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Car logo detection and classification by Deep Learning base Transfer Learning

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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. This work's primary contribution is a multiclass logo using convolution mapping in nonlinear space and random forest ensemble learning. In the experiment, 400 pictures with 10 classes were analysed to increase accuracy by about 20%.

Keywords— Logo classification, Logo recognition, Deep Learning, Convolutional Neural Networks.

1. INTRODUCTION

Automatic logo recognition is gaining traction as a result of the increasing number of applications. Logo identification is considerably more challenging than other tasks like logo and object recognition because of the lack of unique information. Logos are often used in business to distinguish one entity from another and to identify a company's goods and services. Swatches and/or textures are often used in their work. Identity management on the internet, copyright infringement, context-specific advertising placement, and vehicle recognition are just some of the issues that logo recognition may help with. Despite the fact that companies do not have to update their logos on a regular basis, since the context in which the logo appears changes for each of the same company's products, it is difficult to recognise the logo. Changes in backdrop, perspective distortions, distortions due to warping and occlusions, as well as variations in colour and size, all contribute to the difficulty of precise logo identification [1]. It's becoming more difficult to identify a mark due to the growing quantity of customised goods (brands). A high computational capacity is required for logo recognition technique to enable multi-class classification effectively [3].

AI has often been used to address object recognition problems. Object identification problems are often solved using Convolutional Neural Networks (CNNs), which have a complicated structure and many hidden layers [2,5,6]. Logo identification is often tackled using a variety of techniques derived from CNNs. Using pre-trained CNNs to recognise logos is an example from [28,40]. The computational complexity of these methods is very considerable. As a result, these computationally expensive alternatives may only be used in certain circumstances. Since logo recognition is so computationally intensive, it will likely stay a secret for some time.
Vehicle logo recognition has a wide range of uses. For the most part, this is a highly sensitive area when it comes to surveillance and security measures like the control unit system found in military camps, government buildings, intersections with traffic lights, and at checkpoints throughout the city and its surroundings, as well as throughout the nation's territory. Under normal circumstances, people have little trouble recognising and distinguishing logos. Data breaches are common in densely populated cities because of the high density of both vehicles and people. Vehicle logo detection and identification thus need highly automated procedures with great accuracy.

Using deep learning models to ensure logo identification without a lot of computing resources is the main aim of this research [5]. It's been shown that CNN-based models can generalise vast picture datasets with millions of photos. Before being transformed to a vector, the picture input is rectified, filtered, and compressed many times in various hidden layers.

There is a growing number of businesses and brands with customised logos, which makes logo identification even more difficult by requiring a large amount of processing capacity to enable effective multi-class categorization. Classification model and logo recognition algorithm are built in such a manner that they may be utilised in a wide range of situations, including online product marketing and context-specific advertising placement. The creation of a real-time logo recognition system for a mobile app may be one research path [5,7].

A rising need for vehicle classification and identification technologies that can automatically identify a vehicle's manufacturer based on pictures collected has been highlighted by designers through this thesis, with increasing demands for information security and common use of video surveillance. The ability to accurately evaluate a vehicle's brand is only possible with completely automatic logo detection.

2. MOTIVATION FOR THEWORK

Pattern Recognition has become a subfield of artificial intelligence and digital image processing. This science's researchers and specialists continue to create method for analyzing unique characteristics, patterns or mechanisms in digital images. There are numerous applications and technologies associated with this science in everyday life, like remembering names in control systems, logos, and geometric patterns. The broad concept of recognition of pattern is all the tools that allow computers to comprehend patterns in the very same way that humans do, if not more effectively in certain cases. We would then concentrate on logo recognition throughout this thesis.

The detection of vehicle logos from surveillance camera pictures is indeed a crucial step towards vehicle recognition, which is needed for a wide range of applications in automated surveillance and intelligent transportation systems. The task is difficult given the small size of logos and their broad range of shape, colour, and illumination changes [3,4]. A method for quickly and cost-effective detecting vehicle logos is proposed that is based mostly on visual attention method found in human vision. As a result, there is indeed a pressing need for the development of vehicle identification and categorization technologies capable of automatically identifying the vehicles manufacturer based on images captured. Thus, automatic logo detection is critical because it enables accurate identification of a vehicle's brand.

