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The study of deep learning for automotive logo recognition and classification

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ABSTRACT

Most vehicle manufacturer recognition (VMR) techniques are established in vehicle logo recognition because a vehicle's logo is the most obvious sign from the vehicle's manufacturer. However, due to the difficulty in accurately segmenting a vehicle logo on the picture with demand in resilience against many imaging scenarios, logo recognition can still be challenging. After subjective overview about this scope, a convolutional neural network (CNN) method for VMR is investigated in this research, which does away with the need for exact logo detection and segmentation. A powerful pertaining approach has also been developed to improve real-world applications to lower the high computational cost for kernel training on CNN-based systems. The contribution of this paper is to study the multiclass logo employing random forest ensemble learning and convolution mapping in nonlinear space. To boost accuracy by roughly 35%, 800 images from 15 types of car classes were investigated in the paper.

Keywords: CNNs, deep learning, pretraining, VMR.

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1. Introduction

In contrast to the conventional feature extraction approach based on prior knowledge, depth learning theory has advanced quickly in recent years. Depth neural networks are more adaptable and general because they can build feature descriptions in response to training data. (CNN), the subset for deep learning models is effective recognition techniques that have been created recently. While local area sensing, the weight sharing, with the subsampling, convolutional neural networks [1].

CNN training is a supervised learning technique that involves both a forward and a backward propagation stage. Training samples are sent for a network during the forward propagation stage to determine the network's actual output. Recognizing vehicle logos can aid in identifying a vehicle because they are among the most distinctive marks on cars. Vehicle logo recognition (VLR), used to monitor traffic and manage vehicles, has recently gained popularity as a study issue in ITSs. [2,3].

The foundations of models that can effectively handle computer vision issues are deep learning and CNNs. For example, the mass detection model used by Computer-Aided Diagnosis (CAD) systems is based on RetinaNet. RetinaNet is a type of deep CNN in which a one-stage object detector is quick and efficient [4,5].

The cascaded deep convolutional network presented in this study can recognize car logos without needing license plates. A region-presented network with a convolutional capsule network makes up this two-stage processing approach. The region proposal network first creates prospective region proposals that could include the structure of layer-skipping CNNe car logos. A convolutional capsule network divides these region proposals for a background with several vehicle logotypes. [6]

The vehicle makes, and model recognition (VMMR) from frontal photographs of automobiles is presented as a novel recognition scheme in this research. When car models from the same or different brands are examined, the structural elements found in the frontal look of the vehicles exhibit various visual qualities and their ability to discriminate changes. In light of the specifics, we use the different levels of discriminative power for the structural peripheral to carry out a recognition task on the two stages sequentially. [7]

The challenge is solved in this work using the (Mask R-CNN). In two separate experiments, several datasets and detection algorithms have been combined. First, we used vehicle logos as one characteristic which defines the manufacturer to distinguish vehicles with similar forms from different manufacturers. The dataset training with 60 epochs, 400 step iterations, an accuracy of 0.91, with mAP (Mean Using Filter-DeblurGAN and VL-YOLO [8].

Both a judgment and a deblurring technique are features of Filter-DeblurGAN. Consequently, dependent on the blur result, which could determine with accuracy if an image needs to the deblurred. Additionally, it can deblur photographs of various Under order to identify erroneous and absent vehicle markings in challenging lighting settings.[9]

this paper suggests the method of car logo identification with recognition. Adaptive image enhancement is utilized to increase detection accuracy in the automobile signs in photographs taken in complicated lighting settings by more than 2%; the target detection method is improved in this research to increase the detection accuracy of vehicle logos in diverse images by more than 3% [10].

Figure 1 depicts a standard network architecture for the (CNN), which typically contains an input layer, numerous convolution layers, the pooling layer, a complete connection layer, and a classifier. The convolution layer is responsible for preserving the various local features, and the extracted features are stable in both the translational and rotational dimensions. A pooling layer takes samples of the features acquired from a convolution layer. This makes the retrieved features more resistant to a slight change in shape while simultaneously simplifying an output for the convolution layer. In most cases, different kinds of pools are used, such as average value pools, full value pools, random pools, etc. An output layer analysis used feature vectors we have previously learnt, with the study choosing the analysis based on many challenges. SoftMax, Support Vector Machine (SVM), and other methods are frequently employed. [1]

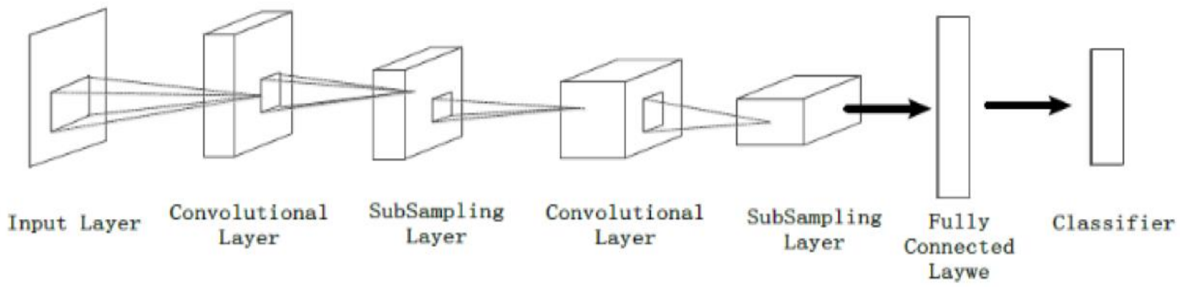

Figure 1. Convolution neural network CNN structure

A machine learning method called Convolutional Neural Network (CNN) is modelled after the human brain. With several modern CNN features, including feature maps, sub-sampling, and shared weights, the suggested technique successfully detected handwritten digits. The renowned LeNet-5, which also performs digit recognition [11]

