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Car logo detection and classification approaches: A review

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ABSTRACT

Vehicle identification systems rely on logo recognition to identify vehicles (VLRS). Convolutional Neural Networks are used to automatically learn characteristics for car logo recognition (CNNs). However, CNNs struggle with rotated or noisy pictures. CNN's Random Forest classification technique is used to create an image recognition system. Random forest decision tree ensemble and train. AI has overcome object recognition problems. Convolutional Neural Networks (CNNs) are a popular type utilized to address object recognition issues due to its complicated structure and hidden layers. Logo recognition is often solved using CNN-derived techniques. The creators of used pre-trained CNNs to recognize logos. These technologies are also computationally expensive. This limits the use of computationally expensive alternatives. A logo's recognition accuracy with little computing burden remains a mystery.

Keywords— *Logo classification, Logo recognition, Deep Learning*

1. INTRODUCTION

The number of apps is driving automated logo recognition. Logo identification is more challenging than object or logo recognition owing to the lack of original data. Businesses often use logos to identify themselves and their goods. Shapes, colours, text, and textures are often used [1]. Logo recognition is important for several applications, including online brand management, copyright infringement, context-specific advertising placement, and vehicle recognition [20,32]. Even while companies do not need to alter their logos often, the context in which they appear varies for each product of the same company. Changing backdrops, perspective distortions, warping, occlusions, colours, and sizes are some of the challenges with precise logo recognition [1]. The growing number of goods (brands) with customised logos further complicates logo recognition. Logo recognition requires significant processing power to enable multi-class classification [3].

The uses of vehicle logo recognition are many. The control unit system at military camps, government buildings, at crossroads and traffic signals, at checkpoints across the city and surrounding regions, and far beyond the nation's territory, are sensitive places. Humans can easily identify and distinguish logos in everyday settings. However, in densely populated cities with high vehicle and human densities, data breaches are common. To recognise and identify car logos, automated methods are needed.

This project's main aim is to utilise deep learning models to ensure logo recognition without needing a lot of computing resources [5]. These models can generalise large datasets of millions of pictures. The input picture is rectified, filtered, and compressed several times before being transformed to a vector.

To effectively handle multi-class categorization, considerable processing power is required to accommodate a growing number of businesses or brands with customised logos. Algorithms for online product marketing, contextual advertising placement, and brand recognition are all intended to be utilised in a variety of situations. Develop a real-time logo recognition system for a mobile app [5,7].

This thesis highlights the necessity for developing vehicle classification and identification systems capable of automatically recognising the vehicle's manufacturer based on pictures collected. Fully automated logo identification is essential for accurate brand evaluation.

As one of the most readily recognisable markings on cars, vehicle logos have lately acquired prominence as a study topic in intelligent transportation systems. The ability to recognise car emblems helps in vehicle identification [4,8,10,28,30]. For example, if the logo does not match the vehicle's licence plate, the plate is a fake. Plate replacement is significantly associated with activities before a crime. VLR can also direct autonomous vehicles and intelligent traffic systems [10]. Vehicle brand recognition is a popular study subject in intelligent traffic [1,4]. Vehicle logos are important identifiers that may assist an intelligent transportation system categorise various vehicles. Among other uses, vehicle logo recognition may be employed in highway toll systems or to target certain cars for public safety. Practically, it is becoming more important to quickly identify and recognise car emblems. The first stage is to guarantee recognition efficiency and accuracy.

Additional parameters must be added to number plate recognition algorithms to ensure reliable vehicle identification. One of the most important components of an AVR system is the vehicle logo [17]. A car logo may be used to authenticate, identify, and recognise a vehicle. Manufacturer identification is now easy using logo detection. Thus, automated logo recognition is essential for surveillance and ITS [8]. Because road surroundings are always changing, vehicle pictures often catch a wide range of backdrops and lighting situations. Logos will be distorted due to camera movement and shooting angles. The tiny logo space inside a recorded picture further complicates the job. A reliable logo recognition system should be able to distinguish logos from other minor visual trends that may emerge on cars. While logo-based car brand classification has gained attention in recent years, the limiting issue of logo recognition has remained unexplored.

