DOI: 10.24996/ijs.2024.65.1.35

ISSN: 0067-2904

Car Logo Image Extraction and Recognition using K-Medoids, Daubechies Wavelets, and DCT Transforms

Maha A. Rajab[1]*, Loay E. George[2]

[1]*Department of Biology Science, College of Education for Pure Sciences /Ibn AL-Haitham, University of Baghdad, Baghdad, Iraq*

[2]*University of Information and Communication Technology, Baghdad, Iraq*

Received: 5/11/2022 Accepted: 27/1/2023 Published: 30/1/2024

Abstract

Recognizing cars is a highly difficult task due to the wide variety in the appearance of cars from the same car manufacturer. Therefore, the car logo is the most prominent indicator of the car manufacturer. The captured logo image suffers from several problems, such as a complex background, differences in size and shape, the appearance of noise, and lighting circumstances. To solve these problems, this paper presents an effective technique for extracting and recognizing a logo that identifies a car. Our proposed method includes four stages: First, we apply the k-medoids clustering method to extract the logo and remove the background and noise. Secondly, the logo image is converted to grayscale and also converted to a binary image using Otsu's method. Thirdly, the Daubechies wavelet with DCT transforms is applied to extract a feature vector for each image. Finally, the Canberra distance is used to match the tested image's feature vector to all feature vectors in the database. The test results indicate the highest CRR, accuracy, and precision at 99.37%, 99.39%, and 99.80%, respectively. This system is applicable to intelligent surveillance systems.

Keywords: K-Medoids, DCT transforms, Daubechies Wavelet, Logo Recognition, CRR.

استخلاص صورة شعار السيارة والتعرف عليها باستعمال K-Medoids وموجة Daubechies وتحويلاتDCT

مها عبد رجب[1]*, لؤي ادور جورج[2]

[1]قسم علوم الحياة, كلية التربية للعلوم الصرفة /ابن الهيثم, جامعة بغداد, بغداد, العراق

[2]جامعة تكنولوجيا المعلومات والاتصالات ، بغداد ، العراق

الخلاصة

يعد التعرف على السيارات مهمة صعبة للغاية نظرًا للتنوع الكبير في مظهر السيارات من نفس الشركة المصنعة للسيارة. لذلك فإن شعار السيارة هو أبرز مؤشر على الشركة المصنعة للسيارة. تعاني صورة الشعار الملتقطة من عدة مشاكل ، مثل الخلفية المعقدة ، والاختلاف في الحجم والشكل ، وظهور الضوضاء ، وظروف الإضاءة. لحل هذه المشاكل ، تنتج هذه الورقة تقنية فعالة لاستخلاص والتعرف على الشعار الذي

* Email: maha.a.r@ihcoedu.uobaghdad.edu.iq

يميز السيارة. تتضمن طريقتنا المقترحة أربع مراحل ؛ أولاً ، نطبق طريقة k-medoids العنقودية لاستخلاص الشعار وإزالة الخلفية والضوضاء. ثانيًا ، يتم تحويل صورة الشعار إلى تدرج رمادي وأيضًا تحويلها إلى صورة ثنائية باستعمال طريقة Otsu. ثالثًا ، يتم تطبيق موجة Daubechies مع تحويلات DCT لاستخراج ناقل سمة لكل صورة. أخيرًا ، تُستعمل مسافة Canberra لمطابقة ناقل ميزة الصورة المختبرة مع جميع متجهات الميزات في قاعدة البيانات. تشير نتائج الاختبار إلى أن أعلى نسبة CRR ودقة هي 99.37٪ و 99.39٪ و 99.80٪ على التوالي. هذا النظام قابل للتطبيق في أنظمة المراقبة الذكية.

1. Introduction

A pattern recognition system operates by getting biometric information that indicates an object's identity. It gets a collection of features from the data and compares them to a database template set. Pattern recognition is considered a subfield of artificial intelligence and digital image processing. A logo, a stamp, a fingerprint, a handwritten note, face recognition, and speech recognition are all examples of patterns [1]. A logo is a distinctive graphic, word(s), or collection of both word(s) and graphic symbol(s) that identifies a company's, a public organization's, an institution's, or an individual's products and services. It is also used as a tool for identifying a company, organization, or institution around the world. Despite the fact that logos can be found in different shapes, colors, and patterns, they are restricted by certain design constraints where they must be clear and easily recognizable [2].

Graphic logos are a unique type of visual object that is essential in specifying a person's or an entity's identity. They play an important role in industry and commerce because they help customers remember their expectations for a specific product or service [3]. There are various applications, such as detection of copyright violations, managing brands online, recognizing the vehicle, and so on; logo recognition is a major challenge [4]. Even though companies do not frequently change their logos and the context of the logo that appears for each product of the same company changes, logo recognition remains a difficult challenge. Perspective distortions, different backgrounds, occlusions, warping, different sizes, and different colors are all difficulties facing accurate logo recognition [5].

