Learning To Binarize Document Images

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Abstract

Document images produced by cameras often have varying degrees of brightness. To resolve the problem, we propose a method that divides an image into several regions and decides what binarization action to take on each region based on the rules that are derived from a learning process. Since each region can allow more than one action to take, we are dealing with a multi-label and multi-class classification problem that can be solved effectively by support vector machines. Tests on images produced under normal and inadequate illumination conditions show that our method yields better OCR performance than three global binarization methods and four locally adaptive binarization methods.

1. Introduction

Binarizing images of documents captured with camera presents a new challenge, because such images are produced under illumination conditions that are inferior to those found in a scanning environment. As a result, there are varying degrees of brightness over the images. If we simply apply a global threshold, as we do with scanned images, the binarized results could be too bright in one area and too dark in another area. A more effective way of binarizing such images is therefore desired.

Various binarization methods have been proposed before. Following Sezgin and Sankur [1], we classify them into six categories: (i) histogram-based methods (Sezan [2], Rosenfeld and Torre[3], Pavlidis [4]); (ii) clustering-based methods (Otsu [5], Kittler and Illingworth [6]); (iii) entropy-based methods (Kapur et al. [7]); (iv) object attribute-based methods (Hertz and Schafer [8], Huang and Wang [9]); (v) spatial binarization methods (Abutableb [10]); and (vi) locally adaptive methods (Bernsen [11], Niblack [12], Taxt et al. [13], Eikvil et al. [14], Mardia and Hainsworth [15], Chow and Kaneko [16], Nakagawa and Rosenfeld [17], White and Rohrer [18], Yasuda [19], Sauvola and Pietikäinen [20], Sauvola et al. [21], Kim [22], Trier and Taxt [23], Parker [24], Yanowitz and Bruckstein [25], Kamel and Zhao [26], Yang and Yan [27], Ye et al. [28]).

If a binarization method computes a threshold for an entire image, it is called *a global method*. Trier and Taxt [29] evaluated four such methods ([5-7] and [10]) and concluded that Otsu's approach [5] outperforms the other three. On the other hand, if a method computes a threshold for the neighborhood around each pixel or for each designated block in the image, it is called a *local method*. Trier and Jain [30] evaluated these methods ([11-16], [18], and [23-25]) and concluded that those proposed by Bernsen [11], Niblack [12] and Eikvil et al. [14] are the top-ranked local threshold methods in terms of the error rate and rejection rate for character recognition, and also for the visual criterion. More complete surveys of image thresholding techniques can be found in [1] and [29-35].

As noted earlier, using cameras to produce document images creates a new challenge for document image binarization. To address the problem, Park et al. [36] proposed block adaptive binarization of business card images produced by a PDA camera. This method is very similar to that of Eikvil et al. [14], which partitions an input image into blocks. For a given block, b, a larger concentric block, denoted as $L(b)$, is found and Otsu's method is applied to it. If the difference between the means of two classes, determined by Otsu's method, exceeds a certain threshold, block b is classified as a content block; otherwise, it is classified as a background block. Content blocks are binarized according to Otsu's thresholds, while background blocks are set directly to white or black based on the average of gray values found in them. The method in [36] differs from that of [14] in the way content blocks are differentiated from background blocks, and also in the way the sizes of b and $L(b)$ are set.

Our method also divides a document image into smaller areas, but differs from the methods proposed in [14] and [36] in a number of respects. For example, instead of dividing an image into fixed-size blocks, we divide it into $k \times k$ regions, using the value of k obtained in experiments. Dividing each image into the same number of regions ensures that the binarization effect is relatively invariant with respect to the resolution of the camera. Within each region r, one of the following four actions is applied: set the whole of r to black, set the whole of r to white, use Otsu's method to compute the threshold for r, or use the smallest Otsu threshold in the neighboring regions as the threshold for r. A learning process is used to establish the rules for deciding which of the above actions should be adopted for each region. The rules are expressed as decision functions, which take a number of features extracted from r as input. The experiment results demonstrate that the above factors have a significant impact on the successful performance of our method.

