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Handwritten Devanagari characters recognition using correlation of gradients in local neighbors

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Abstract: The field of Handwritten Devanagari Character Recognition (HDCR) is drawing increasing attention in last few years. This manuscript is focus on the new feature extraction algorithm Correlation of Gradients in Local Neighbors (CGLN) for the handwritten character recognition (HCR) problem. Histogram of Oriented Gradient (HOG) and Scale Invariant Feature Transform (SIFT) are already used in this (HCR) field except CGLN which produced good results than HOG and SIFT for object detection problem like human in images, pedestrian detection and image patch matching. Correlation of Gradients in Local Neighbors algorithm extracts good directional and curvature features than a normal standard histogram based gradient methods. This algorithm is tested on two Devanagari handwritten databases, ISIDCHAR and V2DMDCHAR. The images of databases are also normalized with and without preserving aspect ratio. Using CGLN method and SVM classifier, the best results obtained that justified the efficiency of CGLN algorithm for handwritten character recognition problem. 96.03 % and 95.38 % recognition accuracy have been achieved on V2DMDCHAR and ISIDCHAR databases respectively.

Key words: Devanagari, Correlation of Gradients in Local Neighbors, Handwritten character recognition

1. Introduction

Optical Character Recognition is an essential part of any document image recognition system in which handwritten character recognition is very vital task. The several factors influence the recognition rate like poor quality of character/document, typical writing style of different writers, similar shape characters etc. that makes feature extraction process tedious. In recent years, handwritten character recognition has discovered numerous methods for feature extraction in which gradient is most popular and famous. Many researchers have also given many techniques to evaluate direction features from the gradient image (Umapada et al., 2007; Goyal et al., 2010; Kumar, 2009). The character recognition problem may be treated as object detection problem except that there are different objects in the form of characters. The methods are used for object detection can also be utilized for handwritten character recognition like HOG, SIFT, gradient etc. In this paper, CGLN (Correlation of Gradients in Local Neighbors), which basically developed for object detection like human in images, pedestrian detection and image patch matching, is used for handwritten Devanagari character recognition. The Development of an HDCR (Handwritten Devanagari character recognition) system is studied by many researchers with different techniques a comprehensive survey can be found in (Pal and Chaudhuri, 2004; Jayadevan et al., 2011).

Devanagari is one of the ancient scripts, which is used to write Hindi, Sanskrit, Marathi etc. languages. Hindi is an official language of India and it is the third most popular language in the world. It consists of 14 vowels and 33 consonants. The shape of handwritten Devanagari characters is shown in Fig. 1. It is written from left to right, has a strong preference for symmetrical rounded shapes within squared outlines, and is recognizable by a horizontal line that runs along the top of full letters. In a cursory look, the Devanagari script appears different from other Indic scripts such as Bangla, Oriya or Gurumukhi. There is a great need of feature extraction technique that should be good to find the curvature feature along with direction feature. CGLN method is extract the features that utilizes 2nd order statistics, i.e., spatial and orientational correlations of local gradients. It enables us to extract richer information from images and to obtain more discriminative power than standard gradient histogram based methods. The image gradients are sparsely described in terms of magnitude and orientation. This method extracts information about not only the gradients but also the curvatures of the image surface.

To promote research work on Devanagari Script, some Handwritten Devanagari Character databases have been provided by (Bhattacharya and Chaudhuri, 2005; Dongre et al., 2012) these databases are named as ISIDCHAR and V2DMDCHAR respectively. Sample images of ISIDCHAR database

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are gray-scaled with 256 levels and V2DMDCHAR database is preprocessed binary images. CGLN method is free from image normalization process but in character recognition, the image normalization has to perform to reduce the intra-class variation. A non-linear with aspect-ratio preserving and without aspect-ratio preserving normalization is done on whole samples before extract the features.

The intensive work has done in recent years, on development of HDCR system. From the 1977, the researchers are working on Devanagari character recognition system. The work is still going to solve the challenges of printed and handwritten character recognition.