The thermal convolutional neural network represents the input image using local data from a lower layer with global data from a top layer, resulting in more expressive features. Figure 2 depicts the structure. The link at the pooling layer S2 in Fig. 2 differs from Fig. 1. The pooling layer S3 is passed through before the eigenvector is created after a portion of S2 has been turned into a feature vector and supplied for the subsequent level for the convolution layer. A feature representation of the image comprises the feature vectors of two components [1].

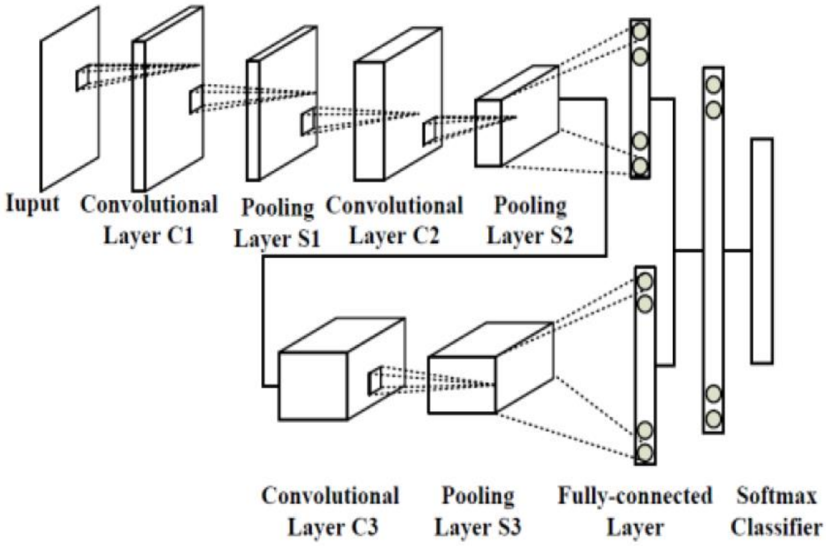

Figure 2. The layer-skipping CNN structure

2. Related work

Information extraction and a method for identifying vehicle targets were both developed by Hongliang Wang and his colleagues using NI (National Instruments) myRIO as their primary tool. Acquiring and analyzing vehicle data is done with a system based on image recognition. In the LabVIEW application framework, ve26+. vehicle target detection uses edge detection, vehicle license plate recognition uses pattern matching and optical character recognition is utilized to identify vehicle license plates. In this work, we show and analyze the testing results of the proposed design proposal. The strategy is straightforward and effective. The sensor can recognize the car in question using information such as its colour, logo, and license plate.The term "logo recognition" was coined by István Fehérvári and his colleagues. A few-shot logo recognizer and a universal logo detector are the two components that make up the pipeline. A class-neutral deep object detection network is one of the most common applications for the unified logo detector. A box-creating logo generator that can also generate text. After that, they are categorized using a logo recognition system trained on triplet loss and use proxies to conduct closest neighbour searches. The researchers also developed a database known as PL2K, which contains 2000 logos created from 295K photos of Amazon. The pipeline has a recall rate of 97% when tested on the publicly accessible PL2K validation set and 0.565 mAP when tested on the FlickrLogos-32 test set. Both of these sets are available to the public. The researchers also put multiple CNN models through their paces on pre-existing logos to demonstrate that triplet-loss combined with proxies effectively determine which images are similar.The primary arguments of the paper are A process consisting of two steps, the first of which is the detection of logos in rectangular portions of a picture by a semantic logo detector, followed by the classification and branding of those logos by a logo recognizer. In their paper [12], Shuo Yang et al. present an accurate and effective approach to identifying vehicle logos (VLDs) in challenging circumstances. Modifying the YOLOv3 framework for VLD and employing challenging sample training are the first steps in detecting microscopic objects. Second, researchers developed a new VLD database called VLD-30. This database makes it possible for everyone to construct a teaching strategy that is driven by data and to improve detection. The findings indicate the effectiveness of the data-training strategy that was suggested and the ability of the modified YOLOv3 to detect car logos in complex scenarios.Among the most important takeaways from the study are: Identifying automobile logos in difficult environments and conditions and Creating a new dataset for the VLD-30 A CNN model extracts microscopic object properties. An improved model representation is achieved by applying a supervised pre-training approach. The strategy provided by Jatupon Benjaparkairat and Watanachaturaporn Pakorn [13] is practical for monitoring the actual world. On the other hand, in contrast to many other published efforts, this one uses a sliding window technique to locate possible automobile brand emblems. The winner of the comparison of the candidate regions is the location that has the most Sobel edges. This region's logo can be detected thanks to a classifier called Nearest Neighbor and SIFT-based attributes. Photos from traffic video surveillance were gathered throughout various daylight scenarios to validate the method. This article offers a strategy using 3,176 photos sourced from 9 manufacturers. Evaluation of the system technique, which has an accuracy rate of 85% overall, is performed with the help of confusion matrices. The paper's most important findings are: To recognize SIFT features, a nearest neighbour classifier was employed in conjunction with an ROI constructed using Sobel edge features and a Windows-based methodology.Using COLOR HISTOGRAM and EUCLIDEAN DISTANCE