The crucial step in our approach is establishing rules to decide which action should be applied to each sub-divided region. To do this, we utilize support vector machine (SVM) method [37-38]. Two innovations of SVM are responsible for its success: (1) the ability to find a hyperplane that divides samples into two groups with the widest margin between them; and (2) the extension of the concept in (1) to a higher-dimensional setting using a kernel function to represent a similarity measure on that setting. Both innovations can be formulated in a quadratic programming framework whose optimal solution is obtained in a reasonable amount of time. This makes SVM a practical and effective solution for many pattern classification problems. In this paper, we divide training images into a number of regions and label the appropriate actions for them, after which we commence the SVM learning process and construct the decision functions. Since the total number of regions is relatively small, compared to the alternative approach in which pixels are labeled, it is relatively easy for humans to label the regions using a graphic-user interface. The proposed binarization method thus constitutes an interesting application of the SVM approach in the area of image analysis.

The remainder of the paper is organized as follows. In Section 2, the proposed binarization method is introduced. In Section 3, we discuss the learning algorithm. Section 4 details the experiment results. Then, in Section 5, we present our conclusions.

2. The Proposed Binarization Method

As our approach involves the computation of thresholds using Otsu's method, we begin by giving a brief summary of that method. Given a gray-scale image, Otsu's method sets a threshold as the gray value v that attains the maximum variance between the class of pixels whose gray values are below v and the class of pixels whose gray values are above v.

When the background and foreground intensities are well separated, Otsu's method yields good binarized results. However, if the image intensities are inseparable, the resulting threshold value is unsuitable. Figure 1a shows a document image taken by a camera. From the histogram of the image, shown in Figure 1b, we observe that the gray scales associated with the foreground pixels are mixed with those associated with the background pixels; thus, it is difficult to determine a good threshold value for binarization. In fact, when applying Otsu's method, we find that the threshold value is 185, causing part of the image to become blurred. Clearly a different binarization solution is required.

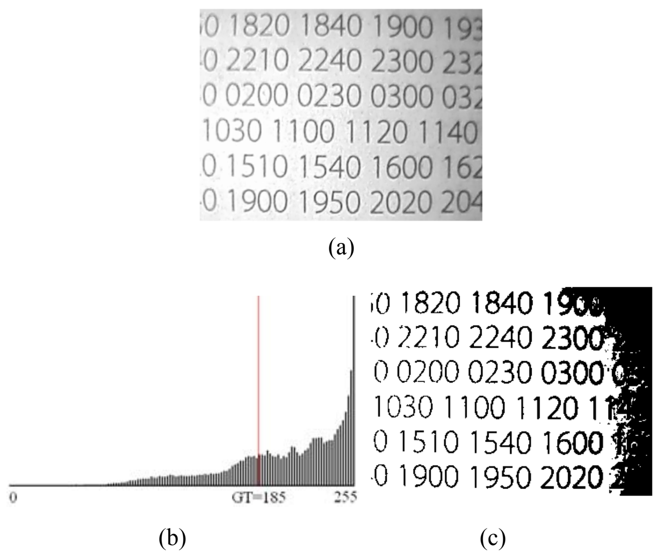


Figure 1. (a) A document image obtained by a camera under the inadequate illumination condition. (b) The histogram of (a). (c) The document image binarized using Otsu's method.

An immediate solution is to divide an image into several regions and apply a thresholding method to each region separately. However, the image should not be divided according to the layout structure of the document, since the whole image (shown in Figure 1a) falls within the same text region of the layout structure, while the brightness varies extensively over the region. Instead, we divide the image into equal-sized regions. For example, we divide the image in Figure 2a into

3×3 regions and apply Otsu's method to obtain a local threshold (LT) for each region. The Otsu thresholds usually vary according to the regions. For example, in Figure 2b, the thresholds are 204 over region A and 156 over region B. The resulting binarized image, shown in Figure 2b, is more satisfactory than the result shown in Figure 1c.

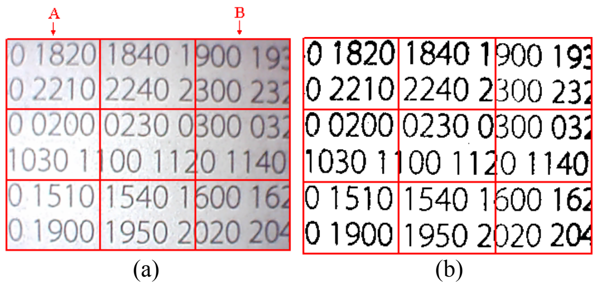


Figure 2. (a) A raw image partitioned into 3×3 regions. (b) The binarized image using Otsu's method to find the local threshold for each region.