The contour points are used to compute the Chain-code histograms features by Sharma et al. (Sharma et al., 2006) for HDCR. These features are calculated in each block, those are created by the segmentation of a character image. They have found 64-Direction features for characters recognition. They suggested a quadratic classifier scheme and obtained 80.36 % accuracy with the 11270 samples. A thickening process by thinning and pruning operation is suggested by (Arora et al., 2007) to remove distortions in Devanagari hand-written character. Then a differential distance based technique is used to detect spine and shirorekha in Devanagari hand-written character. 89.12 % recognition accuracy has obtained by 50000 samples.

Regular expressions (RE) are utilized by P. S. Deshpande et al. (2008) in HDCR, where a handwritten character is converted into an encoded string created by chain-code features. At that point, Regular expressions of stored templates are matched with it and rejected samples are sent to a minimum edit distance classifier for recognition character. 82 % recognition accuracy has stated on 5000 samples. In paper (Kumar, 2009), there are five feature-extraction methods on handwritten characters are compared. A number of features included are Gradient, Kirsch directional edges, Chain code, Distance transform, and Directional distance distribution. From the conducting tests, it is found that Gradient method with SVM classifier outperformed than others and Kirsch directional edge performed least. Gradient and Directional distance distribution are performed almost same with MLP classifier and the chain-code-based feature is better than Kirsch directional edges and Distance transform. A new gradient direction feature is also proposed by author in which the gradient is quantized into four directional levels and each gradient map is divided into 4 × 4 regions. This is combined with total distances in four directions and neighborhood pixels weight.

In Hanmandlu et al. (2007), the recognition depends on the modified exponential membership function fitted to the fuzzy sets. A reuse policy is use to improve the speed of the learning process and gained 90.65 % recognition accuracy. The features used for handwritten Devanagari characters recognition by Pal et al. (Pal et al., 2007; 2008) are gradient directional information obtained from the arc tangent and Gaussian filter. A combined use of SVM and MQDF is applied for the classification. Another paper of Pal et al. (2009) is also presented 12 different classifiers and four sets of features. Features used are computed based on curvature and gradient information gained from binary as well as gray-scale images. In literature, many techniques have used for HDCR system but still there are many challenges to evaluate (Figs. 2 and 3).

Fig. 1: Samples of printed and handwritten Devanagari characters (a) Vowels and (b) Consonants (c) Addition consonants in V2DMDCHAR database

Fig. 2: Samples of ISIDCHAR database

Fig. 3: Samples of V2DMDCHAR database

2. Databases

The samples of printed and handwritten Devanagari characters (vowels and consonants) are shown in Fig. 1 (a) and (b). The Fig. 1 (c) is shown addition characters those are included by V2DMDCHAR database. Correlation of Gradients in Local Neighbors method has been experimented on two databases: ISI Devanagari characters (ISIDCHAR) database (Pal et al., 2008), and Vikas J. *D*ongre and Vijay H. Mankar's (Dongre et al., 2012) characters (V2DMDCHAR) database.

The ISIDCHAR database has 36172 character samples. It has not divided into training and testing samples. This database has 47 classes with variable size per class. The database is in gray-scaled images with noisy background and some isolated noisy objects. The foreground information of image is in varying gray-level. The samples of ISIDCHAR are shown in Fig. 2.

V2DMDCHAR has 20305 character samples in total. The character database has 50 classes with variable size per class. The database has already pre-processed like gray to binary conversion, removal of isolated objects. The background represented in white and foreground in black. Some samples are shown in Fig. 3 (Table 1).

Table 1: Number of train and test samples in each class of ISIDCHAR database

Symbol	Class	Train	Test	Symbol	Class	Train	Test	Symbol	Class	Train	Test
अ	1	552	237	ग	17	548	235	ध	33	476	205
आ	2	546	235	घ	18	604	260	न	34	546	234
इ	3	548	236	ड़	19	546	235	प	35	564	242
ई	4	546	235	च	20	548	235	फ	36	543	234
उ	5	550	237	छ	21	544	234	ब	37	473	203
ऊ	6	550	236	ज	22	548	236	भ	38	534	230
ए	7	542	233	झ	23	537	231	म	39	548	235
ऐ	8	550	236	ञ	24	542	233	य	40	548	236
ओ	9	541	233	ट	25	550	237	र	41	543	234
औ	10	546	234	ठ	26	546	234	ल	42	545	234
अं	11	546	234	ड	27	539	232	व	43	602	258
अः	12	543	233	ढ	28	533	229	श	44	545	234
अँ	13	387	166	ण	29	547	235	ष	45	499	215
ऋ	14	496	213	त	30	546	235	स	46	536	230
क	15	548	236	थ	31	517	222	ह	47	529	227
ख	16	550	237	द	32	532	228			25299	10873

