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Detection of Logo and Package in Indian Food Products

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Abstract

In our rapidly developing industrial society, brand recognition and packaging have become crucial role in driving consumer pattern. We know that logos are typically designed from texts, images, or both text and images. As part of this methodology here are the few things considered in logo detection including whether the logo is printed on the package and to determine the package name. We know that the logos in package is very important any brands to sustain its position and quality in the packing field. The development of the new approach includes the employment of algorithms for image processing and for improved identification of logos and to identify package name. However, primarily, it applies the Convolutional Neural Networks (CNNs) and additionally, it is employed techniques of transfer learning with the progeny of the base models. Also, the object detection frameworks such as ResNet50 is also incorporated into the system. These methods use region proposal network, multiscale feature maps, and anchor boxes to enhance the logo detection process among the images and make it more efficient. Advantage of using Faster RCNNs is that it allows the software to learn features in a hierarchical manner and learn logos on other conditions of images, or transfer learning, which allows it to detect logos with higher accuracy compared to other available methods.

Keywords: *Convolutional Neural Network, faster R-CNN, transfer learning*

1. Introduction

From practice, we know that branding and the package design forms a crucial necessity due to the competition in the market towards conveying the expected brand or the product to the consumers. This is the identification and authentication of logos on packing, especially for packing but not limited to packing of products are essential in both brand recognition campaign as well as quality check. To show this challenge the research proposed methodology will employ better image processing techniques and machine learning algorithms while refining logo and package identification. Many researchers have performed to work on the improved logo detection system. For example, in [9] the fast logo detection based on CNNs was introduced demonstrating high accuracy but significant requirement for computational resources and training time and in [10] the real-time logo detection approach YOLO was introduced that reformulates the problem of object detection as a list of regressed components. However, instead of accurately segmenting out the objects, YOLO tends to predict the objects fast, and therefore, it can miss a lot on details. This research-related method utilizes the relevant advancements in the area of computer vision and deep learning for the detection of the logo as well the packaging on the respective condition. To gain high level of accuracy and robustness, the following will be incorporated by the system, A severe broad database containing preprocessed wide range of product images of different sizes, orientation and under different lighting conditions. To achieve segmentation the proposed method uses Mask R-CNN as it is an efficient instance segmentation technique that can separate logos from the background image. To make improve on the edges of images where logos have been detected, the machine employs some algorithms such as the Canny Edge Detection Algorithm and the Sobel Operator Algorithms to carry out better in the logos' detection. Thie paper focuses on improving the synthetic CNN model for specialty by integration of improved object detection architecture like Faster R-CNN. Training involves such elements of classification and localization functions and losses Splitting of the dataset into training and validation through OPTIMIZERS including the ADAM and SGD optimizers, and finally trained through efficacy metrics including; precision and recall @F1 Score and Intersection over Union (IoU & F1 Score). It includes components, such as an easily understandable connections array where it is possible to upload images and in which the system demonstrates whether the logo is present or absent, and whether it is located in the given position or not where the logo is or in fact where one is plus where it is placed and to determine the package name.

2. Literature survey

Here are the various methodologies and techniques for logo detection and recognition includes: [1] Recently, Hsu, Cheng-Lin, et al, proposed a new system, called DeepLogo which is essentially a 'logo detection' system where deep learning method was used; the particular work also uses the CNN for feature extraction and done quite well in logo detection task. [2] Romberg et al, Stefan in the year 2011 describe logo identification in image understanding while giving details on how CNN is able to tackle variations in logo designs and compliances from backgrounds. Bianco, Simone, et al [13] give some aspect of fine-grained classification of logos, using some aspect of deep learning, pointing out the effectiveness and characterization of differences in logos. Cai, Zhaowei, et al [4] (2017) poses logo in image detection using region proposal, context aided region proposal network and feature map from the CNN.Li, Yin, et al [5] provides the solution on logo detection in complexity images by combining the basic image processing hand with deep learning with focal stress on noise, occlusion, and variations. [6] In Ren, Shaoqing…, the authors apply the Faster R-CNN architecture for the logo detection problem to demonstrate that regions proposal network aids in increasing the effectiveness of the logo detection process. Selvaraju, Ramprasaath R., et al [7] further discusses the transfer learning to analyze the logo detection and the method improvements that improve the subsequent phases of methodology by decreasing the time needed for training and increasing the logo detecting rate.

Wiwi Prastiwinarti, et al [8]. This paper presents a new method of detecting physical defects in the packaging boxes of products using the image process and deep learning especially transfer learning with two input images. Wei Liu, et al [9] proposed another multi-task logo detection and classification architecture that can use LogoNet for the reusability of the features to make better final performance. In the paper titled, Redmon, Joseph, et al [10] presented its application for logo detection through the utilization of the YOLO-Logo object detection technique arguing that the use of the YOLO algorithms in logo detection are faster and accurate in real-time. Mark Hubenthal, Suren Kumar [11] from Amazon Inc proposed a method to enhance the open-set logo recognition, for its pre-training, the authors used paired samples of image and text, for the second, an upgraded loss function, ProxyNCAHN++, that enhances the metric learning base and integrated class-specific hard negatives into the equation.