3. RELATED WORK

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.

Logo recognition is defined by István Fehérvári 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 0.6mAP 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 utilized to improve model representation.

For real-world monitoring, Jatupon Benjaparkairat and Watanachaturaporn Pakorn [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 recognized 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 utilized 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 utilized using a windows approach, and a nearest neighbour classifier was used to recognize 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 standardized 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.

4. PROPOSED WORK

Step 1: Data collection and Preprocessing

Data collected from https://www.kaggle.com/binhminhs10/image-car-logo, in this dataset total 40 classes and 12000 images.In this paper select ten classes with 4000 images. After selected the images preprocessed and augmented.

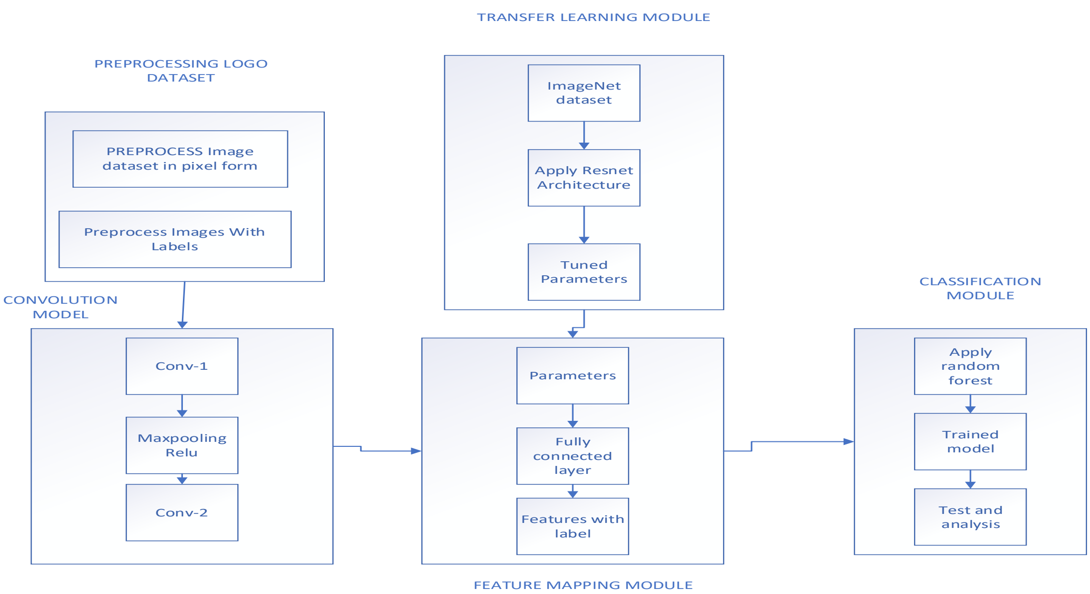


Figure 1: Proposed flow chart

Step 2: Transfer learning

In this step, a CNN is used to construct the transfer learning architecture shown in Figure 2. ImageNet was used to build the parameters for the CNN model (ResNet50). Low-level characteristics may be extracted from ROIs generated by mammography images by using this technique. Using four ResNet convolutional layers (Conv) with an activation function for ReLU mapping and a basic fully connected layer (FC), the CNN model was created for transfer learning. This can be shown in Table 2. Using transfer learning, the pre-trained CNN model was able to provide better results and create feature vectors for mass categorization. The pre-trained CNN model produces only low-level features.