Furthermore, as the number of brands with personalized logos grows, recognizing them becomes a much more difficult challenge. To efficiently enable multi-class classification, logo recognition systems require significant processing capacity [6]. One of the essential signs of a car is a logo. In intelligent transportation systems in modern cities, automatic vehicle logo recognition plays an essential role. Vehicle tracking, policing, and security are some of the applications for vehicle logo recognition [7–8]. Yet, an alternative method of detecting a car's type is to recognize its logo. This is particularly useful in intelligent surveillance systems, which commonly work with low-quality images and need a fast response. On the other hand, existing solutions are ineffective or unsuitable for processes involving low-quality images [9].

The main problem is recognizing cars, which is a difficult challenge because of the wide variety in the appearance of cars from the same manufacturer. Thus, the logo of the car is used to recognize it. But the process of extracting a logo faces several problems, such as a difficult background, differences in size and shape, the appearance of noise, and lighting circumstances. This paper's goal is to produce an effective technique for extracting and recognizing color logo images that is robust under several imaging circumstances at the same time.

The rest of the paper is prepared as follows: Section 2 offers an overview of the related works. Section 3 presented the proposed method. Section 4 described the results and discussion. Finally, the conclusions of this paper are presented in Section 5.

2. Related Works

Because of the wide variety in the appearance of cars from the same manufacturer, it is difficult to categorize cars. In recent years, several studies have been carried out for car type recognition. D. F. Llorca et al. [10] presented a new approach to car logo recognition based on histograms of oriented gradients (HOG) and support vector machines (SVM). The overall recognition rate was 92.59%, according to the findings. Yue Huang et al. [11] proposed a convolutional neural network (CNN) approach for logo recognition that eliminates the need for exact logo discovery and partitioning.

Furthermore, an effective pretraining technique has been implemented to decrease the high computational cost of kernel training in CNN-based systems, allowing for better real-world applications. The best accuracy rate was 99.07%, according to the test results. Ruilong Chen et al. [12] proposed a web-based image recognition framework that can handle small and large datasets. Models are efficiently generated utilizing this recognition framework and a weight update technique. Another new aspect of this work is that it proposes using Cauchy prior logistic regression with conjugate gradient descent to solve multinomial classification problems.

The Cauchy prior allows the weight update process to reach a faster convergence speed, potentially lowering the computational cost for both online and offline techniques. The experimental results explain the highest accuracy, up to 98.80%. Foo Chong et al. [13] presented a car logo identification utilizing a deep convolutional neural network (CNN) and a whitening modification technique to remove the redundancy of neighboring image pixels. To train and generate weight filters for the networks, a backpropagation approach with a stochastic gradient descent optimization technique has been used. The best accuracy rate was 99.13%, according to the test results. Sushil et al. [14] proposed a system to detect and identify car logos using deep-learning networks.

This system consists of three stages: the preprocessing of the car logo image by making a label for the object that represents the logo; the convolutional neural networks (CNN) used to build a transfer learning model based on ResNet50; and finally, the classification stage done by random forest ensemble learning technology. The test results indicate the highest value achieved for accuracy, precision, and recall is 79% for all these measures. Xiaoli et al. [15] presented a model based on using YOLOv4 to detect vehicle logo images in difficult backgrounds. To enhance the backbone feature extraction network, the CSPDenseNet was first established, and a shallow output layer was added to replace the shallow information of small targets. The neck structure was then rebuilt using the deformable convolution residual block to capture the different and asymmetric shape aspects. Finally, a new detection head based on a convolutional transformer block was suggested to lessen the impact of complex backgrounds on vehicle logo detection. The test results indicate the accuracy value achieved is 62.94%.

3. Proposed Method

The proposed car logo recognition system consists of four main consecutive stages: (1) image clustering, (2) preprocessing, (3) feature extraction, and (4) matching. Figure 1 illustrates the structure of the proposed car logo recognition system. Each stage is composed of many steps that are used to identify each test sample and determine whether it belongs to the same type of car or not.