3. Correlation of gradients in local neighbors

Correlation of Gradients in Local Neighbors (CGLN) is proposed by Otsu et al. (2008) for the object detection. This method can be considered as a further extension of HOG and SIFT, which deal with 1st order statistics (Histograms). CGLN deals with 2nd order statistics (correlations) which means correlations with neighbor's pixels. Image gradients, in CGLN, are sporadically described in terms of their magnitudes and orientations (Fig. 4).

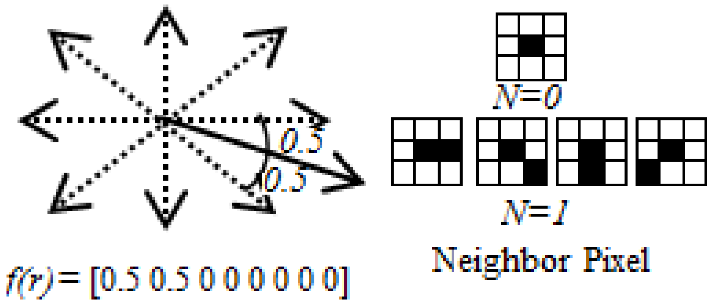

Fig. 4: Gradient vector formation and mark patterns for correlation of gradients in local neighbors

Table 2:- Number of train and test samples in each class of V2DMDCHAR database

Symbol	Class	Train	Test	Symbol	Class	Train	Test	Symbol	Class	Train	Test
अ	1	614	264	ङ	18	47	21	फ	35	301	130
आ	2	332	143	च	19	300	129	ब	36	272	117
इ	3	347	149	छ	20	305	131	भ	37	286	123
ई	4	338	146	ज	21	303	131	म	38	290	125
उ	5	378	162	झ	22	287	123	य	39	310	134
ऊ	6	319	138	ञ	23	121	53	र	40	305	132
ए	7	355	153	ट	24	329	141	ल	41	294	127
ऐ	8	331	143	ठ	25	288	124	व	42	326	141
ओ	9	312	135	ड	26	365	157	श	43	240	104
औ	10	307	132	ढ	27	283	122	ष	44	312	135
अं	11	136	59	ण	28	293	126	स	45	266	114
अ:	12	64	28	त	29	291	126	ह	46	298	128
ऋ	13	11	6	थ	30	296	128	ळ	47	205	88
क	14	347	150	द	31	303	130	क्ष	48	249	107
ख	15	320	138	ध	32	294	127	त्र	49	78	34
ग	16	308	133	न	33	305	132	ज्ञ	50	273	117
घ	17	338	146	प	34	315	136			14187	6118

For better explanation of Correlation of Gradients in Local Neighbors, assume an image *I(x,y)*. The image gradient $(\partial I/\partial x, \partial I/\partial y)$ can be obtained at each pixel of the image onwards then compute image magnitude $M = \sqrt{(\partial I/\partial x)^2, (\partial I/\partial y)^2}$ and the orientation angle $\theta = \arctan\ (\partial I/\partial x, \partial I/\partial y)$. Image Gradient can be gained by different operators: - Roberts, Sobel, kirsh and more. The image gradient is gained using Roberts operator as:

$$\partial I/\partial x = I(x+1, y+1) - I(x,y),$$
$$\partial I/\partial y = I(x+1, y) - I(x, y+1),$$

The gradient orientation vector (GO Vector) ***f*** is gained using orientation angle θ by coding it into D orientation bins as shown in Fig 4. The Nth order correlation function of gradients in local neighbors is defined as:

$$R(D_0,\dots, D_N, a_{1,}\dots a_N) = \int_I w[M(r), M(r+a_1),\dots, M(r+a_N)]\, fd_0(r)\, fd_1(r+a_1)\dots fd_N(r+a_N)\, dr$$

