Logo Detection Using Painting Based Representation and Probability Features

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***Abstract*—In this paper, a coarse-to-fine logo detection scheme for document images is proposed. At the coarse level of the proposed scheme, content of a document image is pruned utilizing a decision tree and a small number of features such as frequency probability *(FP)*, Gaussian probability *(GP)*, height, width, and average density computed for patches. The patches are extracted employing the piece-wise painting algorithm (PPA) used for text-line segmentation. The fine level of the proposed scheme refines the detection results by integrating shape context descriptors and a Nearest Neighbor (*NN*) classifier. We evaluated the proposed approach using a public and two large industrial datasets. From the experiment on Tobacco-800 dataset, the best precision and accuracy of 75.25% and 91.50% were obtained respectively.**

Keywords: Logo detection/recognition, Piece-wise painting, Gaussian probability, Frequency probability, Shape context.

I. INTRODUCTION

Logos are unique signs primarily used by companies or individuals to identify products or services to consumers. They also serve in different applications of document image analysis (DIA) including document classification, retrieval, understanding, etc. [1, 2]. Basically, the problem of using logo information in DIA applications involves two main steps: (a) detecting the probable logo from a document image, and (b) recognizing or retrieving the detected logo candidate from a database. The later ones are referred as recognition [1] and spotting [7] while the former is called logo detection which constitutes the preliminary step of any logo processing application. A number of systems have been proposed for logo detection in the past [2-13]. They mainly rely on three main steps: i) primitive detection, ii) feature extraction, and iii) classification.

Primitive detection aims to represent the document images with a set of primitives to be used at the feature extraction level. Connected component labeling has initially been used in various logo detection systems [2-6]. Since, connected components may be fragmented or joined to another component, connected component based primitives are very sensitive to noise and degradation result in missegmentation cases. To solve this problem, geometry consistency [3], neighboring criterion [4] and XY tree grouping [5] of connected components have been utilized.

Local detectors from computer vision field such as gradient [4], Harris-Laplace [7], Hessian [8], Canny edge and He & Yung [9] have been used to obtain primitives (key points/regions) for logo detection/retrieval. However, these detectors are not still suitable for the problem of logo detection in DIA applications, as they are dedicated to computer vision and gray level images where intensity variability plays an important role in the detector accuracy. Furthermore, local detectors based on compactness [4] and feature rectangle [11] have been applied on document images for logo detection.

Many feature extraction techniques have been employed in the literature for logo detection. Geometric-based features (width, height, aspect ratio, density, etc. of primitives) have commonly been used in many systems [2, 4, 5, 6]. Domain-based features such as coordinates of logos, context distances between a logo candidate and reference points (positions) have also been included in the feature sets to improve the detection results in [4, 5, 6].

Shape context and SIFT [7], SURF [8] BSM [12], local and global invariants [13] features extracted from entire document image have also been employed for logo detection/recognition. The drawback of these approaches is time complexity. To reduce the complexity, they utilized different indexing techniques. However, indexing process results in strong approximation of the descriptors space while missing some detection accuracy.

For logo detection many classifiers have been applied at the classification stage. When the detection relies on geometric and domain-based features, classifiers such as decision trees [4, 5, 11] or Fisher linear discriminant [6, 9] have been employed. K-Nearest Neighbors [7, 12] and Bayesian Network [13] have been used where descriptors were involved. Geometry matching is also employed to integrate the spatial relation among the detected primitives for the classification in [3, 7, 8].

Conclusions driven from the aforementioned state-of-the-art methodologies highlight that most of the logo detection systems work either with low-level features or with descriptors. Here, we propose to use both low-level features and descriptors at different levels for detection of logos in document images.

In this paper, we propose a new scheme for logo detection employing a coarse-to-fine strategy. In the coarse level of our proposed scheme, a text-line segmentation technique called painting [15] is employed to represent a document image with a set of patches. This process facilitates to avoid working directly on pixel and connected component levels. The extracted patches are characterized using geometric and domain based features. Since, a logo serves as a unique, perceptually salient entity that can be quickly recognized by the reader, the relative position of a logo region in the document image is an important feature for the detection of a logo [4, 5, 9-11, 14]. To represent this important characteristic, two new probability features are introduced in this paper called frequency probability *(FP)* and Gaussian probability *(GP)* features. The latter is inspired by the work presented in [14] and we adapted it to document images. It is based on the distance between center of gravity of an extracted patch and center of Gaussian Mixed models obtained from the positions of logos in document images. The former is computed based on the probability of being an extracted patch a logo-patch. Height, width and average density of each extracted patch are also considered as features. The extracted patches are then examined based on a decision tree utilizing the proposed features computed from the patches to either classify them as non-logo or logo patches. In the fine level, the most probable logo-patches (region of interests) are further processed to detect logo using shape context features and a *NN* classifier. The coarse level of the proposed scheme prunes the document content without missing any logo part to maintain the highest recall, whereas the fine level refines the detection results.