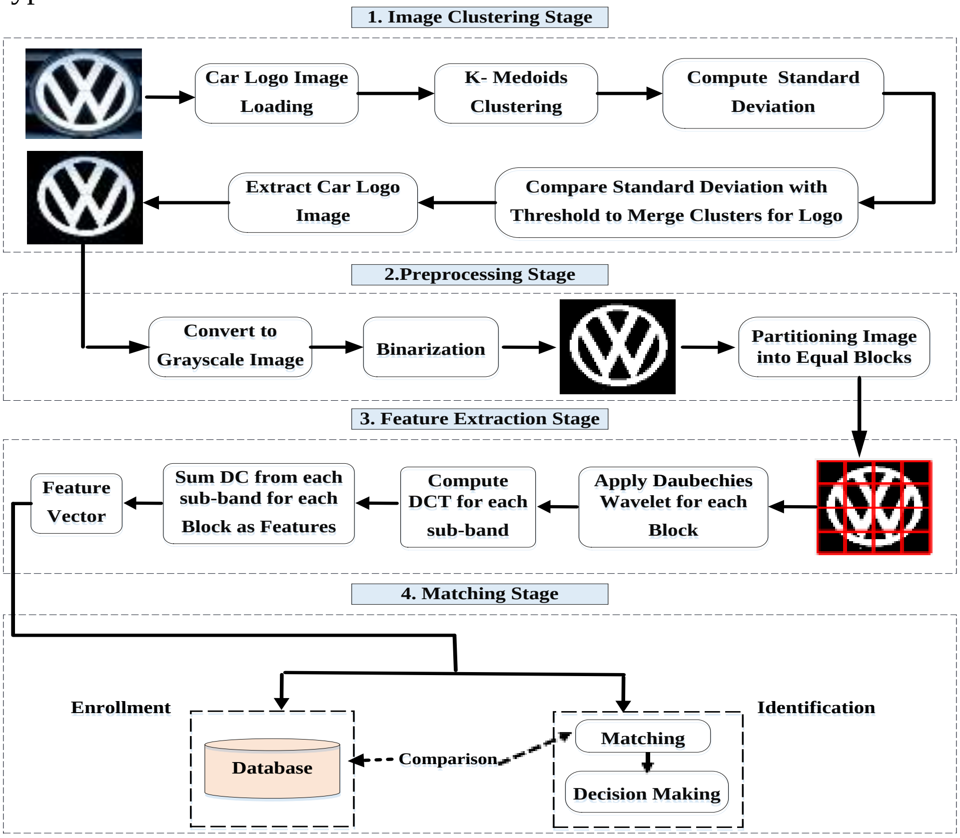


Figure 1: The proposed car logo extraction and recognition system layout

3.1 Image Clustering Stage

The main objective of the clustering is to divide the image into several clusters to isolate the cluster that represents the region of interest. In this paper, we used the k-medoids clustering algorithm to isolate the clusters that contain the car logo information and to delete the rest of the clusters that contain background information and noise. This stage consists of several steps.

3.1.1 Car logo Image Loading

This step loads the color car logo image from the file.

3.1.2 K-Medoids Clustering

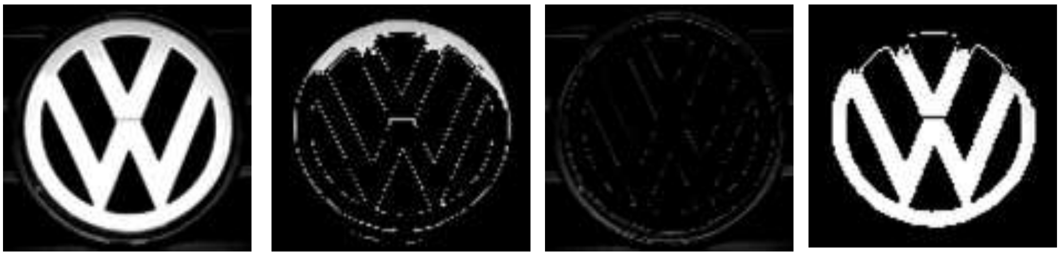
The main role of the k-medoids strategy is to find k clusters in n objects by selecting medoids randomly for each cluster. The remaining objects are grouped with the medoids that are similar to them. It used medoids as a reference point instead of calculating the average value for all cluster elements. The k-medoids algorithm is explained in the following steps [16].

1: Select k data items randomly to represent the initial medoids.
2: The closest medoid has been used to assign the remaining data point to a cluster.
3: Choose a non-medoid data point arbitrarily and calculate the total cost of replacing the previous medoid data point with the non-medoid data point currently chosen.
4: When the entire cost of replacing will be smaller than zero, the replacement process is performed to construct the new set of k-medoids.
5: Steps 2, 3, and 4 are repeated until the medoids are stable in their positions.