to determine the identity of automobile brand emblems, An algorithm that utilizes HOG, KNN, and K-MEANS was developed by Gopinathan and Lalitha [14]. The k-means clustering algorithm and the Euclidean distance were used to shape the data. Additionally, the results of the tests were taken from their respective standardized data sets.MCCA and CCA are the last two steps in the classification process for the logo. While CCA refers to the accuracy at the class level, MCCA refers to the accuracy rate of the VLR scheme. This method is perfect for categorizing intricate and similar designs used on automobile brands. Among the most important takeaways from the study are: A colour histogram can be used to show how the colours in a logo are distributed over the image. Pixel distribution is affected by both the colour histogram and the Euclidean distance. A Euclidean distribution will give you more accurate results than a coloured histogram. Yun Ren and colleagues [15] study the best way to improve Faster R-CNN to recognize minute objects in photographs taken with optical remote sensing. Beginning with the Faster R-RPN CNN phase, the developers use a comparable architecture that skips connections and top-down to implement a single mapping feature with a fine resolution and a little raised height. In addition, the researchers utilized a straightforward sampling strategy to solve the issue of varying photo counts for the various categories. During the training process, they also devised a straightforward data enhancement method called "random rotation." Experiments reveal that the improved mean average accuracy for recognizing narrow remotely sensed objects can be attributed to the upgraded Faster R-CNN algorithm. Among the most important discoveries in the paper are: Random rotation is a simple and effective technique that can be used to prevent a non-uniform class-based distribution during training. Unless otherwise stated, the studies use a modified Faster R-CNN detector based on the ResNet-50 model. A single architecture that internally super-resolves representations of tiny objects is created by Jiannan Li and colleagues [16]. These representations reach features similar to those of huge objects, increasing detection's discriminative power. The researchers have put forth a brand-new Perceptual GAN model. This paradigm reduces the representational gap between small and large things, improving the recognition of basic items. To confuse a competitive discriminator, the generator develops the ability to super-resolve perceived negative little object portrayals into gigantic object portrayals. The discriminator puts the generator under extra perceptual constraints by demanding that created interpretations of microscopic objects be recognizable. The discriminator competes with the generator to identify the generated description. The Perceptual GAN performs remarkably well in the highly challenging Caltech and Tsinghua-Tencent 100K benchmarks, detecting minute items like people and traffic signs.One of the study's most significant findings is that the Perceptual GAN uses continuously updated discriminator and generator networks to produce super-resolved interpretations for microscopic objects.

3. Methods

The first step is acquiring the data and processing the necessary preliminary. The data for this dataset came from the website located at https://www.kaggle.com/binhminhs10/image-car logo. A total of 40 classes are included in this dataset, along with 12000 images. In this piece of writing, pick 15 categories, and each one contains 6,000 photographs. After the pictures were chosen, they underwent some preliminary processing and were enhanced.

CNN is applied in this process stage to design the transfer learning architecture shown in Figure 2. ImageNet was used as a resource in developing the CNN model currently referred to as ResNet50's parameters. The use of this method allows for the extraction of low-level properties from the ROIs that are produced by mammography pictures. These ROIs can be found by clicking here. Transfer learning required the development of a CNN model, which was accomplished by ntegrating four ResNet convolutional layers (Conv) with an activation function for ReLU mapping and a fundamental fully connected layer (FC). This led to the creation of the CNN model. The example in Table 2 perfectly illustrates this notion. Transfer learning allowed the previously trained CNN model to produce superior results and feature vectors for mass categorization. It was made possible because the model gave prior training. Therefore, only low-level characteristics are generated by the CNN model that has already undergone pre-training.