Even so, using Otsu threshold as a local threshold can yield poor results for regions containing background pixels only. For example, region C in Figure 3a would be improperly binarized, as shown in Figure 3b, if the Otsu threshold (= 162) were employed as the LT. In fact, setting the LT to 0 would yield a satisfactory result, as shown in Figure 3c. A reasonable condition for setting the LT to 0 is to take reference of μ and σ, which are the mean and variance of C's gray values respectively. When the σ value is high, there is good mixture of black and white pixels, so we can use the Otsu threshold as the LT. On the other hand, when the σ value is low, we can set the LT to 0, provided the μ value is high. Figure 3 is an example of the latter case, where the σ value of region C (= 9.3) is low. Thus, it is reasonable to set the LT of C to 0, since its μ value is 158 – a rather high value.

If the σ and μ values of a region are both low, it is reasonable to set the LT to 255. Figure 4a provides such an example, in which the σ values of regions D, E, and F (= 7.1, 5.1, 4.6, respectively) are low and their μ values (= 34, 32, 29, respectively) are also low, since these regions are parts of a figure. Using Otsu's threshold as the LT would turn some of the pixels white, as shown in Figure 4b. Instead, 255 could be a better LT, as shown in Figure 4c.

In Figure 5a, region G is filled largely with white pixels, and some neighboring regions are also dominated by white pixels. In this case, using Otsu's threshold (= 161) as the LT would turn many white pixels black, as shown in Figure 5b. Instead, the lowest neighboring Otsu threshold (= 106) serves as a better LT. Here, the minimum value is obtained from region H, which has a good mixture of black and white pixels, as shown in Figure 5c.

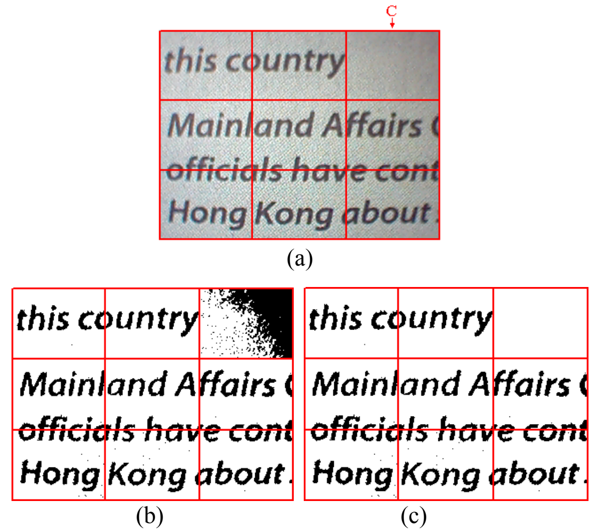


Figure 3. (a) An original gray-scale image. (b) The image binarized using Otsu's method to find a local threshold for each region. (c) The local threshold is set to 0 for region C.

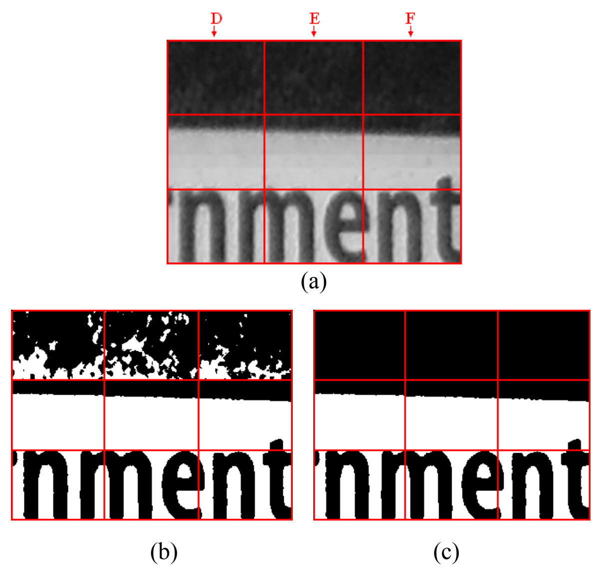
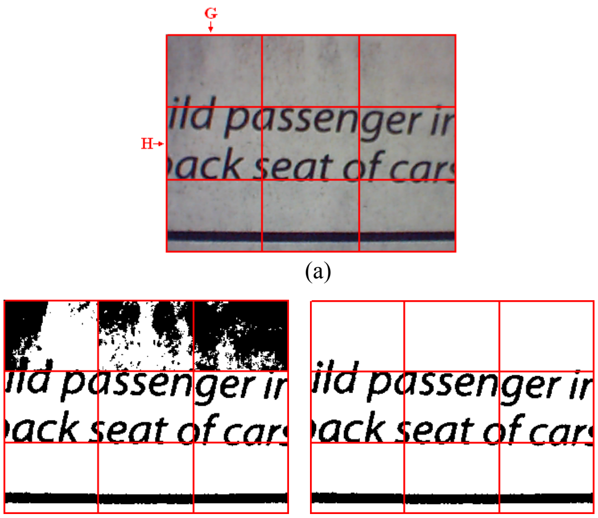