At this step, the image has been divided into several clusters, and these clusters contain information about the logo as well as background information. Based on the experiments, it was found that if the number of clusters selected was greater than three, the process of isolating the logo cluster would become complicated. When the number of clusters is equal to three, sometimes one of these clusters represents the logo and the rest of the clusters represent the background, as shown in Figure 2, where cluster 3 represents the logo, so there is no need to divide the image into more than three clusters. Sometimes, the logo information appears in two clusters while the background information may appear in one cluster, as shown in Figure 3.

Original car logo image **Cluster 1 background** **Cluster 2 background** **Cluster 3 logo**

Figure 2: The result of k-medoids for Volvo car



Original car logo image **Cluster 1 logo** **Cluster 2 background** **Cluster 3 logo**

Figure 3: The result of k-medoids for Volkswagen car

3.1.3 Compute Standard Deviation

As shown in the previous step, the number of the resulting clusters is 3, but we cannot determine which cluster of these clusters represents the logo. For this, the standard deviation needs to be calculated for each cluster. Then the value of the largest, middle, and smallest standard deviations that have been used to extract logo information needs to be stored.

3.1.4 Compare Standard Deviation with a Threshold to Merge Clusters

After that, choose an appropriate threshold and compare it with the middle standard deviation value; if the middle value of the standard deviation is greater than or equal to the threshold, we combine the clusters that have the highest and the middle value of the standard deviation, which represents the logo information. Figure 4 explains the result of clustering the tested image into three clusters, where the first cluster represents the background and has a standard deviation equal to 5.2141, while clusters two and three represent log information and have a standard deviation equal to 25.6001 and 23.1696, respectively.

Original car logo image | Cluster 1 background Std=5.2141 | Cluster 2 logo Std=25.6001 | Cluster 3 logo Std=23.1696 | Extract logo from merge cluster 2 and cluster 3

Figure 4: The result of standard deviation and extract logo of merging two clusters

But if the value of the standard deviation for the middle cluster is less than the threshold, the logo cluster becomes the cluster that has the highest standard deviation, as illustrated in Figure 5, where the second cluster represents the logo information and has a standard deviation equal to 42.3850 while clusters one and three represent the background and have a standard deviation equal to 1.2325 and 4.7239, respectively.

Original car logo image | Cluster 1 background Std=1.2325 | Cluster 2 logo Std=42.3850 | Cluster 3 background Std=4.7239 | Extract logo from cluster 2 has largest Std

Figure 5: The result of standard deviation and extract logo from larger standard deviation

3.1.5 Extract Car Logo Image

This is the last step of the clustering stage, in which we only get the color car logo image as shown in the last image of Figures 4 and 5.

3.2 Preprocessing Stage

It was established to improve the efficiency of the feature extraction stage by modifying the image data. In the preprocessing stage, several tasks have been conducted to improve the image quality. These tasks are explained in the following steps:

3.2.1 Convert to Grayscale Image

The color car logo image extracted from the previous stage, as shown in Figure 6 (a), is converted to a grayscale image, as shown in Figure 6 (b).

3.2.2 Binarization using Otsu's Method

A global thresholding value is utilized to convert the grayscale image to a binary image, and this value is chosen using Otsu's method. Otsu's thresholding technique relates to the linear discriminant metrics, which assume that the image consists just of the object (foreground) and background, with the background heterogeneity and diversity discarded. Otsu chose the threshold to reduce the overlap between the class distributions. Otsu works by making a scan of all potential threshold values and computing the minimum value of the pixel levels for each aspect of the threshold. The aim is to determine the threshold value for the sum of foreground and background with the least entropy [17]. Figure 6 (c) explains the result of applying Otsu's method to car logo images.

3.2.3 Partitioning Image into Equal Blocks

This step aims to split the binary image into equal blocks to facilitate the process of getting distinctive features in the feature extraction stage, as illustrated in Figure 6 (d), where the binary image is divided into four blocks in red color.

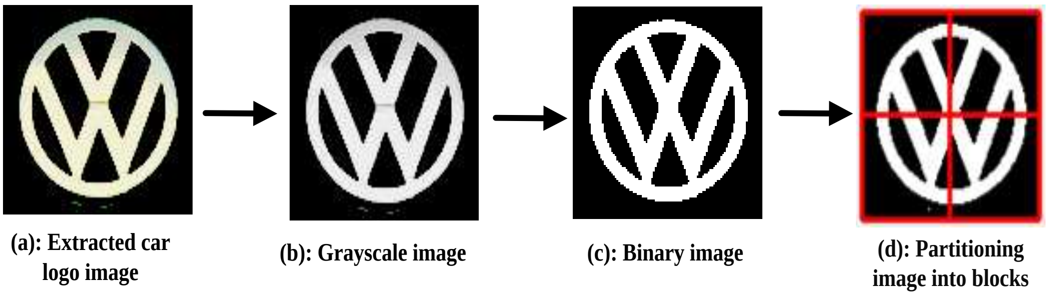


Figure 6: Preprocessing stage results

3.3 Feature Extraction Stage

After dividing the image into equal blocks in the previous stage, we focus on extracting distinctive characteristics from each block to obtain the best results in the matching stage. This stage consists of two steps, as described below.