3. Methodology

The proposed methodology for Logo and Package detection uses Faster RCNN to detect the logo printed in the package. The methodology contains following section i) Data Collection and Preprocessing, ii) Trained images iii) Image Regions iv) Faster R-CNN training v) Post Processing and Inference which is shown in the below Fig 1:

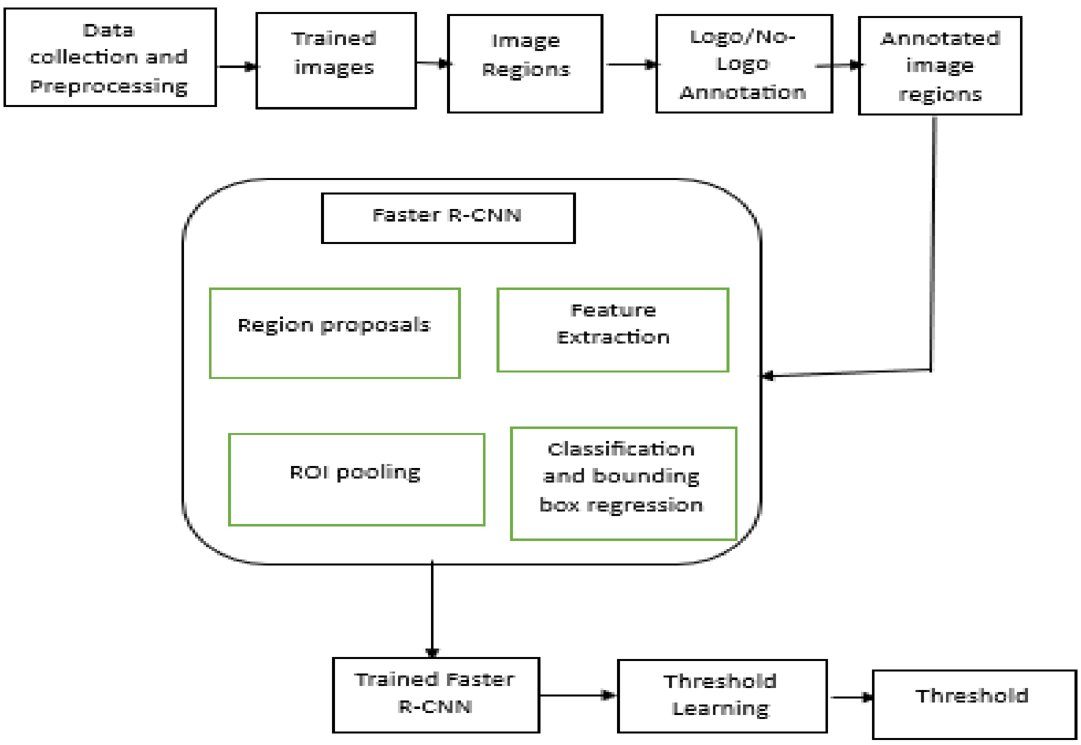

Figure 1: System Architecture

3.1. Data Collection and Preprocessing:

An objective of the paper was on the collection of data and it can be noted that this can be achieved in the formation of a relatively

expansive set of data Images which included different logos and packaging. That is why sizes, orientations, occlusions and lighting of faces in the dataset has to be different in order for the face to be potentially recognizable under several conditions. Sources of logos include downloaded logos from logo databases, logo snaps, shots of logos from the internet, printed photos of logos from packed products. There are other technologies that also used for annotation and these are Labeling or otherwise known as VGG Image Annotator (VIA) in VIA, in which the annotation is documented in codes commonly in XML or JSON. Some of the preprocessing methods that are usually applied include: resizing the images into the desired size because all layers of CPPN-CNN require the images to be of equal dimension, normalized scales of [0;1] or [-1; 1] to enable the machine to learn during training, data augmentation to increase variability within the images, and random rotations, flipped, scaling, and color changes.

3.2. Trained images

Then process begins with Trained Images then is a set of images used in preparing the object detection model. A picture can contain several logos which need to be detected and, as a result, the point where these logos can be found in the picture is usually marked. Thus, labelling process has a high relation with the next step of the modelling phase of the training phase due to its potent impact in making prediction regarding the subsequent phases. The next procedure is Object Proposal to identify logos. This step is important because it helps to narrow down the area that the model must search in that image. The proposals of objects can be made in different ways and one of them is the selective search while the other one has been introduced as the region proposal networks that have been included in the Faster R-CNN.

3.3. Image Regions

Once the candidate regions are defined, they are said to be Image Regions collectively Regions and ImgRegions are comparable in terms of their definition. These regions are then subjected to what is referred to as Logo/No-Logo Annotation whereby each of these segments is labelled by hand or with the help of such tools to indicate whether a logo is present as part of the area or not. These marked regions are known as Annotated Image Regions that offer the precise points necessary for training.