Table 1 Resnet Architecture

Input : Image		
RESnet	Conv Block 1 (4*48*64) Pooling (2*24*64)	Conv + ReLU
		Patch 7*7
		Max Pool 3*3
	Conv Block 2 (2*24*64)	Conv + ReLU 1*1(64)
		Conv +ReLU 3*3 (256)
		Conv +ReLU 1*1 (512)
	Conv Block 3 (2*24*64)	Conv + ReLU 1*1 (128)
		Conv +ReLU 3*3 (128)
		Conv +ReLU 1*1 (512)
	Conv Block 4 (2*24*64)	Conv + ReLU 1*1 (256)
		Conv +ReLU 3*3 (256)
		Conv +ReLU1*1 (1024)
	Conv Block 5 (2*24*64)	Conv + ReLU 1*1 (512)
		Conv +ReLU 3*3 (512)
		Conv +ReLU1*1 (2048)
FC + ReLU (Dropout= 0.5)		
Output (Sigmoid):[0,1]		

Step 3: CNN Mapping

Based on the premise that M features are linked to each M-vector, weight matrices and related control parameters operate to generate M matrix features. Figure 4 shows the CNN model's construction. We can create pictures with fewer filters than the state-of-the-art using four convolution layers, two max pooling layers, and a fully connected layer. The convolution layer's neuron count is vital. Its members often interact and benefit from one other's prejudices and abilities. To reduce overfitting, it uses a convolutional filter and dropout. throughout practise and testing. Notably, feature mapping utilises kernel sets to map output. Convolution creates a new function map F. The kth layer f(s, d) equation

$$C_u^k(s,d) = w_u^k I^k(s,d) + b_u^k \dots\dots\dots\dots(1)$$

Table 2: Performance metrics analysis on proposed approach and existing

Approach	Accuracy	Precision	Recall	F-score
CNN	54	56	54	53
CNN-RF	79	79	79	78

To compare current CNN and random forest classifiers, see Table 2. Figure show CNN-RF progress. And CNN is the issue. Ten logo classes are used. CNN utilises SoftMax classifier and CNN-RF Random Forest after 50 Epochs. CNN-accuracy RF's were 79 percent.

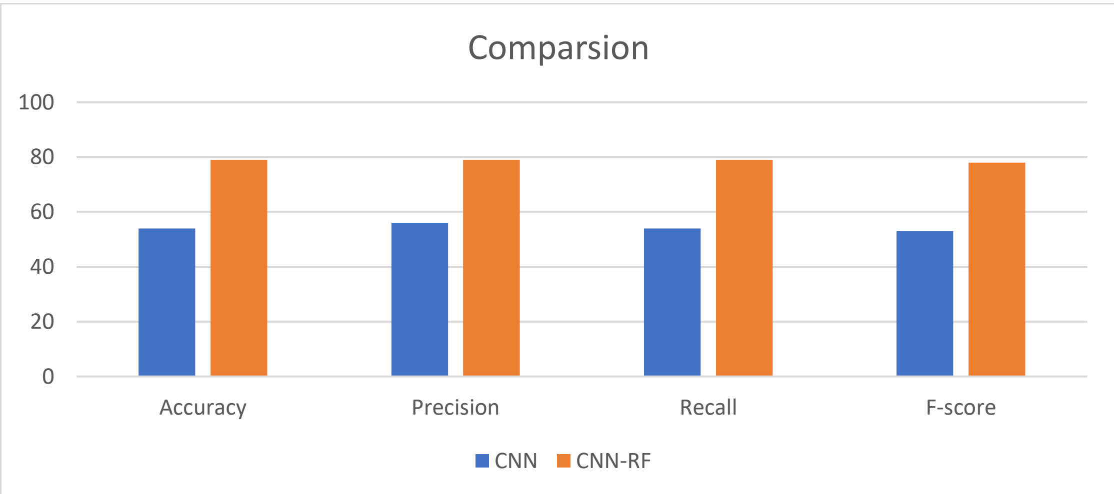


Figure 2: Comparison of different approaches on performance metrics

Table 3: Class wise Performance metrics analysis on proposed approach and existing

Class	Precision (CNN)	Recall (CNN)	F- score (CNN)	Precision (CNN-RF)	Recall (CNN-RF)	F- score (CNN-RF)
Class-1	58	74	65	85	89	87
Class-2	55	28	37	72	75	73
Class-3	72	56	63	77	76	76
Class-4	74	61	67	76	87	81
Class-5	38	75	50	82	82	82
Class-6	39	40	39	85	73	78
Class-7	50	43	46	74	77	75
Class-8	58	58	58	81	67	73
Class-9	50	51	50	76	76	76
Class-10	62	47	54	81	81	81

In Table 3 and figure 2 analysis class wise performance metrics. In experiments use ten logo classes with 4000 images. In figure 2 show proposed approach improve all classes significantly and average difference 10-15% in all performance metrics like precision, recall and f score.