Where a_i is displacement vectors from the reference point r, f_d is the d-th element of f and *w* is a scalar weighing function, e.g min. The Displacement vectors are computed with local neighbors because they are highly correlated. Above equation have many free parameters N, a_i and weight *w*, by which it can take many forms. In our experiments, the values of free parameters are as $N \in \{0,1\}$, $a_{1x,y} \in \{\pm \nabla r, 0\}$ and $w(.) \Rightarrow \min(.)$. The practical formulation of Correlation of Gradients in Local Neighbors (CGLN) is given by (Fig. 4):

0th order
$$R_{N=0}(d_0) = \sum_{r \in I} n(r) f_{d0}(r)$$

1st order
$$R_{N=0}(d_0, d_1, a_1) = \sum_{r \in I} \min\ [n(r), n(r+a_1)] f_{d0}(r) f_{d1}(r+a_1)$$

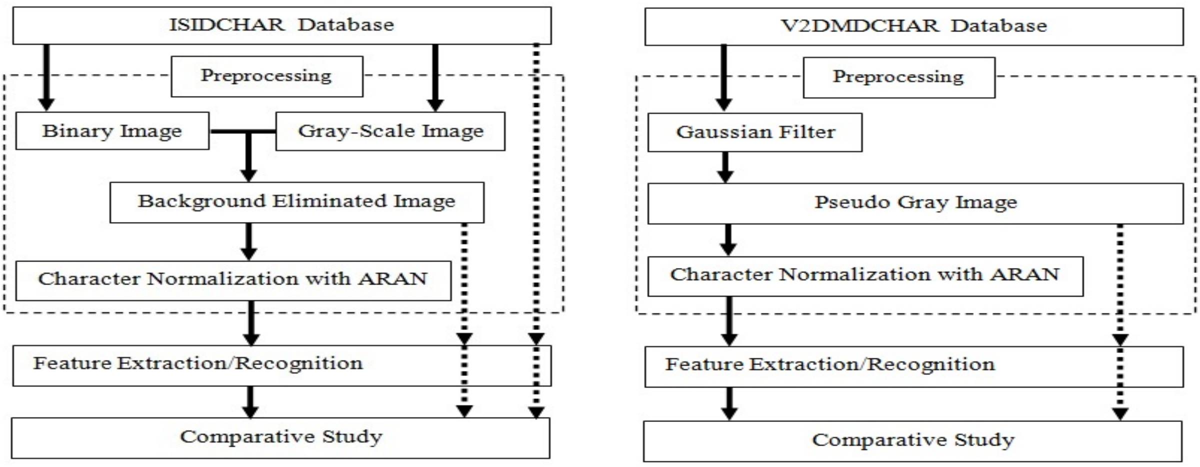

Fig. 4: (a) Recognition stages for ISIDCHAR database (b) Recognition stages for V2DMDCHAR database

4. Methodology

Optical character recognition consists of four primary stages: preprocessing, segmentation, feature extraction and classification. In case of isolated handwritten character recognition (in our case) the primary stages are character normalization, feature extraction and classification.

4.1. Background elimination

Binarization process by Ostu et al. (1975) algorithm is one of the important steps in handwritten character recognition system. That process gives binary image (with level 1 for foreground and level 0 for background) which is not preserve any gray level information of handwritten image. Gradient based feature extraction algorithms are performed better with good Gray levels of sample image. Background elimination process need to carry out to preserve the gray levels while removing the background. Background elimination process starts with getting a binary image by Otsu and then according to binary image, background is removed in original image such that the foreground has a new level of 255 minus the original level and background has gray level 0. Fig. 5 is shown the effect of binarization and background elimination process on original samples of ISI Devanagari handwritten database.

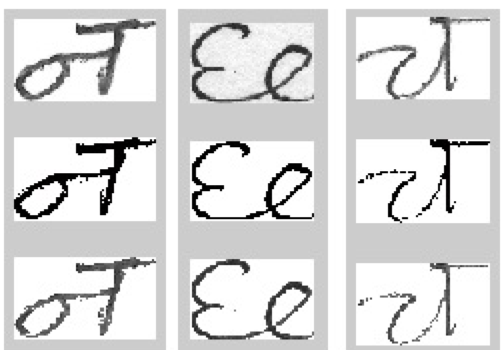

Fig. 5: Examples of background elimination: top - original image middle: - binarized image
Bottom: - background eliminated image