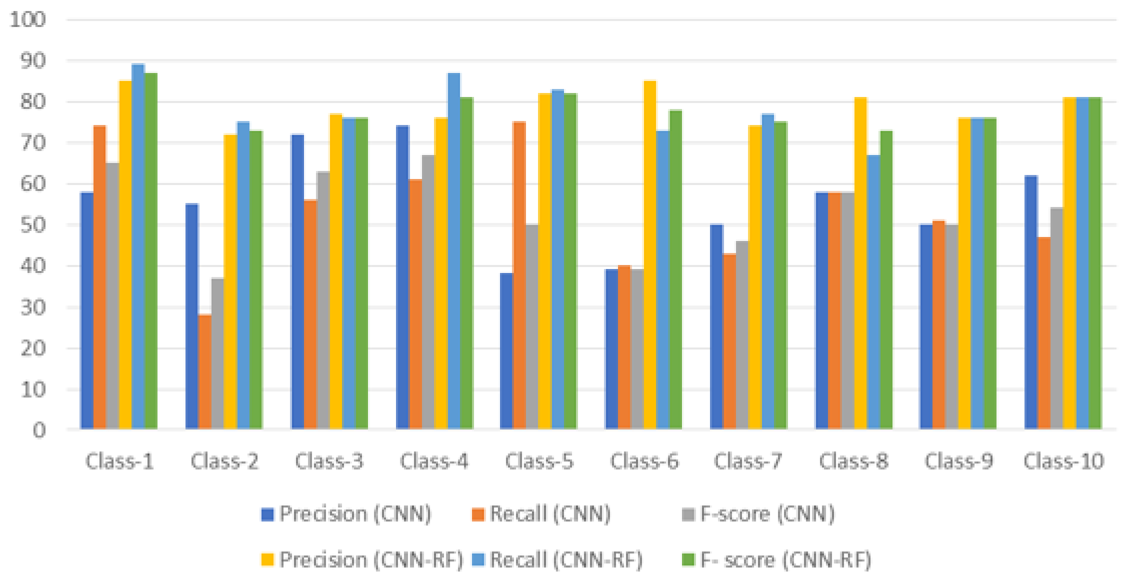

Figure 3. Statistics for each class

Table 3. Resnet architecture

	Input :image	
	Conv 1 (4x48x64)	Conv +ReLU
		Path 7x7
	Pooling (2x24x64)	Max pool 3x3
	Conv 2	Conv +ReLU 1x1
		Conv +ReLU 3x3
	(2x24x64)	Conv +ReLU 1x1
RESnet	Conv 3	Conv +ReLU 1x1
		Conv +ReLU 3x3
	(2x24x64)	Conv +ReLU 1x1
	Conv 4	Conv +ReLU 1x1
		Conv +ReLU 3x3
	(2x24x64)	Conv +ReLU 1x1
	Conv 5	Conv +ReLU 1x1
		Conv +ReLU 3x3
	(2x24x64)	Conv +ReLU 1x1
	FC + ReLU (Dropout=0.5)	
	Output (sigmoid):[0,1]	

CNN is a type of feed-forward neural network and deep structure and convolutional computation. That is for a deep learning method that best exemplifies the field. LeCun proposed LeNet as a method for reading handwritten digits. The input, hidden, and output layers comprise the most fundamental CNN architectures, which have been set in stone [17].

We created a dataset called VL that includes six different categories of vehicle logos, including those from Mercedes-Benz, Volkswagen, and Honda. With Toyota, every class has 400 photos. These pictures are all taken from security footage captured by cameras on a highway's entrance. To capture images frame by frame from these films

Figure 4. Samples of the dataset VL

The flowchart for the presented system as shown in Figure 5.

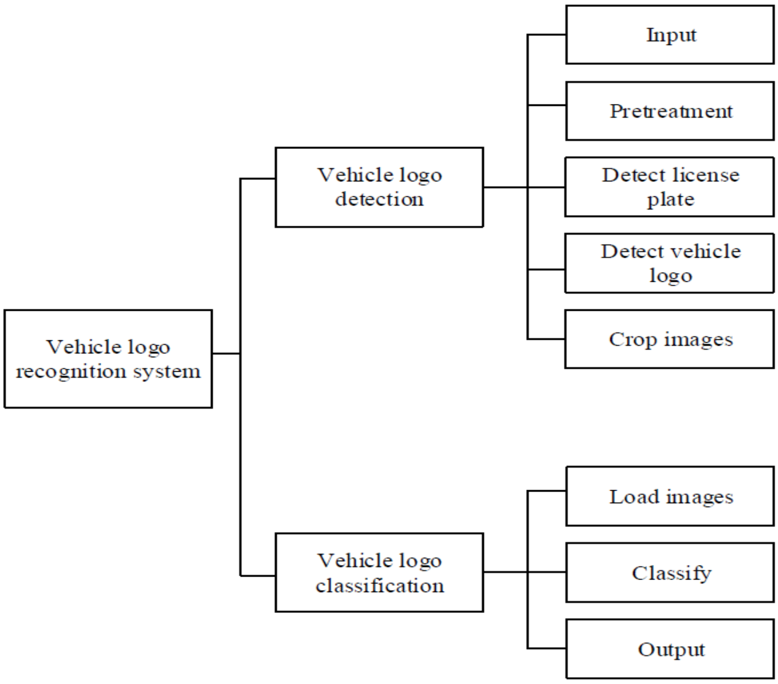

Figure 5. The system for recognizing car logos is structured.

Vehicle logo detection with classification is the first two phases of vehicle logo recognition. The information preparation for vehicle logo classification is done by vehicle logo detection.

And the following are the key responsibilities of the vehicle.

- seeing video captured by the camera.
- Pre-process video pictures before using them.
- locating the license plate's mounting place.
- locating the vehicle logo's location area.
- cropping a vehicle logo's position area by designating it as an area of interest.

The following is a crucial duty for a vehicle logo categorization module:

- A region of interest is loaded from the vehicle logo detection module.
- Differentiating a vehicle's logo.