Hand-crafted features like SIFT, HOG, and others are now being used with trainable classifiers like SVM, boosted classifier, and others [10,22]. Because weather, vehicle position, and stain, among other variables, readily affect car logo pictures, traditional shapes show their flaws. Except for traditional classification, CNN can automatically evaluate input data characteristics. Because of its strict hierarchy, CNN resists geometric distortions like scaling, inclination, and shifting. CNN recognises car logos based on such characters effectively. As a consequence, this thesis proposed using CNNs and deep learning to recognise car logos.

2. LOGO-DETECTION SYSTEM

The system for a logo-detection system [29] is divided into two sections: detection and recognition of logos. The proposed system's architectural design is illustrated in figure 1.

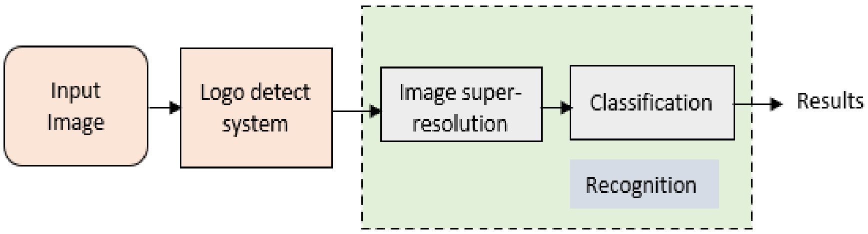


Figure.1: Logo Detection System

Both a multi-scale sliding window technique and mathematical morphological evaluation are used to identify car logos. It consists of four stages: picture improvement, which comprises morphological transformations, filtering, and post processing; and morphological activities, which results in the vehicle logo candidate area. An SVM classifier's judgement results would be utilised to decide whether the next sliding window module would be activated [11,13]. The sliding window module is triggered whenever a decision value goes below a threshold. Or the candidate area's decision value is combined with other candidate areas' decision values to form a new description. It is then input into another pre-trained binary SVM classifier to evaluate whether structure recognised the logo. Figure 2.2 shows the logo detection method.

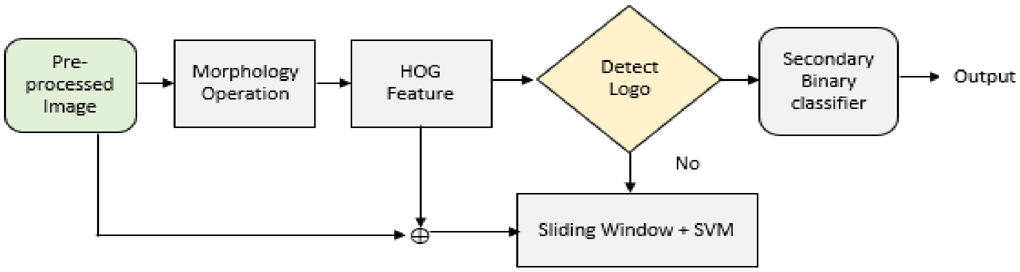
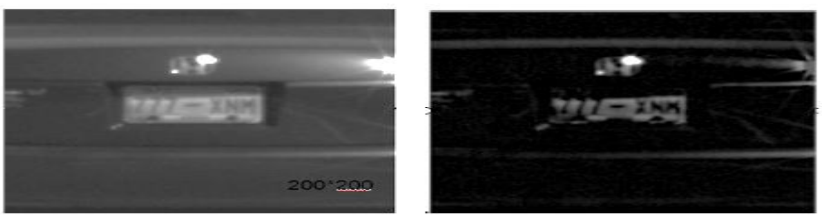


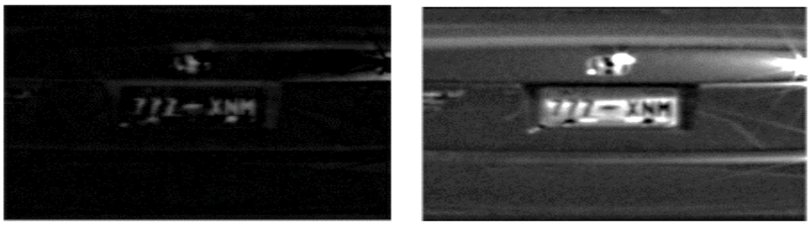
Figure 2: Flow of the proposed of the system for detecting logos

2.1 Image Enhancement

Throughout this step, designers modify the image's contrast and intensity. Histogram equalization is the technique used to adjust the intensity. Numerous techniques, such as top/bottom hat transformations, can be used to increase the contrast.



