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Discovering Logo Identification through Machine Learning

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Abstract - Logo detection is the process of identifying and localizing logos within images or videos, involving recognizing specific brand logos and determining their spatial coordinates within the visual content. This task is essential for various applications such as brand recognition, copyright protection, and contextual advertising across fields like social media monitoring, autonomous driving, and market research. Logo detection aids in tracking and analyzing advertisements, making it crucial in marketing and media industries. In this paper, the authors have studied and described the process of Logo detection along with its types and also have discovered the techniques used in various researches that have dealt with Logo detection. This study further paves way for a developing a better logo detection technique by analyzing the use of existing techniques.

Key Words: Logo, Detection, Deep Learning, Machine Learning.

1.INTRODUCTION

Logo detection is the process of identifying and localizing logos within images or videos. It involves recognizing the presence of specific brand logos and determining their spatial coordinates within the visual content. This task is integral to various applications such as brand recognition, copyright protection, and contextual advertising. It has gained significant importance due to its wide range of applications. It serves as a valuable tool in diverse fields, including social media monitoring, brand promotion, autonomous driving, intelligent transportation systems, market research, and the detection of illegal logo use, among others. Moreover, logo detection plays a crucial role in tracking and analyzing advertisements across various platforms, making it an indispensable technology for marketing and media industries. It can be seen as a sub-problem of object detection in images and videos, aims to recognize the loge name and find the locations of logo objects in the input image[5]. Logo detection is the task of localizing and identifying logos in images , with practical applications such as brand protection, brand-aware product search and recommendation[7]. It has found diverse applications across various domains. These applications include the recognition of product brands to safeguard intellectual property on e-commerce platforms, identifying vehicle logos for intelligent transportation systems, and managing product brands effectively on social media platforms. This technology plays a vital role in safeguarding intellectual property and enhancing brand management in the digital age.

2. Applications of Logo Detection

Logo detection finds applications in various real-world scenarios. It is used for vehicle logo recognition in traffic monitoring systems, ensuring copyright compliance on digital platforms, placing contextual advertisements. It has an abundance of practical applications in the real world. It is integral to marketing, where it serves to recognize and protect a product's brand for intellectual property rights, aids in marketing analytics, and enhances digital advertising efforts. In smart transport management systems, it plays a vital role in recognizing and identifying vehicles. Furthermore, logo detection finds applications in online product-brand management, particularly on social media platforms like Instagram and Pinterest. It is also employed for quality control purposes in car advertisements, helping to identify and rectify errors effectively. Logo detection tries to identify the locations of the logos within an image [3]. Detected regions can further be assigned to the specific class of the logo, known as logo recognition [3].

3. Types of Logo

Logo of a company can be classified in 11 different types according to their shape, size, appearance etc.

1. Wordmark or Logotype: A logo design that consists of the brand name spelled out in a stylized font or typographic treatment.
2. Symbol or Icon: A logo design that uses a graphical symbol or icon to represent the brand without any accompanying text.
3. Combination Mark: A logo design that incorporates both a symbol/icon and the brand name text.
4. Emblem: A logo design where the brand name is enclosed within a symbol or icon, creating a unified and cohesive design.
5. Lettermark: A logo design that consists of the brand initials or abbreviation stylized in a unique way.
6. Abstract Logo: A logo design that uses abstract shapes or forms to represent the brand in a non-literal way.
7. Mascot: A logo design that features a character or figure as the brand representative.
8. Pictorial Mark: A logo design that depicts a specific image or illustration as the central element of the logo.
9. Dynamic Logo: A logo design that is interactive or changes based on user input or external factors.

10. 3D Logo: A logo design that uses three-dimensional effects or depth to create a realistic or unique visual.
11. Vintage or Retro Logo: A logo design inspired by past design trends, styles, or eras.
12. Handmade or Crafted Logo: A logo design created with hand-drawn elements or crafted to give a personalized and artisanal touch.

4. Overview of existing Logo Detection techniques

1. RetinaNet comprises a backbone network and binary sub-networks that leverage various features from the feature maps of the backbone network.

2. Faster R-CNN integrates the region proposal algorithm into the CNN model. The Faster R-CNN model consists of a Region Proposal Network (RPN) and a solid R-CNN with shared convolutional feature layers.

3. R-CNN is a widely used deep learning framework for object detection at scale. It combines CNNs with region proposals.

4. Saliency map-based object detection, particularly in logo detection, is a prevalent method that uses saliency maps to identify and segment salient objects. Ming and other researchers have introduced approaches using saliency maps for this purpose.

5. Weakly supervised object detection, as researched by Wang and colleagues, utilizes weakly supervised learning to detect and localize objects. Their approach involves segmenting semantic candidate regions through a region proposal technique and calculating probabilistic latent semantic discrimination.

6. Region-of-Interest (ROI) segmentation has been explored by various researchers, who have proposed systems for ROI extraction using algorithms like selective search.