The target and location technologies can be combined to form vehicle detection technology. Its primary objective is to locate and identify any automobile logos in the supplied image. Currently, a variety of techniques have been proposed by researchers to identify the location of a vehicle's logo. These techniques include using the edge features with the edge detection operators to improve positioning accuracy using wavelet transformation to determine a vehicle's logo and accurately classifying [18,19].

In this study, we enhance the previously described vehicle logo detection algorithm, which incorporates a vehicle symmetry feature and relies on learning from relative positions in the license plate with the vehicle. Since the car's logo is primarily situated in the middle of the vehicle, precisely over the license plate. As a result,

we start by locating the license plate. The length of the search box is then adjusted to the distance of the license plate.
For pre-processing and before training our dataset VL, we resize these photos to comply with an input layer's specifications since different CNNs have distinct input image sizing needs. Additionally, we add labels for each image before randomly dividing it from training sets with test sets. The training sets to test sets ratio are 2:1.

For data augmentation, 15 classes comprise the dataset VL, but more samples should be in each category.
We add random changes to our dataset to make our training samples feasible. For instance, randomly rotating images, translating images vertically or horizontally, or randomly zooming inside photos. Our dataset is big enough with the aid of these random algorithms. Every type of vehicle on the dataset now includes 800 images thanks to data augmentation. In turn, this prevents overfitting during CNN training, improving the final model's generalizability.
For training process, the car logo classification network is built using a VGGNet based on the study of numerous models. Visual Geometry Group with Google DeepMind have researched the deep convolutional neural network VGGNet. VGGNet examined convolutional neural networks' depth performance. To build 1619 layers deep CNN, VGGNet repeatedly stacked 3*3 tiny convolution kernels with 2*2 top pooling layers. VGGNet is now frequently used to extract image features. VGGNet's structure is straightforward, and it is very scalable. It uses 3*3 convolution kernels with 2*2 pooled cores to continually deepen a network topology and boost performance. In addition, VGGNet creates a convolution layer in series using a number of tiny convolution kernels. VGGNet has a higher ability to extract features compared to AlexNet 7*7 convolution kernel since it has a more minor.

3. Results and discussion

The data in this study originate from the Chinese Traffic Sign Detection Benchmark (CCTSDB) established by Changsha University of Science and Technology.

Figure 5. Example of cars

A comparative test is carried out on a selection of photographs, including vehicle logos, taken under various lighting situations. This test aims to determine whether or not the adaptive image enhancement method suggested in this study is compelling.
As seen in Figure 3, we chose three photographs that best demonstrate the results of the image improvement process. These images were taken in standard, low, and high-lighting situations. A comparison demonstrates which used images to original CTSD data are not uniformly lighted. Still, instead, they are locally indistinct, so it isn't easy to notice and distinguish them. This can be seen in the demonstration provided in Figure 6a. After an adaptive picture improvement, the RGB histogram becomes more uniform as a whole, logos become more obvious, the contrast and brightness of the photos are substantially improved, the images' details are amazing, and the original image quality is retained. This is all illustrated in Figure 6b. This not only makes it simpler to recognize and locate logos, but it also ensures that the requirements for identifying insignia on automobiles that were established in this research are satisfied.
The adaptive enhancement algorithm that was suggested in this study is capable of effectively enhancing the image quality under complex lighting conditions while also providing good samples for subsequent detection. This is conducive to the improvement in detection performance, as shown by the contrast analysis of images with those as well as mentioned above three distinct lighting conditions. In addition, the algorithm is capable of effectively enhancing the image quality under complex lighting conditions.
We choose three photographs that best demonstrate the results of the image enhancement process:

- Images were taken in normal lighting
- Images were taken in dim lighting
- Images were taken in bright lighting

