorithm [proposed method]	99.5%
Vehicle Logo Recognition Based on LBP with KNN [proposed method]	91%
Vehicle Logo Recognition Based on GLCM with KNN [proposed method]	88.5%
Vehicle Logo Recognition Based on combination LBP and GLCM with KNN [proposed method]	88.5%

Generally, the proposed SURF algorithm in this thesis ascertain better result than most of the previous studies, except the study [10] which supplied vehicle-logo recognition method based on Tchebichef Moment Invariants and SVM. This method achieved 100% accuracy rate in noise-free and its accuracy in noisy environment is 92%. While the cases of this thesis are included a noisy and noise- free logo images that means the methods in this study is tested in noisy environment and best result is 99.5%.

Other inference about the results of this thesis, the Case 1 contains noise free and noisy logo images; it gets a better result than Case 2 that includes only noisy logo images. Likewise, the number of logo images in Case 2 is lower than Case 1 and that indicates the number of logo images is an important factor in influencing the result. The success of the SURF algorithm is due to its ability to distinguish shapes in several directions and discrimination in the rotation mode. As well as its speed and ease to understanding that made of it suitable for vehicle logo recognition with high performance rate.

LBP with KNN is obtained superior result in Case 2, its accuracy rate in Case 2 is 72%. While SURF algorithm realized 59% and GLCM with KNN get 54%

in Case 2. This result leads to the power of LBP to get good result in the noisy images. In addition, GLCM parameters are more effective in Case 2 according to the size of this case and the type of its logo images.
The advantage of LBP operator in real-world applications is its stability to monotonic grey level changes.

Modifying K value in KNN classifier with LBP provides a variety in results and can improve the performance by applying different values of K.
Combined LBP with GLCM to extract the features with KNN to classify these features did not increase the performance. This reason may be due to the nature of the logo images and being a variety of noisy and noise-free images. As mentioned formerly, the combination between LBP and GLCM is done in default case for both methods and without changing of K value in KNN classifier.

5.2. Limitation:

The goal of this thesis is vehicle logo recognition, so the logo images were cropped to contain the logo only in the images. This means this study is not for detection the logos which the detection will be applied in future works.

CHAPTER 6

CONCLUSION AND FUTURE WORK

This chapter provides the summary of this study and the important points through the experiences of this work. Also, several ideas for the future work are presented in the second section of this chapter.

6.1 Conclusion:

Vehicle logo recognition is an important system in the surveillance and the Intelligent Transportation Systems [ITSs]. In this thesis, vehicle logo recognition system was investigated by three methods (SURF algorithm, LBP with KNN and GLCM with KNN). LBP and GLCM were used as feature extractors and KNN was used as classifier.

First, this thesis was started with brief introduction about the logo recognition and specified explanation for vehicle logo recognition. The importance of vehicle logo recognition and the idea of its work were summarized in Chapter 1. Then, Chapter 2 presented an overview of the previous studies and researches in this domain. But the previous studies that presented methods for vehicle logo detection or license plate recognition were excluded from previous literatures in Chapter 2 because they are not related mainly with the main topic of this thesis.

Chapter 3 provided a description about the materials and methods that were used in this thesis. This chapter begins with introduction of data collection employed. The dataset collected by two ways, first one, the logo images of 10 manufacturers were collected from the websites of the manufacturers.
The total is 1000 original logo images were produced of this way. Second way, logo images for 10 manufacturers were captured by standard camera in real

condition and a total of 200 logo images were acquired. Both cases focused on logo images from different directions. Then, second section specified the methods that were investigated in this thesis. The methods are: 1) SURF algorithm, 2) Local Binary Pattern (LBP), 3) Gray Level Co-occurrence Matrix (GLCM) and K- Nearest Neighbors (KNN). All of these methods were explained and illustrated how they work.

The experiments and the results of applying the methods in vehicle logo recognition were presented in Chapter 4 and the results were illustrated in details with tables and figures.
Chapter 5 discussed the main points and the result obtained of this thesis.
In general, the number of images in database, especially the size of training set, the type of images which are noise-free or noisy images and using the suitable methods, all of these conditions can effect in the performance and the result of the system.

After the comprehensive studies, best result was achieved by SURF algorithm, with a 99.5% accuracy rate. SURF algorithm was used only to extract the features and classify them. LBP was applied to extract the features and KNN to classify these features. The same thing was utilized with GLCM and KNN. The result of LBP and GLCM were 91% and 88.5%, respectively. These results are from Case 1.

The value of K in KNN can affect the performance and chosen the correct value of K can increase the accuracy.
Case 2 contains less logo images in training set and the images were noisy. Case 2 accomplished results lower than Case 1. This result indicates to the influences of the size and the nature of the logo images.

Generally, the accuracy rate of the methods followed in this thesis, we conclude that the SURF algorithm attained best result in Case 1 that means the performance of the SURF is better in big training set. In addition, the power of SURF algorithm in invariant rotation that helps much in the recognition because the logo images were from different directions. LBP with KNN

achieve best result in Case 1 when K value is equal to 3, while the result of LBP in Case 2 is attained more superior than SURF and GLCM in Case 2. This elucidate to capacity LBP to provide good result in noisy images and its stability in real-world conditions.

GLCM and its results in various conditions of changing its parameters were stable (ranging between 88.5%- 88%). While the results in Case 2 is more variety because its parameters affect in small size of training set and the noisy in the images.

Last experiment in this thesis was combined LBP and GLCM in default case for both methods, this fulfilled performance rate 88.5 % and not increase the performance in this situation.

Finally, SURF is the preferable in vehicle logo recognition with a big number of training images and for its properties as the invariant rotation, robust and fast. This conclusion is based on the accuracy rate of the proposed SURF in this thesis and in its results in the previous studies too.

LBP and GLCM are not popular in vehicle logo recognition but they provided acceptable results in this thesis especially in different conditions and with changing value of K in KNN and the parameters of GLCM. LBP is characterized by its calculation simplicity. The parameters of GLCM give chance to improve the performance and use different properties suitable for each situation.

6.2 Future Work:

Future plans will be focused on to improve the recognition performance of vehicle logos in more natural conditions, such as: under rainy weather, snowing on some parts of the logos and reflection of sunlight. This work did not focus on detecting the location of vehicle logo, so this may be done in the future. In addition, the methods which reached a high performance rate in this thesis may be used to detect and identify the logo of vehicles on video recordings. This

lead to concentrate on the speed of the algorithms and the ability to use them in real time applications.

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