(a) Original **(b) Top Hat**



(c) Bottom Hat **(d) After enhancement**

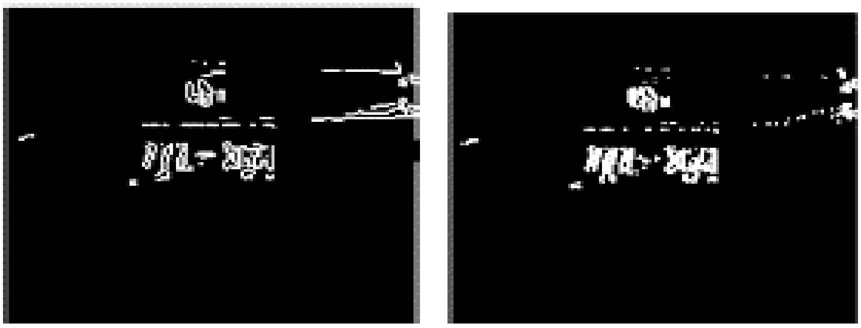
Figure : Image Enhancement [29]

2.1.1 Hat Transformation

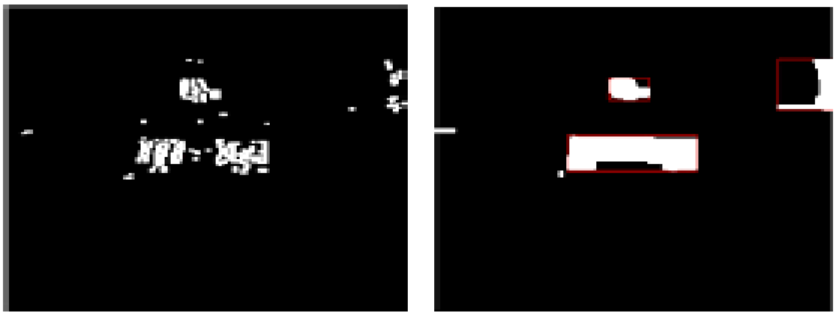
Contrast enhancement is accomplished through the use of hat transforms. There seem to be two transformations:The top hat procedure is indeed the result of subtracting an opened image from the original, while the bottom hat procedure is the consequence of subtracting the closed image from the initial image. The top hat procedure darkens the context and accentuates foreground objects. As a result, this procedure can emphasize the characters while obscuring the unimportant background. When the image obtained is converted to a binary image and then all the small connected regions are removed, just a few foreground areas remain and the majority of unimportant objects have indeed been relocated.

2.1.2 Morphological Operations

The term "mathematical morphological operations" refers to a wide range of image processing techniques that manipulate images based on their shapes. Li. Siyu et al. (2015) extracted logos using just the closed and open operations. By diminishing the object boundaries, erosion causes them to shrink. Closure is indeed the dilation which enables objects to broaden, accompanied by erosion, and the opening operation is just the reverse. Such processes can be altered by selecting the appropriate structuring element, which controls the number of objects that would be eroded or dilate. In figure 3 (a), the Sobel operator is represented by a rectangle-shaped structured element. Then, designers perform subtraction usually column-by-column over the Sobel image to eliminate any horizontal lines that could interfere with the detection of the vehicular logo region.



(a) Sobel operation **(b) Differential Picture**



(c) Closed image **(d) Opened image**

Figure 3: Morphological procedures [29]

Researchers have used the same rectangle structured feature for open and close operations in figure 2.4 (d). Such four measures result in a picture that contains key areas for vehicle licence plate and logo. To place the vehicle licence plate, developers introduce several checks and conditions depending on the characteristics of the vehicle licence plate to all the remaining objects mostly in picture, including the region and aspect ratio.