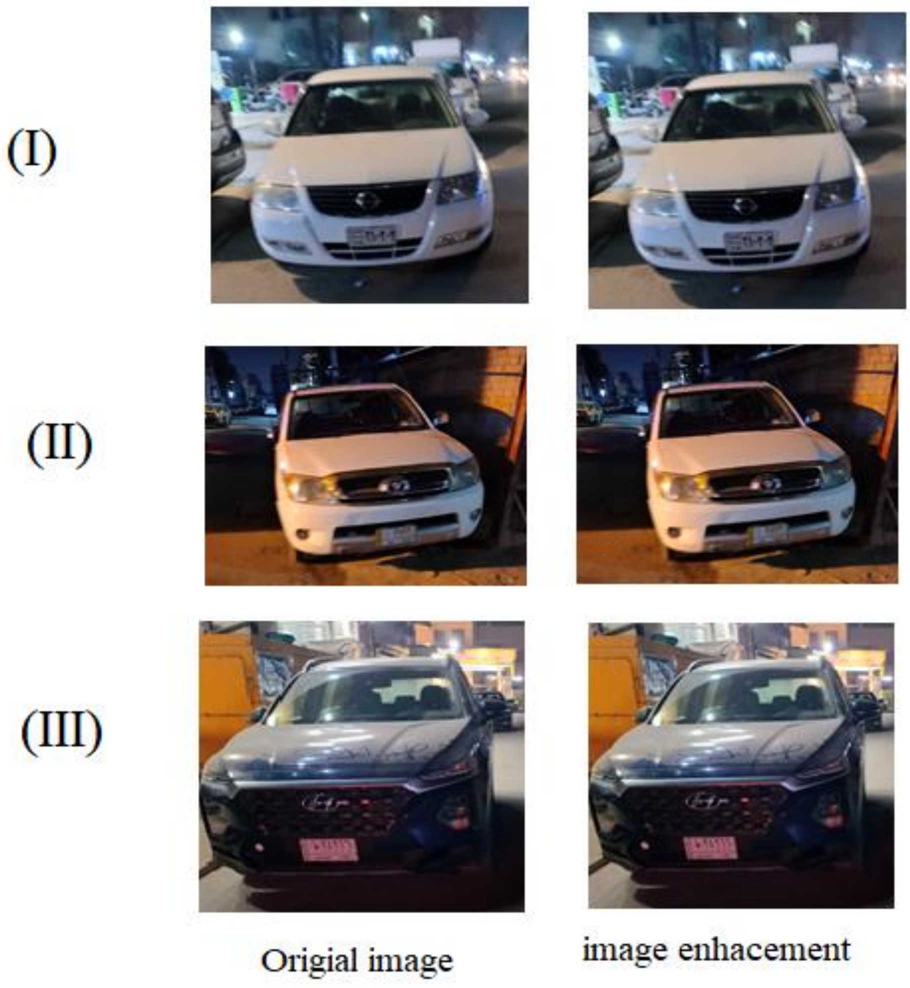

Figure 6 (a). Image enhancement in common situations

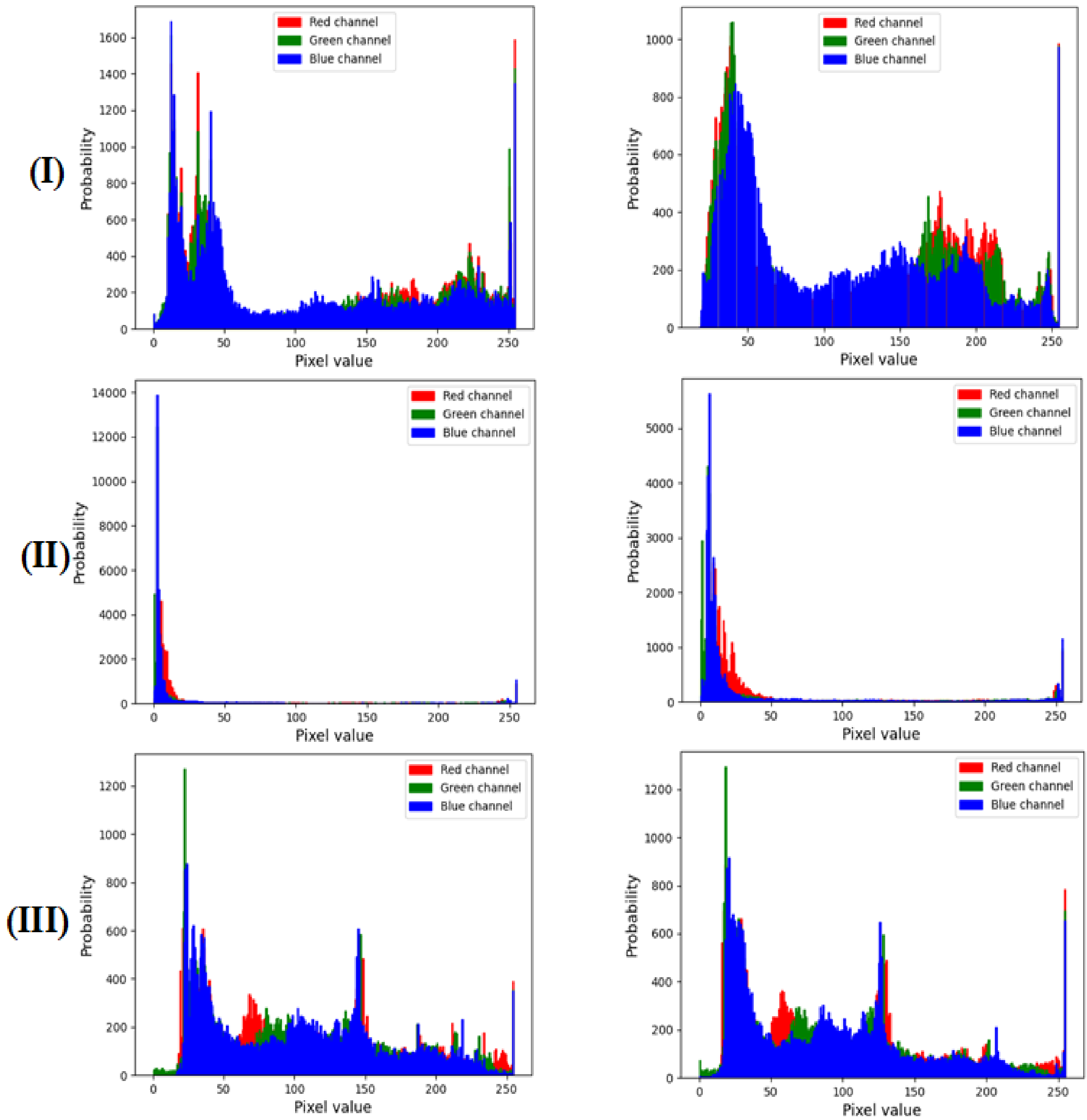

Figure 6 (b). Image enhancement in common situations

Figure 6 shows how image enhancement works in common situations. Figure 6 (a) displays a comparison between the original image and the one after enhancement in normal lighting conditions, dark lighting conditions, with strong lighting conditions, respectively; Figure 6 (b) displays a comparison between the original image and the one after RGB histogram enhancement in normal lighting conditions, dark lighting conditions, with strong lighting conditions, respectively. Pictures are taken in typical lighting situations; in dim lighting conditions; and in bright lighting conditions.