3.3.1 Apply Daubechies Wavelet for each Block

Daubechies wavelets are a type of discrete wavelet transform (DWT) that has a maximum number of vanishing moments for a specified support. The goal of this type of 2D-DWT is to decompose the image into approximation coefficients (CA) and detailed coefficients (CH, CV, and CD) (horizontal, vertical, and diagonal) acquired by wavelet decomposition of the input image. The Daubechies wavelet (db2) is employed because it is real and continuous, and it has the lowest root-mean-square (RMS) error when compared to other wavelets [18]. Daubechies wavelet (db2) is applied in this paper for each block to decompose each block into four sub-bands, as shown in Figure 7.

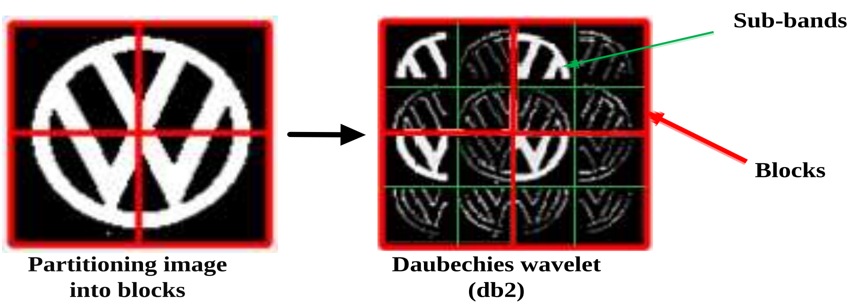


Figure 7: The result of applying Daubechies wavelet (db2)

3.3.2 Compute DCT for each Sub-Band

The discrete cosine transform (DCT) transforms an image from the spatial domain into the frequency domain by dividing the image pixel matrix into N*N blocks. To extract features from an image, we employ 2-D DCT to convert it into its equivalent DCT matrix as equations (1) and (2) [19].

$$F(u,v) = \frac{1}{MN}\alpha(u)\alpha(v)\sum_{i=0}^{M-1}\sum_{j=0}^{N-1} f(i,j)cos\left[\frac{(2i+1)u\pi}{2M}\right]cos\left[\frac{(2j+1)v\pi}{2N}\right] \quad (1)$$

where, u = 0,1,2….. M-1 , v = 0,1,2…….. N-1, while α(w) is described below:

$$\alpha(w) = \begin{cases} \frac{1}{\sqrt{2}} & w = 0 \\ 1 & otherwise \end{cases} \quad (2)$$

Here, i and j are special domain coordinates, while u and v are frequency domain coordinates. DC (Direct Current) is the first coefficient, whereas subsequent coefficients are AC (Alternate Current) [20]. In this paper, the distinctive features of the logo image are acquired using DCT, and this process is done by dividing the image into blocks, and then we divide each block into four sub-bands using a Daubechies wavelet. Thus, DCT is computed for each sub-band, and it produces a DC and an AC.

3.3.3 Sum DC for all Sub-Bands from each Block and Normalized

DC and AC are coefficients produced by applying the DCT for each sub-band in the previous step. The DC, which is represented by the image information, is collected for all sub-bands from each block and then normalized to get the best characteristics of the matching stage as shown in equation (3), but the AC is ignored.

$$DC_{Norz}(i,j) = \sum_{i_s}^{i_e}\sum_{j_s}^{j_e}(DC(i,j))^{0.25} \quad (3)$$

Where (i_s, j_s) and (i_e, j_e) are the sub-band coordinates belonging to the block, DC (i, j) represents the DC for sub-bands.

3.3.4 Feature Vector

The sum of the DC resulting from the previous step represents the feature vector kept in the database for the matching process.

3.4 Matching Stage using Canberra Distance

In this stage, the similarity is computed between the feature vector taken from the tested logo image and the feature vectors saved in the database. The Canberra distance is used to measure similarity in this paper. The Canberra distance is commonly utilized to determine acceptable values and can be used to test the distance between two points and their relationships. The Canberra distance Canb between vectors x and y in a d-dimensional real vector space is given in equation (4) [21].

$$Canb(x,y) = \sum_{i=1}^{d}\frac{|x_i-y_i|}{|x_i|+|y_i|} \quad (4)$$

Where (x_i,y_i) represent the feature vectors of the tested image and the training image, respectively.