The rest of the paper is laid out as follows: Section 2 describes our proposed scheme. Section 3 discusses the experiments and results. Finally, Section 4 provides some conclusions and future work.

II. Proposed Scheme

An overview of our system architecture is demonstrated in Fig. 1. Details of different steps are described in the following subsections.

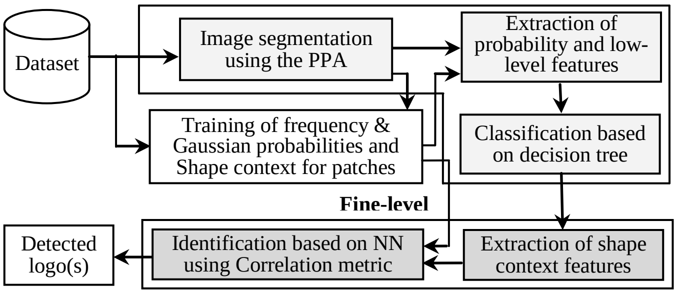


Fig.1. Overview of the proposed logo detection scheme.

A. Image segmentation using PPA

The *PPA* is originally used for handwritten text-line segmentation [15]. In the *PPA*, initially, the input document image is decomposed into vertical stripes based on width of the input document image from left to right. Here 5% of width of document image is considered as width of stripe. Subsequent to the division of the input image into stripes, the gray value of each pixel in each row of a stripe is modified by changing it into the average gray value of all pixels present in that row of the stripe. The resultant gray-scale image is converted into two-tone [15]. Two-tone image obtained from the image of Fig.2 is shown in Fig.3. The rectangular black areas obtained employing the *PAA* are called patches. The extracted patches represent foreground information irrespective of its content (text, graphic, logo) in the document image. This representation provides a novel representative symbol in order to deal with different types of documents containing various logos composed of graphical, textual and mixed of graphical and textual information.

B. Feature extraction

Employing the PPA on a document image provides several patches (see Fig.3). Among all the extracted patches only a small number or none of them contain a logo or parts of a logo. To prune the extracted patches and find the most probable logo-patch(s), in this research work, two novel probability based features are introduced using prior knowledge of logos' positions. A few geometric features are also included in the feature set for the purpose. Details of the proposed feature extraction techniques are presented in the following.

1) Frequency probability feature

Position of a logo in a document can be represented in different ways such as probability map for blurred shape model [12] and geometrical position [4, 9]. In this research work, we introduce a new frequency based probability feature extracted from a frequency probability map to characterize the locations of logos in different documents. The frequency probability map is computed based on frequent appearance of logos in different positions of document images during training step as follows.

Suppose a document image is denoted by $I^K_{H\times W}$, where H and W are the height and width of the image I^K, respectively. K varies from 1 to T, where T is the number of document images in training set. We define a matrix $FM_{H\times W}$ called frequency probability map, which is initially set into 0. Throughout training phase FM is modified employing $FM_{(i,j)}=FM_{(i,j)}+1$ if $I^K_{(i,j)}$, which is a pixel value positioned at (i, j) coordinate in the image I^K, is a pixel of a logo components. Otherwise no change will be performed in $FM_{(i,j)}$. To convert the values of FM cells between 0 and 1, each FM cell is divided by the maximum value of FM using $FM_{(i,j)}=FM_{(i,j)}/Maximum(FM)$, for i= 1, ..., H; j= 1, ..., W. Since all the elements of the FM have a value between 0 and 1, elements with values close to 1 signify higher probability of presence of logo and elements with values close to 0 indicate lesser probability of representing logos at those positions. Fig. 4 demonstrates the top of frequency probability map (*FM*) obtained from 100 training samples of Tobacco-800 dataset [17]. The rest of *FM* has a probability of zero and is not shown in Fig. 4.

To obtain a frequency probability (*FP*) for a patch, the patch is mapped on the *FM* and an average probability is computed from the probability values corresponding to all the foreground pixels in that patch.