2.1.3 Multi-Scale Sliding Window

In most cases, the vehicle logo has been located directly above the vehicle's licence plate. Thus, that once vehicle licence plate is discovered in the images, researchers can crop the area immediately above the licence plate, that most predicting phenomena the vehicle logo. If the discovered licence plate has a height of H and width of W, therefore the approximate location of the logo region, namely innovative ROI, can indeed be determined using a height of 3H and a width of 3W. Figure 2.5 illustrates the innovative ROI segmentation. The HOG features are extracted from all candidate areas within the new ROI and fed into the SVM classifier. Designers define a threshold value to determine whether or not to activate the sliding window module. If the SVM decision value is greater than 0.95, the area is considered to be a vehicle logo, and the candidate area is passed directly to the final binary SVM classifier [20,29]. Otherwise, a sliding window will be used. When the sliding window module is turned on, it will slide vertically all along axis that divides the licence plate into two equal-sized areas.

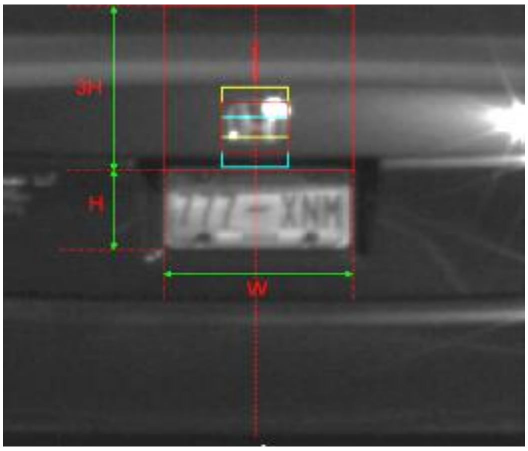


Figure 4: Flow diagram of the Logo Detection System [29]

Due to variable size of individual vehicle logos, the window would be scaled via a factor 's' between 0.8 and 1.2 with a 0.2 step. Designers determine the maximum SVM decision value for each scale stage by extracting HOG features from all of the windows and feeding them to SVM classifier. Finally, by trying to compare the maximum values acquired at each scale, researchers must choose window with the greatest yield as the detection output.

2.1.4 Binary SVM Classifier

To ascertain if the detected area encompasses the information needed for classification of vehicle logo, developers make a new descriptor and feed it into a binary SVM-based classifier. Fig. 3.6 illustrates the new feature. The black region represents the highest (or max) decision values calculated mostly by prior SVM classifier via a sliding window, and the adjacent region represents the decision value calculated by the prior SVM classifier. Eventually, researchers integrated them to generate a new descriptor depicted in figure 3.6.

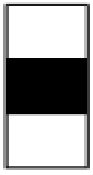


Figure 5: The new descriptor [29]

Sushmitha et al. [2] frame conversion, pre-processing, movement segmentation, feature-based extraction, and consistent object and tracking are all needed to perform vehicle tracking. The technique starts by turning a video into frames. Then the RGB picture is pre-processed using a grey scale image method to correct the colour. Finally, the foreground picture is determined by background subtraction. Using blob assessment. The picture is recognised in the clear object area, and any extra noise in the foreground is eliminated. Tracking is used to locate moving objects. Consecutive video frames are utilised to acquire more targets. The item is identified as a vehicle, and each frame's detection is shown.

- The paper's architecture considers the importance of multiple vehicle detection, tracking, and identification.
- The proposed alternative methods quickly detected and followed the target of video surveillance. A motion segmentation is a method of separating motion from a picture.

NI (National Instruments) myRIO was utilised to create information extraction and a vehicle target identification method by Hongliang Wang et al. An image recognition-based system is used to acquire and analyse vehicle data. In the LabVIEW application framework, vehicle target detection uses edge detection, VLR uses pattern matching, and vehicle licence plate identification uses OCR (Optical character recognition). This paper presents real testing and analysis of the suggested design idea. The approach is simple and accurate. The sensor can identify the target car based on its colour, logo, and licence plate. The paper's main points are:

- NI myRIO for vehicle detection and extraction.

An algorithm of OCR was used to recognise the target vehicle's licence plate in real-time, mainly using NI myRIO.