Figure 4. (a) An original gray-scale image. (b) The image binarized using Otsu's method to find a local threshold for each region. (c) The local thresholds for regions D, E, and F are set to 255.



(a) (b) (c)

Figure 5. (a) An original gray-scale image. (b) The image binarized using Otsu's method to find a local threshold for each region. (c) The local threshold is set to the minimum of the neighboring thresholds for region G.

The above examples show that there are four possible actions we can take for each region r, namely: set the LT of r to 0, 255, $T_{Otsu}(r)$, or $T_{min}(r)$, where $T_{Otsu}(r)$ is the Otsu threshold for r, and

$$T_{min}(r) = \min\left\{T_{Otsu}(r), \min_{s\in\Lambda(r)} T_{Otsu}(s)\right\},$$

where $\Lambda(r)$ is the set of neighboring regions of r. The following features help determine which action would be appropriate for each region: $T_{Otsu}(r) - T_{min}(r)$, $\mu(r)$, and $\sigma(r)$; the last two terms are, respectively, the mean and the standard deviation of the distribution of gray-values in r.

In summary, we extract the following features from each region r:

Feature 1: $T_{Otsu}(r)$-$T_{min}(r)$;

Feature 2: $\mu(r)$;

Feature 3: $\sigma(r)$.

From these features, we must decide which of the following actions would be the most appropriate for binarizing region r:

Action 1: set LT = 0;

Action 2: set LT = 255;

Action 3: set LT = $T_{Otsu}(r)$;

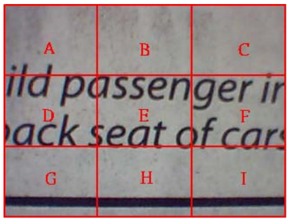
Action 4: set LT = $T_{min}(r)$.

3. Constructing Adaptive Binarization Rules Using Support Vector Machines

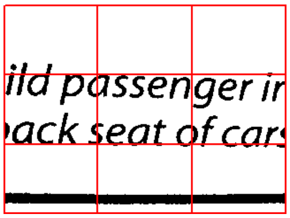
Having specified the three features, we use the SVM method to determine which binarization action to take for each region. SVM provides a learning algorithm that constructs decision functions from training data. SVM is especially effective for binary classification problems in which an object is assigned one of two labels. In such cases, a decision function assumes only two values, which are the same as the two labels in question. It is thus called a binary decision function. Assuming that the two labels are –1 and 1, a binary decision function f works in such a way that if $f(\mathbf{x}) \geqq 0$, $\mathbf{x}$ is assigned label 1; otherwise, it is assigned label –1.

To apply SVM to the binarization problem, we must first map the problem to the SVM setting. We do this by dividing each image into $k\times k$ regions, which constitute our training samples. How to find an appropriate value of k is considered in Section 4.2. From each region r, we extract the three features, $T_{Otsu}(r)$-$T_{min}(r)$, $\mu(r)$, and $\sigma(r)$, to form a 3-dimensional feature vector; thus, the dimension of our Euclidean space is fixed at 3. The four actions are then taken as four labels so that if an action y is deemed appropriate for r, the latter is assigned the label y.