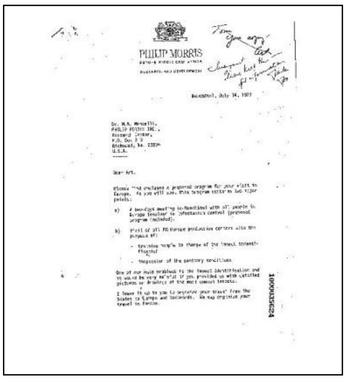


Fig.2. Original document image.

Fig.3. Patches extracted employing the PPA.

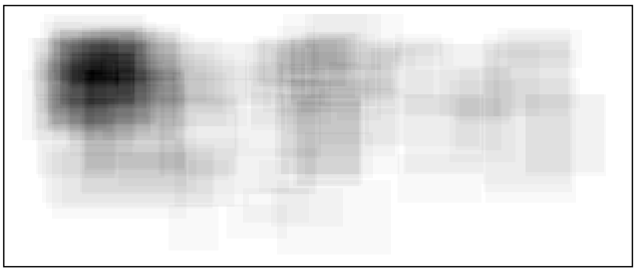


Fig.4. Pictorial description of the FM.

2) Gaussian probability feature

The positions of logos in video frames have been characterized using four different mixed Gaussian distributions [14]. Similar to the video frames, logos in document images have also a clear positional preference in contrast to text content and other information. They normally have a higher probability of occurrence at the top and bottom than at the center of documents. To represent this attribute, besides using the frequency probability (*FP*) feature, the distance of a patch from predefined positions of different logos is also considered as a feature in the proposed feature set. To compute this feature a Boolean matrix $B_{H\times W}$ is created. Initially Boolean matrix B is set into 0. Through the training step $B_{(i,j)}=1$ if $I^{K}_{(i,\ j)}$ is a pixel belongs to logo components (foreground) based on the ground truth of the logo.

Based on aforementioned point about higher probability of logo locality at the top and bottom than at the center of the documents, the Boolean matrix B is divided into 3 equal horizontal blocks. Top and bottom blocks are then considered and each of which is divided into 3 vertical blocks. We approximate the probability by a mixed Gaussian distribution. Since, six blocks are considered for modeling the logo positions, six bivariate Gaussian distributions are used to represent this probability.

A Gaussian probability (*GP*) feature for an extracted patch P is calculated using the following equation.

$$P\left({}^{L_P}/_{p_P} = 1\right) = \sum_{i=1}^{6} \frac{1}{2\pi\times\sqrt{|\sigma_i|}}\times e^{\frac{-(L_P-\mu_i)\times(L_P-\mu_i)^T}{2\sigma_i}} \quad (1)$$

where the location of patch P is denoted by $L_P= (x, y)$, (x, y) is centroid of patch P, σ_i is the covariance matrix at block i and μ_i is the expectation that the logo will be in block i (i = 1, 2, 3, 4, 5, 6 represents the six blocks: top left, top center, top right, bottom right, bottom center, and bottom left, respectively). $P(L_P|p_P= 1)$ is the Gaussian probability (*GP*) of the p_P if p_P is a patch which may contain logo regarding its location L_P.

In the Tobacco-800 dataset [17], logos are located only on the top of documents. Fig. 5 shows a clear pictorial description of gravity centers of logo-patches extracted from the training documents and all of them are located on the top of documents. Using this fact, three vertical blocks for the horizontal top block are considered to compute mixed Gaussian parameters during the training step of our proposed scheme on Tobacco-800 dataset [17].

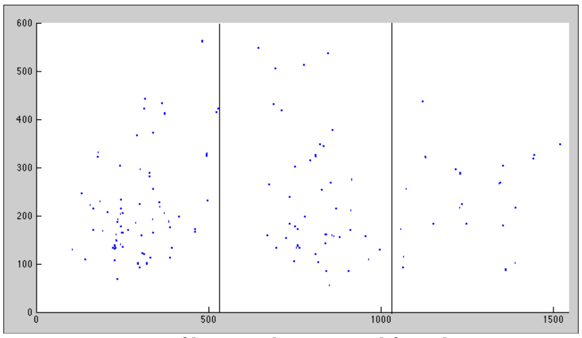


Fig.5. Gravity centers of logo-patches extracted from the training images located on the top of documents and corresponding 3 vertical blocks considered for computing bivariate Gaussian mixed parameters.

3) Low level features

To complete our proposed feature set at the coarse level, the average density, height and width of every patch are computed and included in the feature set. Furthermore, statistical standard deviation of height of connected components in the patch is computed and counted in the feature set.