7. LogoNet features a backbone for feature extraction, a spatial attention module, and a detection head, inspired by HourglassNet.

8. Generic logo detection focuses on localizing logo candidate regions using bounding boxes without class identification.

9. AlexNet is composed of 5 convolutional layers, 3 max-pooling layers, and 3 fully connected layers, using ReLU activation functions. It employs a sequential architecture with layers stacked sequentially.

10. CaffeNet is a single-GPU version of AlexNet, utilizing a sequential architecture with two paths for convolution on 2 GPUs to address memory constraints.

11. VGGNet, introduced by the Visual Geometry Group, includes variants VGG-16 and VGG-19. VGG-16 is more popular and features 13 convolutional layers, 5 max-pooling layers, and 3 fully connected layers. VGG-19 has 16 convolutional layers but is otherwise identical to VGG-16. VGGNet emphasizes depth for improved performance and uses 3x3 convolution kernels and 2x2 pooling uniformly throughout its architecture.

5. Existing Literature

Salma Sahel et al. [1] Initially, the authors started by cleaning the dataset and checking if the annotation files were correct. Then the dataset needed to be fed into each of the training models. Since it takes too much time to build the model, the model needs to be stored and then reused. After that, they chose samples of pictures from the dataset to train each model on them, in order to produce weights. The remaining images were used for testing the models in order to find each one's testing accuracy. It has been found that R-CNN takes more time and GPU space, but obtained higher accuracy. Hence, the increased accuracy comes with a cost. This is because the FR-CNN first applies CNN and then the zones where compared to the R-CNN which makes the regions first and then applies CNN. When comparing the R-CNN and the FR-CNN to the RetinaNet, it was revealed that the RetinaNet takes fewer test time when compared to R-CNN, it demands more training time when compared to the FR-CNN and it takes more space than both R-CNN and FR-CNN because it checks layers more, because the quality of the image matters less to RetinaNet.Waqas Yousaf et al. [2] have proposed, training is largely influenced by the number of epochs which has an impact on the classification performance. Parameter setting like learning momentum, depth, and batch size is also important during the training of deep networks. To achieve the high accuracy PatchCNN and AlexNet needs less epochs and acceptable training time. On the other hand, deeper networks like ResNet require large number of epochs to attain the highest accuracy. AlexNet showed the best results at 10 epochs while ResNet showed its best results at 10 epochs. ResNet consumes large time as compared to AlexNet. For better performance it is mandatory to monitor the training process. In case of patch- CNN, the best results are obtained at only 10 epochs.Gautam Kumar et al. [3] have proposed, automatic logo detection is a well-known domain of research to the computer vision community. Logo detection is a specific case of object detection problem. Further they proposed their whole method is divided into training and prediction steps (inference) as two phase approach. In the first phase, fine-tuning of the standard deep CNN has been done for the Logo classification task. In the second stage, an inference methodology has been adopted to perform logo detection. However, the proposed method is not modelled such that it can detect the multiple brand logo in the same image. Rahul Kumar JAIN et al. [4] proposed LogoNet: densely layer-aggregated hourglass architecture with a spatial attention mechanism to detect logos. This framework refines final output feature maps to provide better performance. This method achieves a significant performance gain within considerable computation time. Yu Bao et al. [5] proposed logo detection as a sub-problem of object detection has a wide range of applications in many domains. This paper conducted an experimental study of R-CNN for logo detection. The scale of logo, simple logo, and variability of logo are the main difficulties for detection.Simone Bianco et al. [6] used Convolutional Neural Networks as a robust alternative for low-quality images. The proposed pipeline involved selecting candidate subwindows using Selective Search, augmenting the training set using Transformation Pursuit, and performing Query Expansion for increasing recall. The method proved to be effective even with CNN features that were trained for a different task, producing results close to the state of the art.Muhammet Bastan et al. [7] presented a two-stage open-set logo detection system (OSLD) that can recognize new logo classes without re-training. They also constructed a new open-set logo detection dataset (OSLD) with 12K logo classes, and released it for research purposes. Then they evaluated OSLD on this dataset and on standard Flickr-32 dataset, demonstrated good generalization to unseen logo classes and outperformed both openset and closed-set logo detection methods by a large margin.Goncalo Oliveira et al. [8] mentioned pre-training a deep network with a similar domain dataset is advantageous, by using transfer learning they avoid having to build a new large scale dataset for their domain to train a deep network from the scratch. The flexibility given by the original Fast Region-based Convolutional Network (FRCN) model is greatly suitable for the brand detection problem. Steven C.H. Hoi et al. [9] This paper presented "LOGO-Net" — a large-scale logo image database to facilitate large-scale deep logo detection and brand recognition from real- world product images. LOGO-Net consists of two datasets: (i)"logos-18": 18 logo classes, 10 brands, and 16,043 logo objects, and (ii) "logos-160": 160 logo classes, 100 brands, and 130,608 logo objects. Discussed the challenges and solutions for constructing such a large-scale database, tackled the deep logo recognition and brand recognition tasks by exploring a family of emerging Deep Region-based Convolutional Networks (DRCN) techniques, and finally conducted an extensive set of benchmark evaluations. Shuo Yang et al. [10] The experiments, they compared the proposed with some recent detection algorithms, including Faster-RCNN (VGG16), SSD, and YOLOv2 (Darknet19). Faster- RCNN is a fast two-stage detector which achieves good performance for general object detection.