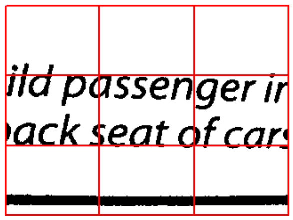
Two other problems must also be addressed. First, for certain regions, there may be more than one appropriate binarization action. We can observe this problem by examining the image in Figure 6a, which is divided into 9 regions from A to I. Among the regions, A and C carry a single label, T_{min}, D to I carry labels T_{Otsu} and T_{min}, and B carries 0 and T_{min}. To demonstrate that multiple labels are reasonable for some of these regions, in Figure 6b, we show the binarized result using a common threshold T_{min} as the LT of each region. Meanwhile, Figure 6c shows the binarized result using the alternative threshold to T_{min} as the LT of those regions for which two options are allowed. Both binarized results are acceptable. Thus, when preparing training data for the learning process, we allow multiple labels to associate with the training samples. We find that, among the 1,098 regions obtained in our data set, 352 regions carry a single label and the remaining 746 regions carry multiple labels. A similar situation can be found in text categorization (Joachims [39], Schapire and Singer [40]) or scene classification (Moutell [41]). For example, a news article can belong to two categories, such as *earn* and *trade* in the Ruthers-21578 dataset (see [39-40]).



(a)



(b)



(c)

Figure 6. (a) An original gray-scale image. (b) The image binarized using $T_{\min}$ as the LT of all regions. (c) The image binarized using the alternative to $T_{\min}$ as the LT of those regions for which two options are allowed.

In addition to the multi-label problem, we also need to deal with the multi-class problem. That is, there are four labels or class types in our application, but SVM can only deal with two class types at a time. To resolve these two problems we follow the solution proposed in [39] by using SVM to construct as many decision functions as there are labels (see also Bottou [42]). Therefore, assuming that the four labels in our application are {1, 2, 3, 4}, we use SVM to construct four binary decision functions $\{f_1, f_2, f_3, f_4\}$.

To construct f_i for i = 1, 2, 3, 4 in the training phase, we divide the training samples into two groups. The first group, called the positive group, consists of samples with label i, and the second group, called the negative group, consists of samples without label i. Thus, if a sample carries labels j and k, it will be assigned to the positive group associated with f_j and the positive group with f_k, but not to the negative group associated with f_j or f_k. In the testing phase, when a test sample $\mathbf{x}$ is given, we compute $f_i(\mathbf{x})$ for i = 1, 2, 3, 4 and assign label l to $\mathbf{x}$ when

$$l = \arg\max_{i=1,2,3,4} f_i(\mathbf{x}) .$$

4. Experiment Results

In this section, we discuss how to prepare training data, how to divide document images, and how to use SVMs for deriving decision functions. Furthermore, we compare the results obtained by our method with three global methods and four locally adaptive methods. We use OCR performance as the performance criterion in this paper. For the comparisons using image quality as the criterion, we refer the readers to Chou et al. [43].

4.1. Data Preparation

We collected 122 hardcopy documents from newspapers and magazines, and used an ORITE I-CAM 1300 one-chip color camera, with a resolution of 1,300,000 pixels, to photograph them. We then stored the photographs as gray-scale images consisting of 320×240 pixels. The images were produced under two conditions: the normal illumination condition and the inadequate illumination condition. In the former, the room light was on and there were no obstructions between the light and the documents, resulting in more or less uniform brightness across the images. In the latter, although the room light was on, humans or objects cast shadows over the documents, so that the shadowy area appears darker than the rest of the image. In total, 60 images were produced under normal illumination and 62 were produced under inadequate illumination.

We use three measures to evaluate a given binarization method's performance on the 122 camera images. Let A = the number of characters in the 122 camera images (there are actually 3,559 characters); B = the number of characters detected by ABBYY, an OCR software system; and C = the number of characters correctly recognized by ABBYY. The three measures, expressed in percentages, are (i) recall rate = C/A; (ii) precision rate = C/B; and (iii) F_1 score, derived by the following formula [44-45]

$$F_\beta = \frac{(\beta^2+1)\times \text{recall rate} \times \text{precision rate}}{\beta^2 \times (\text{recall rate} + \text{precision rate})},$$

where β is set to 1.

4.2. Determining the Number of Regions

We divide each image into k×k regions and apply our binarization method to each region. We then apply a simple binarization scheme to evaluate the binarized results for each k. This binarization scheme is used to determine the best value of k, and is not taken as our final solution. It is given as follows.