4. Results and Discussion

One dataset has been utilized to assess the efficiency of the suggested car logo recognition system, named Car_Logo_Dataset. The size of the dataset is 14.8 MB. It contains a total of 544 color logo samples, which are stored in the png image format. The car logo dataset contains 32 different classes of cars, each with 17 samples. The dataset is publicly available at [22]. Figure 8 demonstrates the samples of one class of cars selected from the dataset randomly.

The proposed system efficiency and accuracy are evaluated using three metrics: the correct recognition rate (CRR), accuracy, and precision, which are explained as follows:

- The correct recognition rate (CRR) is the percentage of correctly recognized samples among all samples examined according to equation (5) [23].

$$CRR = \frac{Number\ of\ Correct\ Identified\ Images}{Total\ Number\ of\ test\ Images} \times 100\% \tag{5}$$

• Accuracy is the proportion of correct predictions according to equation (6) [24].

$$Acc = (TP + TN)/(TP + TN + FP + FN) \tag{6}$$

• Precision refers to the proportion of positive predictions that are correct out of all positive predictions created according to equation (7) [25].

$$Preci = \frac{TP}{TP+FP} \tag{7}$$

The true positive, true negative, false positive, and false negative are illustrated by the symbols TP, TN, FP, and FN, respectively.

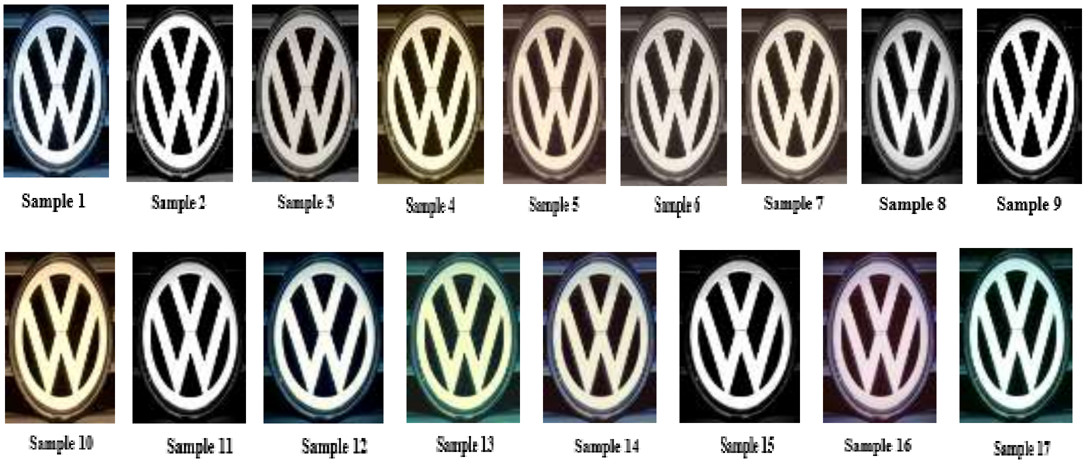


Figure 8: Samples for one class from the dataset

The dataset is split into two parts: testing and training, where each class contains 17 samples: 5 samples for testing and 12 samples for training. Thus, the recognition process is accomplished by passing the test image through all the stages of the proposed system until it reaches the feature extraction stage and obtains a feature vector to test the efficiency of the recognition system. In contrast, the training images go through all the stages of the proposed system, and the features are stored in the database. The matching process is done by comparing the feature vector of the test image with all feature vectors stored in the database using the Canberra distance and recognizing the correct class based on the minimum distance.

The experimental results show the effect of the block size parameter on the CRR, accuracy, and precision; when increasing the block size, the CRR, accuracy, and precision also increased, and vice versa. Figure 9 illustrates the highest CRR, accuracy, and precision achieved, which are 99.37%, 99.39%, and 99.80%, respectively, when the block size is equal to 7×7. Thus, the aim of dividing the image into equal blocks is to obtain discriminant features to facilitate the process of getting the highest recognition rate.