C. Identifying logo-patches using decision tree

Logo detection in document images is a particular field where only a few instances per class are available for training. Moreover, the text content (non-logo portion) is much more than the logo content in document images results in a class imbalanced data problem. See the result of employing the PPA on a document image (Fig. 3), where among the entire extracted patches only one patch contains a logo.

Decision tree (DT) performs well in such a scenario and it has been reported being more suitable to deal with such problems [16]. Furthermore, DTs are designed without assumption about the features space distribution and they can perform better using geometric and domain-based features; as these features are statistically independent, non-homogeneous and not uniformly distributed in most of the cases [16].

In this research work, a decision tree (DT) is used as classifier for the coarse classification of patches into logo and non-logo patches following feature extraction. To design a DT, several automatic algorithms such as CART, C4.5 and CS-C4.5 have been proposed in the literature. Here the CS-C4.5 is used to design the DT. The CS-C4.5 is a cost-sensitive C4.5 DT, which considers a cost matrix during the pruning step to take care about the misclassification of logos. It also uses gain ratio as splitting criterion to deal better with the class imbalanced dataset [16].

Employing the proposed DT, a small number of patches (logo-patches) with higher probability of containing logos are obtained. Due to degradation, low quality image and multi-part logos, we sometimes may not get appropriate patches for logos during the painting operation. Furthermore, very small logo-patches may be eliminated using the proposed DT. To accomplish this problem, the results obtained employing the proposed DT is subjected to a dilation operation using a structuring element of length *MG* and width 1, where *MG* is average gap between extracted patches shown in Fig.3. The length of structuring element is decided based on experimentation. Fig. 6 shows the result of employing dilation operation on the logo-patches obtained from the proposed DT. These patches are called Region of Interests (RIs). For each RI we fix a minimum bounding box, which is then mapped on the original document image. These bounding boxes shown by red may be extended or tightened to have a finer minimum bounding box (green). The foreground information bounded by the minimum bounding boxes (shown by green) is considered for further process at the fine level of our scheme. The logo detection results obtained at the coarse level of our proposed scheme using different datasets are shown in Table II, III and IV.

D. Extraction of Shape Context Features and Classification

Shape context descriptor as a geometric invariant descriptor has been used for the recognition of logos, objects and patterns [7, 18]. The shape context at a reference point captures the distribution of the remaining points relative to that reference point and provides a globally discriminative characterization. In this research work, first the RIs are ranked based on the average of *FP*, *GP* and density features. So the RI with the highest rank in the ranked list of RIs has the priority for further process. Since, each document in the Tobacco-800 contains between 0 and 5 logos, five RIs are needed to be further processed in the fine-level of our proposed scheme. The shape context features are thus extracted for each RI to identify it as a logo or a non-logo at the fine level of the proposed logo detection scheme using a Nearest Neighbor classification with a Correlation distance metric. The logo detection results obtained at the fine-level of our proposed logo detection scheme using the Tobacco-800 dataset is shown in Table V.

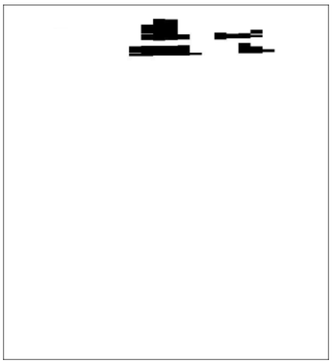


Fig.6. RIs obtained employing the dilation operation on the logo-patches extracted using the proposed DT.

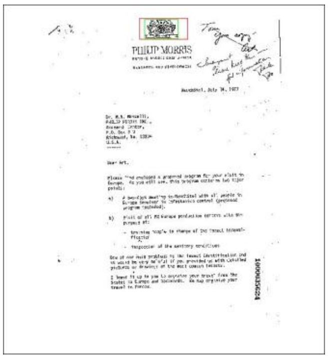


Fig.7. Mapping minimum bounding box on original document indicated by red and finer minimum bounding box (RIs) considered for identification indicated by green.

III. Experiments and Results

A. Dataset

For evaluation of the proposed scheme three different datasets are used. First dataset is the Tobacco-800, which contains 1292 documents of which 412 documents contain 432 logos [17]. Second dataset is the Itesoft1 used in [12]. This dataset composed of 3000 documents of which all of them contain between 1 and 6 logos. Number of classes of documents reported to be 204 [12]. Third dataset is the Itesoft2 dataset recently provided at Itesoft Company in collaboration with PolyTech Tours, France. This dataset is composed of 8200 real-life document images of which 5748 images contain between 1 and 8 logos. Number of classes of logos is 1274. Ground truths for both Itesoft datasets have been provided similar to the Tobacco-800 dataset.