For a given region r, if $\sigma(r)$ is larger than a specified threshold σ_0 (we set σ_0 =15), we set LT = $T_{\text{Otsu}}(r)$; otherwise, we classify the entire r as white if $\mu(r) > \mu_0$, or black if $\mu(r) \leqq \mu_0$, where μ_0 is 128 (= 256/2). Having binarized all 122 images by means of this simple scheme, we apply ABBYY to the binarized images. We use the recall rate, precision rate, and F_1 score to evaluate the OCR results. All three measures suggest that dividing an image into 3×3 regions produces the best results.

Having determined that $k = 3$ is the most appropriate value, we fetch the regions derived by the 3×3 division of all 122 images. There are 1,098 such regions, each comprised of 107×80 pixels. These regions constitute our training samples.

4.3. Constructing Decision Functions with SVM

As stated in Section 3, SVM is employed to construct the decision functions. In addition, we use the LIBSVM toolkit [46] to conduct SVM training. We need to perform four SVM training operations, each of which divides training samples into two groups: one group consists of all samples with label i, and the other consists of all samples without label i for $i = 1, 2, 3, 4$. We employ the soft-margin version of SVM (see [39] and [48]) and the RBF kernel function. The value range of the penalty factor C is set to $\{10^a: a = -1, 0, \ldots, 5\}$. The RBF function involves a parameter γ, whose value range is set to $\{10^b: b = -8, -7, \ldots, 0\}$. To find the best values for (C, γ), we perform a cross validation operation whereby all samples employed in the experiment are partitioned into five folds. We conduct five tasks, using four folds in each task as training data to construct SVM classifiers and the remaining fold as validation data. We then select the values of (C, γ) that maximize the average accuracy rates in the five tasks. By so doing, we find the optimal (C, γ) to be (10, 0.1), resulting in a 98.57% average validation accuracy rate.

4.4. Comparisons with Other Binarization Methods

In order to make comparisons, we implemented seven other binarization methods. Three of them are global threshold methods proposed by Rosenfeld and Torre [3], Pavlidis [4], and Otsu [5] respectively; the other four are locally adaptive methods proposed by Bernsen [11], Niblack [12], Taxt et al. [13], and Eikvil et al. [14] respectively. For the parameters involved in the three locally adaptive methods, we adopted the values suggested in [30]. We would have liked to implement the method proposed by Park et al. [36], as it had been explicitly applied to camera images. However, we were not given the values of parameters for this method. We therefore implemented Eikvil et al.'s method instead, because there is a high degree of similarity between the two methods.

To determine the impact of the different binarization methods on character recognition, we fed all the binarized results into the ABBYY software. Table 1 shows the OCR performance on (i) images produced under a normal illumination condition, (ii) images produced under the inadequate illumination condition, and (iii) all images. The boldface figures in the table indicate the best performances.

Based on the above results, we conclude that our method outperforms the other methods by substantial margins. It also produces satisfactory binarized results for camera images taken under both normal and inadequate illumination conditions.

5. Conclusion

Document images with non-uniform brightness require binarization methods with delicate local thresholds that must be determined according to various conditions. For this purpose, we propose a region-based binarization method. We use the SVM method to construct decision functions from the information provided by training samples and use these rules to decide what binarization action to take for each region. The experiments produce favorable results, judged in terms of the OCR performance.

Table 1. OCR performance of the eight binarization methods.

Binarization Method		Ours	Otsu's	Bernsen's	Niblack's	Eikvil et al.'s	Rosenfeld and Torre's	Pavlidis's	Taxt et al.'s
Images Produced under the Normal Illumination Condition	Recall	**97.40**	94.00	87.50	77.21	91.54	82.13	82.58	88.45
	Precision	**97.08**	94.60	37.14	42.04	89.23	90.41	84.17	51.56
	F_1	**97.24**	94.50	53.12	54.44	90.37	86.07	83.37	65.15
Images Produced under the Inadequate Illumination Condition	Recall	**96.84**	84.61	85.31	85.72	89.06	57.62	78.03	89.62
	Precision	**96.68**	93.10	44.61	42.53	78.95	92.15	79.47	60.67
	F_1	**96.76**	88.64	58.58	56.85	83.70	70.90	78.74	72.36
All Images	Recall	**97.12**	89.31	86.41	81.47	90.30	69.88	80.31	89.04
	Precision	**96.88**	93.85	41.38	42.29	84.09	91.28	81.82	56.12
	F_1	**97.00**	91.52	55.96	55.67	87.04	79.16	81.06	68.84

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