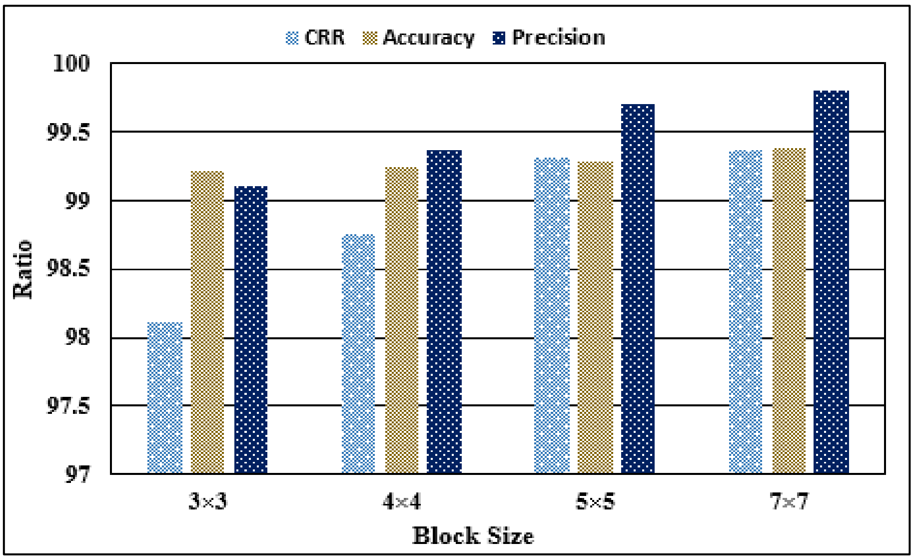


Figure 9: The results of CRR, accuracy, and precision for various block

Table 1 compares our proposed technique to several previously published experiments and demonstrates that it provides outstanding results compared to other studies. It also demonstrates that the suggested method has a higher correct recognition rate and greater accuracy and precision than previous studies.

Table 1: Compare our proposed with previous experiments

Reference	CRR%	Accuracy%	Precision%
[11]	97.00%	-	-
[12]	94.60%	-	-
[14]	-	99.07%	-
[14]	-	79%	79%
[15]	-	62.94%.	-
Our Proposed	**99.37%**	**99.39%**	**99.80%**

5. Conclusion

In this paper, an effective method was proposed for extracting and recognizing car logo images. The dataset used in the proposed system suffers from many problems, such as a complex background, differences in size and shape, the appearance of noise, and lighting circumstances. Thus, this paper solves these problems using k-medoids to extract logo images and remove background, and after that, using Daubechies wavelets with DCT transforms to extract discriminant features. These features are recognized using the Canberra distance to identify the correct class. The block size parameter plays an important role and controls the process of recognition; when the block size increases, the recognition rate also increases, as shown in Table 1. The test results display that the highest CRR, accuracy, and precision are 99.37%, 99.39%, and 99.80%, respectively, when the block size is equal to 7×7.

References

[1] S. Gaur, V.A.Shah, and M. Thakker, "Biometric Recognition Techniques: A Review," *International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering.*, vol. 1, no. 4, pp. 282–290, 2012.

[2] A. Alaei, and M. Delalandre, "A Complete Logo Detection/Recognition System for Document Images," *IEEE Xplore,* pp. 324-328, 2014, doi: 10.1109/DAS.2014.79.