4.2. Character normalization

The ISIDCHAR and V2DMDCHAR databases have different sized samples. First, normalization technique is applied on it to overcome the intra-class variation of samples. In past decade, there were found the numbers of normalization technique (Liu, 2008). A sample images are normalized in fixed size (L) for that Aspect ratio adaptive normalization (ARAN) technique [Fig. 6] is most famous for handwritten characters problem. ARAN technique maintains the Aspect ratio (R_1), which is the ratio of height and width, after normalization.

$$R_1 = \begin{cases} W_1/\ H_1, & if \quad W_1 < H_1 \\ H_1/\ W_1 & otherwise \end{cases}$$

Where W_1 and H_1 are the height and width of the sample image; let assume that W_2 and H_2 are the height and width of normalized sample, which maintains the Aspect ratio R_1 as shown in the Fig. 6(b) the dashed line rectangle is shown the normalized image size L and thick lines rectangle is shown the occupied area by sample image.

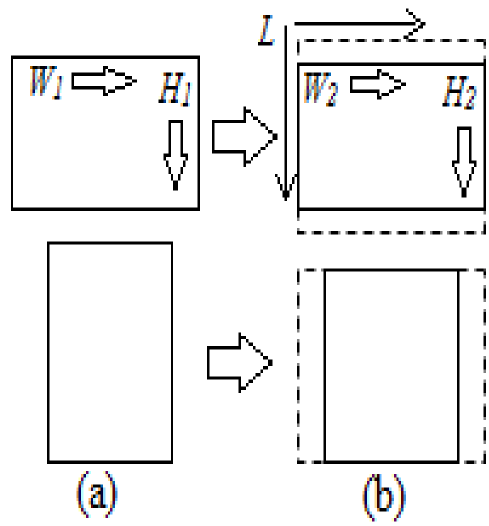

Fig. 6: (a) Samples with different height and width (b) thick line: occupied are of normalized sample after applied Aspect ratio adaptive normalization (ARAN).

4.3. Feature extraction

The V2DMDCHAR handwritten character database contains the binary image and our Correlation of Gradients in Local Neighbors (CGLN) method works on gradient values which are only computed from Gray-scale image. So A 3 x 3 Gaussian low-pass filter with Sigma= 0.5 is applied to get the Gray-scale image from binary image. After that features are extracted from CGLN method explained in section 3. The feature vector size is computed by $D+4D^2$ where D is the orientation bins and 4 are denoting the number of neighbors for local correlation.

4.4. Classification

Support Vector Machine (SVM) classifier which is the most suitable classifier for the handwritten character recognition problem due to freely available (www.csie.ntu.edu.tw/~cjlin/libsvm), is used for classification purpose and also produce good results. LIBSVM was initially used for binary class classification but now it implements the "one against one" method for multi-class classification and previous works of applying this approach to Support Vector Machine. Let assume that n is the number of classes, then n (n-1)/2 classifiers are created and each one trains data from two classes. For training data from the i^{th} and j^{th} classes, following two class classification problems have to solve:

$$\min_{w^{ij},b^{ij},\xi^{ij}} \quad \frac{1}{2}(w^{ij})^T w^{ij} + c\sum_t (\xi^{ij})_t$$

$$\begin{aligned} \textit{subject to} \quad & (w^{ij})^T \phi(x_t) + b^{ij} \geq 1-\xi_t^{ij}, x_t \ i \ class \\ & (w^{ij})^T \phi(x_t) + b^{ij} \leq -1-\xi_t^{ij}, x_t \ j \ class \\ & \xi_t^{ij} \geq 0. \end{aligned}$$

5. Results and discussion

Entire experiments were done on ISIDCHAR and V2DMDCHAR databases with variation in CGLN method and the system configuration was Intel® Core ™ i3-2310 M CPU@2.10 GHz with 4 GB RAM on MATLAB R2014a. Recognition Accuracy is computed to evaluate our method. If characters detected by our method are correct characters then it is counted as *true positives (Tp)* that is divided by the total size of the database.