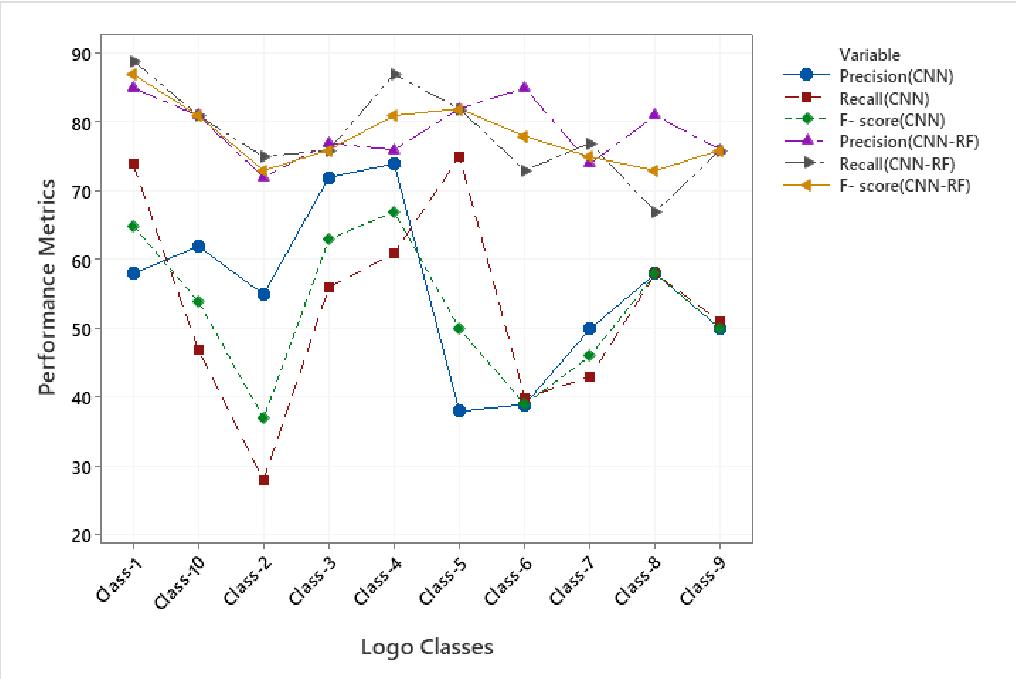
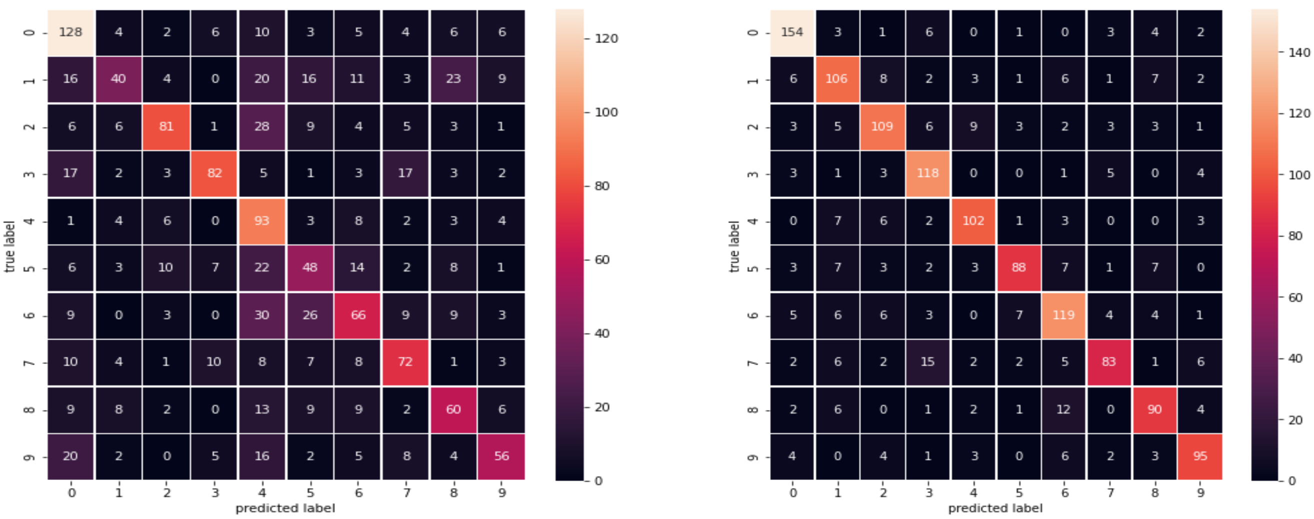