3.4. Faster R-CNN Training

The basic of this workflow is the Faster R-CNN, which the object detection module has trained, and with the help of which the region proposal network helps in the execution of the task by CNN. The Faster R-CNN comprises several components: Below are the component that constitutes the Faster R-CNN; Region Proposal Network is part of the Faster R-CNN.

3.4.1 Region Proposals:

This component may have the ability to encase logos or its ‘rather objects’ inside or construct boxes or regions that may have this probability. That way, if the object is small, it would thus be possible to train the region proposal network (RPN) to predict these regions far more easily.

3.4.2 Feature Extraction

The above extracted regions are then fed into a convolutional neural network which is more commonly known as CNN to get features. They form the region features that when incorporated with the profile of the logos can be used in the differentiation of the logos with other objects.

3.4.3 ROI Pooling

The aspects of the image defined by the Regions of Interest (ROIs) are accumulated into a definite dimensional formation for presenting standard inputs into the further fully connected layers. They say this step does two things; it equalizes the sizes of the proposed regions and since the proposed region need not to be of equal size this is an important step to ensure that the classification and regression occurrences in the next steps are manageable.

3.4.4 Classification and Bounding Box Regression

Equally to this, each ROI is then divided between logo detected region and logo non-detected region. In addition, the bounding box regression is applied to tune the axes of the predicted areas to the certain objects' true shapes.

3.4.5 Post-Processing and Inference

As mentioned before, Threshold Learning is the second critical step after training the Faster R-CNN model. It must be noted that after finding a suitable threshold, the system can eliminate low confidence detections as it will help in eliminating a number of false positives which will in turn increase the precision level of logo detection. The fixed Thus, only those regions which have succeeded to get through the threshold in a new image are considered valid logos by the trained Faster R-CNN model. This makes the final output contain only possible logo detections that are assured to be correct making the system efficient and accurate.

4. Experimental results

The model contains efficient dataset for logo identification and a check on whether they are printed. During the training and also in the validation there were used 258 logo images. Such images include several kinds of logos that may facilitate the rates of the system and offer more appropriate solutions. Accomplishes identifying logos and authenticates the right placements during different experiments as expounded by the above proposal. The example for the result of the paper is given below Fig 2 and Fig 3:

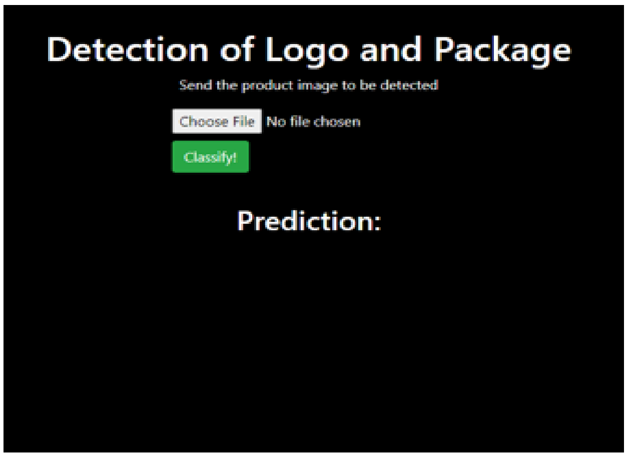

Figure 2: User interface of the proposed system

Figure 3: The system predicts the package and detects the logo

The Performance analysis with respect to Confusion matrix for the above methodology is given below Table 1.

No of Images	TP	FP	TN	FN	Accuracy
150	85	10	50	5	0.90

Table 1: Performance analysis

Performance Analysis is used for assessing the quality of prediction contained in the classification model and consists of the quantities of true positive (85), false positive (10), true negative (50), and false negative (5). This proves that our logo detection system is 90 percent accurate and has an F1 Score of 0 percent. 91% shows that the proposed method is accurate in discriminating logos and verifying them. The Comparative Analysis for the proposed methodology is give in the below Table 2:

Sl No	Authors	Algorithm Used	Accuracy
1	Hue Cheng-Lin et al.	Deep Logo	87%
2	Romberg Stefan et.al	CNN	82%
3	Redmon Josph	YOLO	84%
4	Our Work	Faster RCNN	90%

Table 2: Comparative analysis

Table 2 gives the comparative analysis which contain different authors with different algorithms used. On comparing above accuracy our work has gained more accuracy.

6. Conclusion

This paper uses the state-of-the-art image processing, deep learning algorithms like Convolutional Neural Networks (CNNs), Faster R-CNN, and YOLO on logo and package detection of Indian food products. Hence, through the use of a diversified dataset, this research developed a promising approach towards logo detection and identification. These experiments proved that the proposed method is capable to detect logos under different conditions and some of the commonly used techniques like confusion matrix. The proposed methodology has achieved 90% accuracy. For the future studies, more improvements can be done to improve the scalability and efficiency of the developed system, possibly, with the use of the larger datasets and with the investigation of the other types of the deep learning. In general, this study benefits the enhancement of brand identification as well as the quality of packaging organization, which is crucial in maintaining consumers' confidence and market viability.

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