B. Results and Discussion

Precision (Pre.) and Accuracy (Acc.) used in literature [6] are considered as evaluation metrics of the proposed scheme. To test the proposed scheme on the Tobacco-800 dataset [17], initially, 100 documents which contain logo(s) were used to train the *DT*, *FM* and *GP* parameters (μ_i, σ_i). The average density value of foreground pixels for logo and non-patches were also computed based on the ground truths.

During the learning phase of the *CS-C4.5 DT*, we found that the most relevant features used at the first and second stages of the proposed *DT* were the probability based features and the height of patch proposed in this research work. The logo detection results obtained from the proposed *DT* using the training set are shown in Table I. It may be noted that the costs matrix used for the *CS-C4.5 DT* compared to the standard *C4.5* significantly increased the Acc. of logo class.

Two different tests were conducted on the Tobacco-800 dataset. For the first test we considered only 412 documents which contain logos and for the second one the whole Tobacco-800 dataset (1292 documents) was used. The results obtained at the coarse level of our proposed scheme are tabulated in Table II. Furthermore, the results obtained from our proposed scheme on the Itesoft1 and Itesoft2 datasets are shown in Tables III and IV, respectively. To train the proposed scheme for experimentation on Itesoft datasets, only one instance per class of logos was used. The same procedure employed to conduct the experiment on tobacco-800 dataset was applied to obtain the results on both Itesoft datasets.

It is worth mentioning that the results (Pre. and Acc.) were calculated based on the extracted RIs (patches) from document images. This makes sense because in our proposed logo detection scheme, RIs need to be further processed for the final identification/recognition.

TABLE I. The logo detection results obtained from the training set of Tobacoo-800 [17] based on Extracted Patches

Classes	**Pre. (%)**	**Acc. (%)**
Non-Logo	99.12	94.18
Logo	33.35	94.18

TABLE II. The logo detection results obtained at the coarse level considering different number of RIs in each document of Tobacoo-800[17]

Dataset and Results / **Number of RIs chosen from the ranked list**	**Only 412 images containing logo(s)**		**All 1290 images**	
	Pre. (%)	***Acc. (%)***	***Pre. (%)***	***Acc. (%)***
Only 1 RI with the highest rank	**95.83**	**95.83**	**34.13**	**95.83**
The top 2 RIs	57.82	99.31	20.58	99.31
The top 3 RIs	45.61	99.77	16.22	99.77
The top 4 RIs	41.10	99.77	14.58	99.77
The top 5 RIs	**39.06**	**100**	**13.81**	**100**

TABLE III. The logo detection results obtained at the coarse level considering different number of RIs in each document of Itesoft1[12]

Dataset and Results / **Number of RIs chosen from the ranked list**	**All 3000 images of Itesoft1**	
	Pre. (%)	***Acc. (%)***
Only 1 RI with the highest rank	73.17	73.70
The top 2 RIs	51.51	82.99
The top 3 RIs	38.38	89.54
The top 4 RIs	30.63	93.95
The top 5 RIs	25.22	95.56
The top 6 RIs	**21.51**	**96.53**

TABLE IV. The logo detection results obtained at the coarse level considering different number of RIs in each document of Itesoft2

Dataset and Results / **Number of RIs chosen from the ranked list**	**Only 5748 images containing logo(s)**		**All 8200 images**	
	Pre. (%)	***Acc. (%)***	***Pre. (%)***	***Acc. (%)***
Only 1 RI with the highest rank	68.92	68.36	51.26	68.36
The top 2 RIs	47.70	84.43	35.12	84.43
The top 3 RIs	34.65	88.51	25.78	88.51
The top 4 RIs	27.70	90.49	20.76	90.49
The top 5 RIs	23.51	91.76	17.73	91.76
The top 6 RIs	20.78	92.55	15.76	92.55
The top 7 RIs	18.93	93.06	14.42	93.06
The top 8 RIs	**17.67**	**93.60**	**13.51**	**93.60**

TABLE V. The logo detection results obtained at coarse and fine levels of the proposed logo detection scheme on Tobacoo800 [17]

Dataset and Results / **Different Levels of our proposed scheme**	**Only 412 images containing logo(s)**		**All 1290 images**	
	Pre. (%)	***Acc. (%)***	***Pre. (%)***	***Acc. (%)***
Coarse level (DT)	39.06	100	34.13	95.83
Fine level (Shape context)	100	94.17	75.25	91.50