In this study, a comparison is made between the upgraded CNN model and the original CNN to illustrate the performance of the enhanced CNN model in car logo detection. In the trials, a training dataset comprises 70% of the picture data, a testing dataset comprises 10% of the image data, and a testing dataset comprises 20%. An average accuracy (AP) with a loss are two measures taken from the validation dataset and obtained throughout the training phase. When compared to the first version of the CNN model, the accuracy of classification achieved by the improved CNN model is greater than 10% higher, as can be seen in Figure 7. Loss function from the improved CNN model is displayed in Figure 8 to be both lower with more stable than a loss function of an original CNN model.

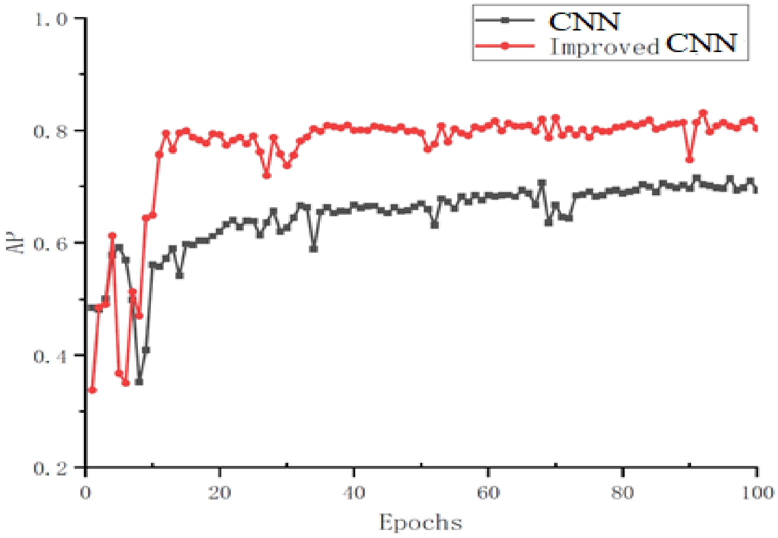

Figure 7. AP of the detection network

We compare the improved CNN model's detection results with those of the baseline CNN as well as those of the Faster R-CNN in order to validate the accuracy of the improved CNN model to the vehicle logo image recognition under complex lighting conditions. As can be shown in Table 1, CNN performs better than the Faster R-CNN model when it comes to detecting multi-scale car brand images. The accuracy of the revised CNN algorithm is enhanced by roughly 3 percent compared to the accuracy of the original CNN algorithm, which effectively improves the accuracy of logo recognition. In addition to this, the model can produce a roughly 5% improvement in the detection rate.

In general, the enhanced CNN model that was presented in this work may boost detection efficiency with accuracy for car logo identification when compared to an original CNN model. This is accomplished by improving the loss function model. First, the road photos obtained under complicated lighting conditions are processed using image enhancement techniques. Next, images are identified using an upgraded CNN network. Finally, the results of the moving vehicle logo are obtained. This procedure is illustrated in Figure 9. The findings of the experiments indicate that the method that we have proposed is able to successfully achieve recognition of car markers despite the challenging lighting circumstances.

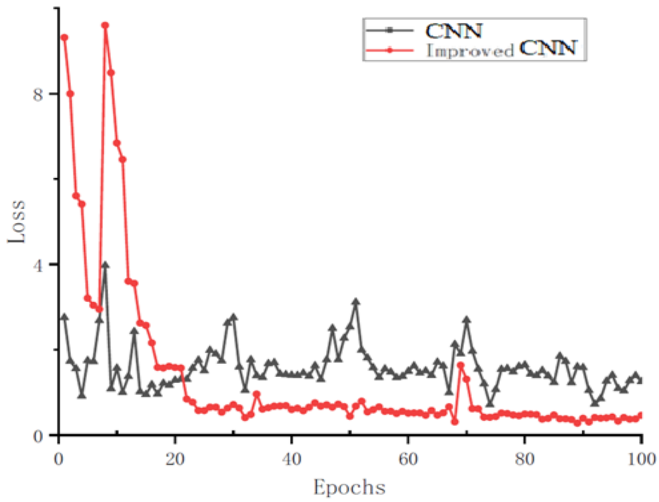

Figure 8. Loss of the detection networks.

Table 2. A comparison of the detection results obtained with the upgraded CNN vs the original CNN.