Logo recognition is defined by IstvánFehérvári et al. The pipeline consists of a few-shot logo recognizer and a universal logo detector. One of the most common uses of the unified logo detector is as a class-agnostic deep object detection network. A logo generator that creates bounding boxes. Then a logo recognition system trained on triplet loss using proxies to perform closest neighbour search categorises them. The researchers also created PL2K, a database of 2000 logos from 295K Amazon images. The pipeline achieves 97 percent recall with 0.6 mAP on the publicly available PL2K validation set and 0.565 mAP on the publicly accessible FlickrLogos-32 test set. The researchers also tested several CNN models on existing logo works to show that triplet-loss coupled with proxies works well for identifying comparable pictures.

The paper's main points are:

- A two-step procedure in which a semantic logo detector detects logos in rectangular regions of an image and a logo recognizer classifies/brands them.

Shuo Yang et al. [10] provide an accurate and efficient method for identifying vehicle logos (VLDs) in complicated situations. For tiny object detection, designers first modify the YOLOv3 framework for VLD and apply difficult sample training. Second, researchers created VLD-30, a new VLD database that allows everyone to develop a data-driven teaching approach and improve detection.

The findings demonstrate the efficiency of the suggested data-training approach and the modified YOLOv3's ability to identify car logos in complicated situations.

Among the paper's key findings:
- Detection of car logos in complicated situations
- Creation of a new VLD-30 dataset
- A CNN model extracts tiny object characteristics. A supervised pre-training method is utilised to improve model representation.

For real-world monitoring, JatuponBenjaparkairat and WatanachaturapornPakorn [13] provide a feasible approach. However, unlike many other published efforts, this one uses a sliding window technique to locate potential car logos. When the candidate regions are compared, the area with the most Sobel edges wins. This area's logo is recognised using the Nearest Neighbor classifier and SIFT-based characteristics. To test the technique, traffic video surveillance images were collected in various daylight situations. We present a method that uses 3,176 pictures from 9 manufacturers. Confusion matrices are utilised to evaluate the system approach, which has an overall accuracy of 85%.

The paper's main results are as follows:
- A ROI based on Sobel edge features was utilised using a windows approach, and a nearest neighbour classifier was used to recognise SIFT features.

To identify car logos using COLOR HISTOGRAM and EUCLIDEAN DISTANCE, Gopinathan and Lalitha [17] devised an algorithm using HOG, KNN and K-MEANS. The data is shaped using k-means and Euclidean distance. Also, test results were taken from standardised data sets.

Finally, MCCA and CCA are used to classify the logo. CCA indicates class-level accuracy, whereas MCCA denotes VLR scheme accuracy rate. This technique is ideal for classifying complex and similar vehicle brand graphics.
Among the paper's key findings:
- A colour histogram can show the distribution of colours in a logo picture.
- Color histogram and Euclidean distance apply to pixel distribution.
- A coloured histogram is less accurate than a Euclidean distribution.

Yun Ren et al. [18] investigate how to modify Faster R-CNN to identify tiny objects in optical remote sensing pictures. Starting with Faster R-RPN CNN's phase, the developers use a single fine-resolution slightly raised mapping feature through a comparable architecture that uses skip connections and top-down. The researchers also employed a simple sampling technique to address the problem of different picture counts for distinct classes. They also developed a simple yet effective data augmentation technique termed "random rotation" during training. Experiments show that the updated Faster R-CNN algorithm improves mean average accuracy for detecting narrow remotely sensed objects.

Among the paper's key findings:
- During training, a non-uniform class-based distribution is overcome by using a simple but effective method called random rotation.
- The experiments utilise a modified Faster R-CNN detector that uses the ResNet-50 model unless otherwise stated.

Jiannan Li et al. [21] create a single architecture that internally super-resolves tiny object representations, attaining comparable characteristics to big objects and therefore making detection more discriminative. The researchers propose a novel Perceptual GAN model that improves tiny item identification by reducing the representation difference between small and big objects. To confuse a competitive discriminator, its generator learns to super-resolve perceived bad small object representations to super-resolved big object portrayals. The discriminator competes with generator to identify the generated description and puts an additional perceptual restriction on generator: created interpretations of tiny objects should be suitable for detection.