Figure 3: Class wise Comparison of different approaches on performance metrics



(a) **(b)**

Figure 3: Class wise confusion matrix (a) Existing (b) Proposed

In figure 3 analysis the class wise correctly classified instances. These instances show in diagonal in figure.3 (a) Existing approach and figure 3(b) proposed approach

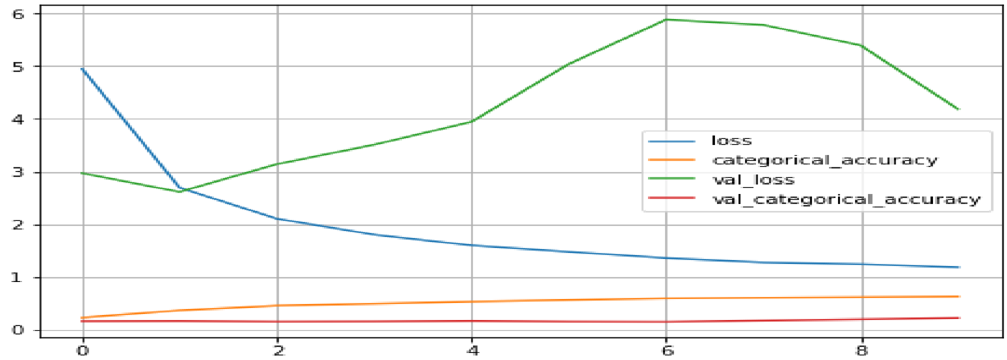


Figure 4 Proposed CNN with Random Forest accuracy and Loss

5. RESULTS ANALYSIS

- As a consequence of combining a pretrained RESNET neural network with a random forest ensemble learner, the proposed approach improves several performance measures.
- The overlapping and mapping in nonlinear space are improved by CNN feature engineering. Classification was enhanced and errors were reduced as a result of this procedure.
- As seen in Figure 3, the optimization improves classification accuracy by helping with logo recognition or categorization across several classes. It enhances both training and testing accuracy.
- The ensemble decision tree classifier in Random Forest enhances pattern recognition. In comparison to simply using CNN with soft max method, the above-mentioned suggested approach improves classification performance metrics.
- Pretrained models used in transfer learning include Resnet because of its residual nature and the feedback method it employs, both of which help minimize learning errors and overfitting.

6. 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 recognize highway entrance vehicle logos using convolutional neural networks. The system has a high recognition accuracy for the highway entrance vehicle logo, is fast and stable, and may be applied to the highway entry. The following are the main reasons to use the suggested method:

Map nonlinear characteristics in linear and nonlinear space. This will be done using random forest using decision tree ensembles. Improve picture sampling using random forest boosting. These reasons increase accuracy by 20%, recall by 23%, and precision by 23%. These shows using 50 CNN epochs and boosting random forest

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