[3] T. Burkhard, A. J. Minich, and C. Li, "Vehicle Logo Recognition and Classification:Feature Descriptors vs. Shape Descriptors," *EE368 FINAL PROJECT, SPRING*, pp. 1- 6, 2011.
[4] S. Bianco, M. Buzzelli, D. Mazzini, and R. Schettini, "Deep Learning for Logo Recognition," *Science Direct of Elsevier*, vol. 245, no. 5, pp. 23-30, 2017, doi: 10.1016/j.neucom.2017.03.051.
[5] R. Boia1, A. Bandrabur, and C. Florea, "Local Description Using Multi-Scale Complete RankTransform for Improved Logo Recognition," *IEEE Xplore*, vol. 28, no. 6, pp. 1–4, 2014, doi: 10.1109/ICComm.2014.6866723.
[6] A. Alsheikhy, Y. Said, and M. Barr, "Logo Recognition with the Use of Deep Convolutional Neural Networks," *Engineering, Technology & Applied Science Research*, vol. 10, no. 5, pp. 6191-6194, 2020, doi: 10.48084/etasr.3734.
[7] N. Farajzadeh, and N. S. Rezaei, "Vehicle Logo Recognition using Image Matching and Textural Features," *Scientific Cooperations International Workshops on Electrical and Computer Engineering Subfields*, pp. 82-86, 2014.
[8] K. P. J. Dikey, "Implementation of Logo Matching & Recognition System Based on Context Dependency for Image & Video," *International Journal of Innovative Research in Computer and Communication Engineering*, vol. 3, no. 4, pp. 3025-3031, 2015,
[9] B. Cyganek1, and M. Woźniak, "Vehicle Logo Recognition with an Ensemble of Classifiers," *Asian Conference on Intelligent Information and Database Systems*, vol. 8398, pp. 117–126, 2014, doi: 10.1007/978-3-319-05458-2_13.
[10] D. F. Llorca, R. Arroyo, and M. A. Sotelo, "Vehicle logo recognition in traffic images using HOG features and SVM," *International IEEE Annual Conference on Intelligent Transportation Systems (ITSC)*, pp. 2229-2234, 2013, doi: 10.1109/ITSC.2013.6728559.
[11] Y. Huang, R. Wu, Ye Sun, W. Wang, and X. Ding, "Vehicle Logo Recognition System Based on Convolutional Neural Networks With a Pretraining Strategy," *IEEE Transactions on Intelligent Transportation Systems*, vol. 16, no. 4, pp. 1951-1960, 2015, doi: 10.1109/TITS.2014.2387069.
[12] R. Chena, M. Hawesa, O. Isupovaa, L. Mihaylovaa and H. Zhub, "Online Vehicle Logo Recognition Using Cauchy Prior Logistic Regression," *International Conference on Information Fusion*, pp. 1-8, 2017, doi: 10.23919/ICIF.2017.8009720.
[13] F. C. Soon, H. Y. Khaw, J. H. Chuah, and J. Kanesan1, "Vehicle logo recognition using whitening transformation and deep learning," *Signal, Image and Video Processing*, pp. 111–119, 2018, doi: 10.1007/s11760-018-1335-4.
[14] S. Kumar, and Ms. Bhuvneshwari, "Car logo detection and classification by Deep Learning base Transfer Learning," *International Journal of Advanced Research, Ideas and Innovations in Technology*, vol. 7, no. 5, pp. 741–747, 2021, available on: https://www.ijariit.com/manuscripts/v7i5/V7I5-1392.pdf.
[15] X. Jiang, K. Sun, L. Ma, Z. Qu, and C. Ren, "Vehicle Logo Detection Method Based on Improved YOLOv4," *Electronics*, vol. 11, pp. 1–19, 2022, doi: https://doi.org/10.3390/electronics11203400.
[16] A. Bhat, "K-Medoids Clustering Using Partitioning Around Medoids for Performing Face Recognition," *International Journal of Soft Computing, Mathematics and Control (IJSCMC)*, vol. 3, no. 3, pp. 1–12, 2014, doi: 0.14810/ijscmc.2014.3301.
[17] J. Youse, "Image Binarization using Otsu Thresholding Algorithm," *International Journal of Soft Computing, Mathematics and Control (IJSCMC)*, pp. 1–4, 2011, doi: 10.13140/RG.2.1.4758.9284.
[18] S. M. Patil, P. S. B. Kasturiwala, S. O. Dahad, and C. D. Jadhav, "Daubechies Wavelet Tool: Application For Human Face Recognition," *International Journal of Engineering Science and Technology (IJEST)*, vol. 3, no. 3, pp. 2392– 2398, 2011.
[19] N. Agarwal, and A .M. Khan, "Application of DCT in image processing," *International Journal of Engineering Research & Technology (IJERT)*, vol. 2, no. 03, pp. 185– 189, 2014.
[20] S. K. Tyagi, and P. Khanna, "Face Recognition Using Discrete Cosine Transform and Nearest Neighbor Discriminant Analysis," *IACSIT International Journal of Engineering and Technology*, vol. 4, no. 3, pp. 311– 314, 2012, doi:10.7763/IJET.2012.V4.372.
[21] Y. Sari, M. Alkaff and, R. A. Pramunendar, "Iris Recognition Based On Distance Similarity and PCA," *AIP Conference Proceedings*, vol. 1977, no. 1, pp. 1– 7, 2018, doi: https://doi.org/10.1063/1.5042900.

[22] M. A. Rajab, 2022, "Car_Logo_Dataset," *Kaggle dataset,* Retrieved from https://www.kaggle.com/datasets/mahaarajab/car-logo-dataset

[23] R. A. Mustafa, H. S. Chyad, and R. A. Haleot, "Palm print recognition based on harmony search algorithm," *International Journal of Electrical and Computer Engineering (IJECE),* vol. 11, no. 5, pp. 4113-4124, 2021, doi: 0.11591/ijece.v11i5.

[24] M. A. Rajab, and L. E. George, "An Efficient Method for Stamps Verification Using Haar Wavelet Sub-bands with Histogram and Moment," *Babylon International Conference on Information Technology and Science (BICITS),* pp. 120 -126, 2021, doi: 10.1109/BICITS51482.2021.9509922.

[25] I. S. Masad, A. Alqudah, A. M. Alqudah, and S. Almashaqbeh, "A hybrid deep learning approach towards building an intelligent system for pneumonia detection in chest X-ray images," *International Journal of Electrical and Computer Engineering (IJECE),* vol. 11, no.6, pp. 5530-5540, 2021, doi: 10.11591/ijece.v11i6.