Tests on the complex Caltech and Tsinghua-Tencent 100K benchmarks indicate Perceptual GAN excels in detecting tiny items like people and traffic signs.

Among the paper's key findings:
- Perceptual GAN generates super-resolved interpretations for tiny objects using the recurrently updated discriminator and generator networks.
- Train the proposed detection pipeline mainly using an end-to-end generator network based on the merger of the VOC 2012 and PASCAL VOC 2007 trainval sets.

Vaijinath and Vrushsen [22] write a software to extract logos from papers. This module may be useful for identifying essential documents such as TCs and other records, improving accuracy and saving time. The Automated logo identification module and its development may cover additional documents. This article uses the SURF and SIFT techniques to recover a logo from a picture. Task may be utilised in the following stage to reduce noise. Module and its execution help extract and match objects, resulting in document-based identification. The researchers got 96% accuracy.

Among the paper's key findings:
- This is done by comparing the logo feature with the current TC or document, and if it matches, it shows the information, whether unique or copied, or it displays the college's name.
- In addition, there are techniques for detecting edges and thresholding that use Gaussian filters.

Gonçalo Oliveira et al. [24] offer an unrestricted image method for automatically identifying graphic logos. With Ross Girshick's FRCN, the technique uses state-of-the-art performance in a broad variety of general-purpose object identification applications (such as challenges of PASCAL Visual Object Classes). Designers look at windows proposal selective search in the pre-processing phase, as well as data augmentation to enhance logo recognition rates. Use of strong CNN models trained on large datasets for visual logo recognition is novel. This framework also allows for multiple graphic logo detections using regions that are likely to contain an item.

Experiments using the FlickrLogos-32 database show that the created models surpass state-of-the-art structures with hand-crafted features and models in terms of noise as well as other changes that a graphic logo may be exposed to. Among the paper's key findings:
- Section II highlights deep CNNs' achievements in automated logo recognition.
- Section III focuses on transfer learning, which allows for less costly frameworks and parameter fine tuning.
- Section IV describes the FRCN object detection architectural style.

To make region proposals virtually free, Shaoqing Ren et al. [25] construct a Region Proposal Network (RPN) that shares full-image convolutional characteristics with detection network. An RPN is a fully connected neural network that predicts scores and object boundaries simultaneously. The RPN creates higher region-based suggestions that Fast R-CNN utilises for detection. The RPN element tells the unified network where to look, utilising popular contemporary neural networks terminology with 'attention' processes.

Among the paper's key findings:
- The detection technique for a highly deep VGG-16 model [3] delivers state-of-the-art item identification accuracy using just 300 efforts per picture at 5 fps (including every step) on a GPU.
- These two algorithms form the backbone of numerous winning records in the 2015 COCO and ILSVRC contests. The source code is available.

Ouyang Yi [27] proposed creating an online frame for categorising car emblems on a natural chaotic backdrop. The aim is to identify a car logo better utilising two phases of logo detection. Pixel-patches Sparse Coding (PSC) is used to enhance sparse-based representation translational invariance and noise suppression. It specifies the look and positions of each component locally. The classification of vehicle logos is followed by the localisation of licence plates using linearized 3-channel pixels regression. On looks for highly structured regions, such as log areas and licence plates, after assessing the architectural sparse coding. the multi-class web-based structural SVM classifier uses the identified areas.

Among the paper's key findings:
- SVM and HOG based on pixel patches. The logo recognition accuracy measures the logo's efficiency.

Christian Eggert et al. [28] examine the benefits of synthetically produced data in the absence of a large training set for deep-learned business logo recognition. The researchers use pre-trained dCNNs to extract features and SVMs to classify them. The researchers generate fake training samples to produce enough training data. The investigators

3. CONCLUSION

Massive data sets pose challenges for autonomous VLR systems. As a result of the present consumer demand, this article employs a CNN hybrid picture composition. The main benefits of researching CNNRF include reduced blurring and noise. The fact that CNNs have problems in this area, as well as the findings of this research. The goal of this thesis is to create a system that can recognise highway entrance vehicle logos using convolutional neural networks.

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