Data	**Algorithm**	**Number of Pictures**	**FPS**	**AP (%)**
Original data	Fast R-CNN	3067	37.6	81.4
	Original CNN		41.7	88.73
	Improved CNN		44.8	90.54
Corrected data	Fast R-CNN	3067	38.9	82.5
	Original CNN		39.5	92.5
	Improved CNN		44.7	94.57

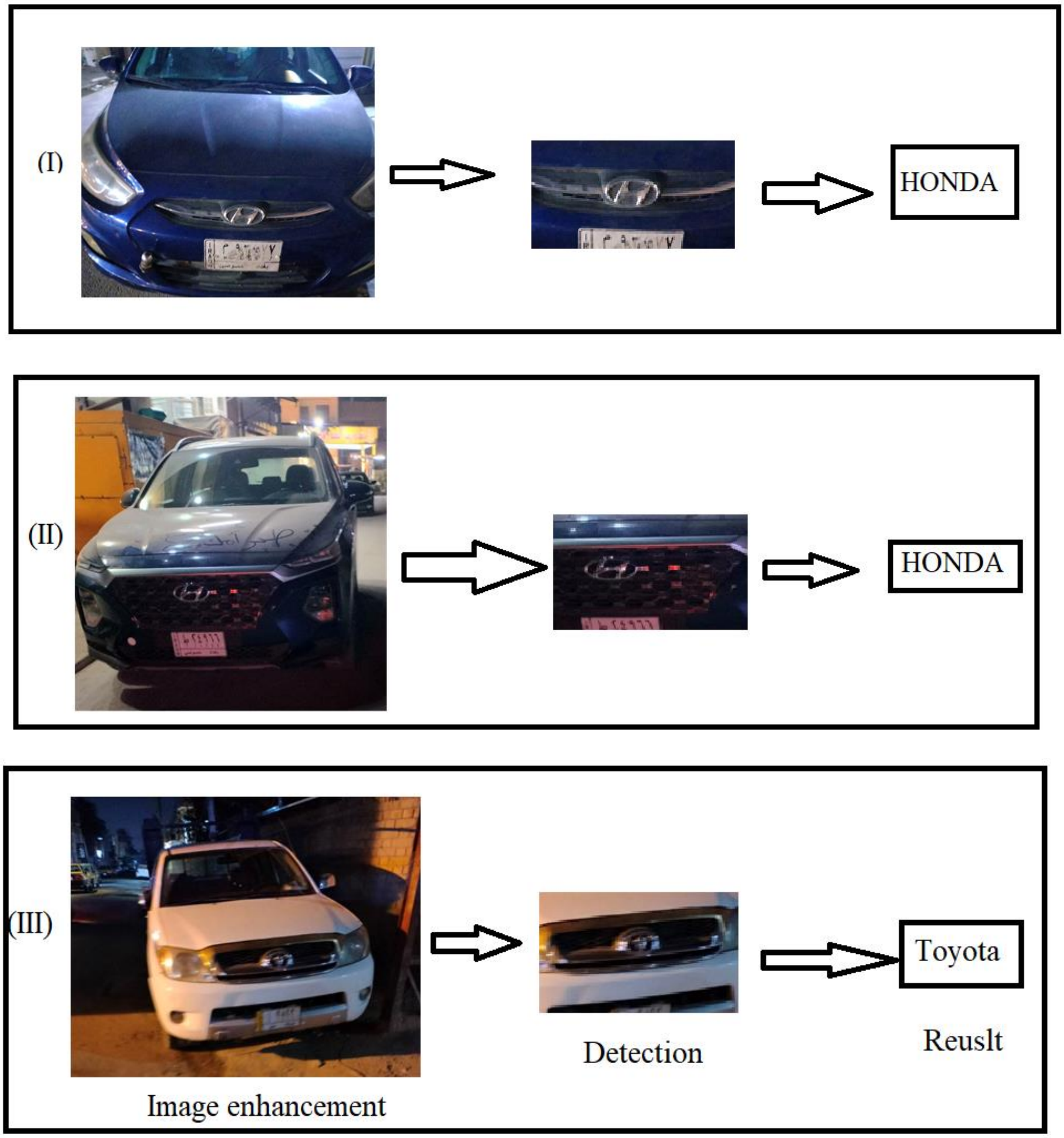

Figure 9. The consequences of logo detection on moving automobiles.

Based on Figure 9, (I) refers to photographs captured under typical lighting conditions; (II) to images captured in low-light settings; and (III) to images captured in bright-lighting settings.
The recognition system can be enhanced by modern antennas and filters. It can be associated with IoT and e-government feasibilities as future trends [20-28].

4. Conclusions

The CNN framework and image enhancement technologies are the foundations of the method for logo identification and recognition proposed in this study. This study gives the case for the necessity of such an approach due to the realization that frequently utilized structures for the detection of objects that are unable to tackle the problem of vehicle logo identification and recognition under complex lighting conditions. The justification for the necessity of such an approach is presented in this research. The results of the experiments that compared the suggested method to the initial CNN algorithm demonstrate that the adaptive image enhancement algorithm indicated in this study can make adequate alterations to picture samples in complicated lighting conditions while simultaneously lowering the rate of missed detection by later detection algorithms. This was demonstrated by the fact that the algorithm could do both things simultaneously. As a result, improving the trained detection model's accuracy and the speed at which it can detect anomalies by increasing the amount of error loss is possible.

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