Compared with it, our method runs much faster than Faster-RCNN. SSD and YOLO are the foundations of our algorithm. Christian Eggert et al. [11] Performed a theoretical analysis of the region proposal stage and derived a relationship between feature map resolution and the minimum object size which can reasonably be detected, assuming a perfect classifier. They also observed that the filters in the convolutional layers can adapt to a wide range of scales when given the chance. Hang Su et al. [12]In this work, they presented a scalable logo detection method including dataset establishment and model learning. This is realised by exploring the web data learning principle without a tedious need of manually labelling fine-grained logo bounding box. Specifically, they proposed a new incremental learning method named Scalable Logo Self-co-Learning (SL2). It uniquely enables reliable self-discovery and auto-labelling of new training images from unconstrained in-the-wild web data to progressively improve the model detection capability in a cross-model co- learning manner.Christian Herrmann et al. [13] The limits of closed set logo retrieval approaches motivate the proposed open set approach. By this, generalization to unseen logos and novel domains is improved significantly in comparison to a naive extension of closed set approaches to open set configurations. Due to the large logo variety, open set logo retrieval is still a challenging task where trained methods benefit significantly from larger datasets. Guangyu Zhu et al. [14] we have presented a multi-scale approach to logo detection and extraction in document images. A trained Fisher classifier performs initial classification at a coarse image scale. Each logo candidate region is further classified at successively finer scales by a cascade of simple classifiers. This approach achieves 84.2% accuracy and 73.5% precision on a large collection of real-world documents. Ahmed Alsheikhy et al. [15] A Deep CNN model was designed for logo recognition based on the DenseNet model. The proposed model was trained and tested on the FlickerLogo32 dataset. Frank Liu [16] To increase the efficiency of the algorithm, I employ a database of PCA-SIFT features and make use of an automatic segmentation algorithm to improve recognition accuracy. By building a feature database from 381 different training images of known storefront logos, the SLRS was able to achieve an impressive 86.0% accuracy on a test set of 100 images, each containing a single logo. With a larger database of storefront logos and more computing power, the SLRS would be able to recognize a wider range of logos in a shorter amount of time.

6. Analysis of Techniques

A careful observation of the techniques used in these research papers were analyzed and the results of these observations are tabulated in Table 1. The performance analysis shows that R-CNN has an accuracy of 99.80 % followed by Patch-CNN of 99.01%. It can also be observed that the accuracy is more for the FLICKR LOGOS- 32 than other datasets. LOGOG-32 PLUS also has given a better result with 99.01%. There is still a scope for improvement of the methods to achieve 100% of accuracy with real time data of all logo types.

Table 1. Techniques used and their performance

Approach and Accuracy Table			
Reference	**Approach**	**DataSet**	**Accuracy**
[1]	RetinaNet	FLICKR LOGOS- 32	95.20
	R-CNN		99.80
	Faster R-CNN		93.60
[2]	Patch-CNN	LOGOG-32 PLUS	99.01
	TL-AlexNet		98.90
	TL-ResNet-18		91.60
	TL-ResNet-50		94.90
	TL-ResNet-101		94.90
[4]	CenterNet	LOGOG-32 PLUS	88.00
	LogoNet		88.30
[6]	CNN Features	FLICKR LOGOS- 32	91.00
	CNN + Query Expansion		97.00
[10]	Vehicle Logo Detection Method	VLD-30	89.90
[12]	Self-Learning(Faster R-CNN)	WEB LOGO	36.8
	Self-Learning(YOLO)		39.4
	Co-Learning(Faster R-CNN)		44.20
	Co-Learning(YOLO)(SL2)		46.90
[14]	Fish Classifier	Tobacco-800	59.00
	Multi-Scale Approach		57.00
[15]	Densenet	FLICKR LOGOS- 32	92.00
[16]	Vehicle Logo Detection Method	VLD-30	89.90

5. CONCLUSIONS

The study's findings highlight the effectiveness of using deep learning and pre-trained models for logo detection, emphasizing its potential impact on real-world scenarios. Several related works were cited, demonstrating the use of deep learning for logo recognition and detection in various contexts and applications. The study referenced a comprehensive list of related works and research papers in the field of logo detection and deep learning. It also analyzed the performance of the techniques and it has been found that deep learning model R-CNN outperforms other models with the datasets FLICKR LOGOS -32. This work has laid the foundation or making progress towards more discovery and innovations of achieving higher accuracy for universal datasets.

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