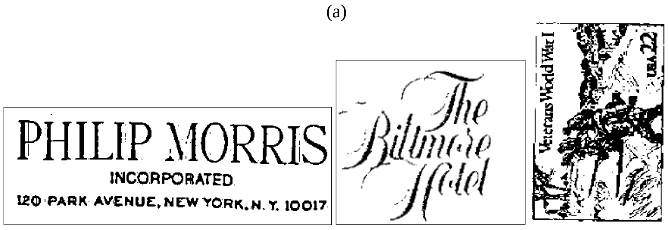
From the results presented in Tables II, III and IV, it can be noted that on an average almost 3, 5 and 6 RIs is necessary to be further processed for identification/recognition of logo/logos in a document of Tobacco-800, Itesoft1, and Itesoft2, respectively. This is quite practical, as the maximum number of logos in Tobacco-800, Itesoft1 and Itesoft2 datasets are 5, 6 and 8 respectively. Furthermore, an accuracy of 95.83% was obtained where documents containing logo(s) of Tobacco-800 were considered for experimentation. The accuracies in all three datasets remain as good as 100% or close to 100%. The results obtained based on experimentation on Itesoft datasets indicate that the proposed scheme could fairly detect/localize logos in such large and complicated datasets.

From the results demonstrated in Table V, it is evident that encouraging accuracies for logo detection are obtained from the proposed logo detection scheme on Tobacco-800 dataset. It is worth mentioning that the proposed scheme for logo detection provides fairly accurate RIs (patches) that a simple identification/recognition technique can significantly improve the results especially precision accuracy. Since, the main contribution in this research work is extraction of accurate RIs for logo detection, only Tobacco-800 dataset was used to provide results at the fine level.

C. Erroneous Samples

Some errors happened during our experiment on Tobacco-800 dataset are shown in Fig.8. From the experiments we noted that most of the errors resulted in because some documents were very poor quality, noisy and skewed (Fig.8(a)). Some false alarms occurred in the experimentation are shown in Fig.8(b). These detected regions are look like logos and our proposed logo detection scheme could successfully localize them. Based on the experimentations on Itesoft datasets, most of the errors occurred because logos were very small in size and they were mainly composed of only very small font textual information.

(a)



(b)

Fig.8. Examples of (a) Misidentified logos and (b) Incorrectly detected logos occurred in our experiment. Results shown in (b) are considered as false alarms.

D. Comparative Results

It may be noted that most of the methods in literature have been tested on the Tobacco-800 dataset [17]. To have a comparison between the results obtained in our experimentation and the results of state-of-the-art logo detection/recognition techniques, we noted the performances of some existing works in literature (Table VI). The highest accuracy of 86.5% and the best precision of 99.4% have been obtained from [3]. From Table VI, it is evident that our logo detection scheme provided better logo detection/ identification results compared to the results reported in the literature.

IV. CONCLUSIONS AND FUTURE WORK

In this paper a logo detection scheme based on the PPA is proposed. A small feature set composed of mainly probability and geometric based features is introduced to obtain a few regions of interests as logo regions which further are verified based on a finer classification. Experimentations on different datasets demonstrate that the proposed scheme can efficiently deal with different documents. Moreover, in our scheme, we have not used any kind of preprocessing techniques such as skew detection/correction, noise reduction and cropping. Using such preprocessing techniques may improve the final logo detection/identification accuracy.

In future, we plan to find more suitable features and classifier which may be directly employed on the extracted RIs to achieve more accurate logo recognition/detection results.

TABLE VI. COMPARATIVE ANALYSIS OF THE RESULTS OBTAINED FROM DIFFERENT TECHNIQUES IN THE LITERATURE ON TOBACCO-800 DATASET

Dataset and Results / **Methods**	**Only 412 images containing logo(s)**		**All 1290 images**	
	Pre. (%)	***Acc. (%)***	***Pre. (%)***	***Acc. (%)***
Li et al. [3]	-	-	99.40	86.50
Zhu & Doermann [6]	-	-	73.50	84.20
Pham et al. [4]	92.98	90.05	44.00	91.00
Zhu & Doermann [7]	82.60	78.50	-	-
Wang & Chen [11]	93.30	80.40	-	-
Wang [13]	94.70	92.90	-	-
Our proposed scheme	**100**	**94.17**	**75.25**	**91.50**

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