First to check the response of CGLN method it is applied on the both the databases with varying the number of bins like 8, 9, 12 and 16 with fixed the remaining parameters [as $N \in \{0,1\}$, $a_{1x,y} \in \{\pm \nabla r, 0\}$ and $w(.) \Rightarrow \min(.)$]. The feature vector size directly depends on the number of bins and blocks so the feature vector sizes are 264, 333, 588 and 1040 respectively. Whole database sample images are normalized in 90 by 90. Box-Cox variable transformation is applied after feature extraction and features are also normalized between from 0 to 1 by min-max function. SVM with Radial basis function (RBF) is used for classification with setup cost (C) and gamma values and entire results are shown only for best setup of cost and gamma value. Table 3 is shown the recognition accuracy which roundup nearest integer. *Norm* and *Norm$_{AS}$* refers to normalization without aspect ratio and normalization with aspect ratio. By Table 3, it can observe the recognition accuracy is increase with the increment in bins upto 12 bins. But still it is not expected accuracy.

Table 3: Recognition accuracy with different bins values

S. No	No. Of Bins	Feature vector size	Recognition Accuracy			
			ISIDCHAR		V2DMDCHAR	
			Norm	Norm$_{AS}$	Norm	Norm$_{AS}$
1	6	150	68	69	71	72
2	8	264	70	72	73	74
3	9	333	73	74	75	76
4	12	588	73	75	76	77
5	16	1040	68	69	68	69

So, next experiments are performed on segmented images. The database sample images divided into block of size 2x2, 3x3 and then applied CGLN in each block with varying the number of bins. Box-Cox and Feature Normalization are also done to get the feature vector. The recognition accuracy results are shown in Table 4. The highest recognition accuracy achieved is 95.38 % on ISIDCHAR database when the background was eliminated (with BG Elim) and Samples normalized with Aspect ratio. It is also clearly observed by table that there is a significant enhancement in recognition accuracy after applied background elimination algorithm on ISIDCHAR database. Table 5 is shown experiment results on V2DMDCHAR database. 96.03 % accuracy obtained when the block size was 3X3 ad no of bins was 4.

Table 6 is shown the comparison of recognition accuracy on handwritten Devanagari character by other researcher. 96.03 % is the highest recognition accuracy achieved by our method on V2DMDCHAR database. But on ISIDCHAR database, 95.38% accuracy is achieved that is less than V2DMDCHAR database.

Table 4: Recognition accuracy of ISIDCHAR at different bins, block sizes, without and with background elimination

S.No	Block Size	No. Of Bins	Feature Vector Size	Recognition Accuracy			
				Before BG Elimination		After BG Elimination	
				Norm	$Norm_{AS}$	Norm	$Norm_{AS}$
1	2x2	4	272	85.63	85.67	88.26	89.93
		6	600	86.33	87.26	88.12	89.18
2	3x3	4	612	93.10	93.22	95.02	95.38
		6	1350	89.22	90.13	91.72	92.38

Table 5: Recognition accuracy of V2DMDCHAR at different bins, block sizes, without and with background elimination

S. No	Block size	No. Of Bins	Feature vector size	Recognition Accuracy	
				Norm	$Norm_{AS}$
1	2x2	4	272	88.53	89.99
		6	600	92.87	93.30
2	3x3	4	612	95.45	96.03
		6	1350	92.12	92.98

6. Conclusions

This manuscript is primarily focus on CGLN method to recognize the handwritten Devanagari characters. This method computes the features from the Gradient Image which contains the direction and the curvature information. It also finds the correlation with the neighbor pixels of sample image. CGLN feature extraction has tested on 2 standard databases that show the strength of this method. The higher recognition accuracy achieved by our experiment is 95.38%, which is higher than already achieved on different Devanagari databases. But still there are opportunities to enhance it by doing work on similar shape characters because it is very typical to distinguish similar shape handwritten characters. Our future work will be focus to find critical regions that distinguish one character from another similar shape characters.

Table 6: Comparison of recognition accuracy by other researchers

S. No	Accuracy Obtained	Feature; Classifier	Method proposed by	Data Size
1	80.36	Chain-code; Quadratic	Sharma (2006)	11,270
2	82	Chain-code; RE & MED	Deshpande (2007)	5000
3	89.12	Structural; FFNN	Arora. (2008)	50,000
4	90.65	Vector Distance; Fuzzy sets	Hanmandlu (2009)	4750
5	94.10	Gradient; SVM	kumar (2007)	25,000
6	95.19	Gradient; MIL	U. Pal (2009)	36,172
7	95.38	CGLN; SVM	Our Method	20,305
8	96.03	CGLN; SVM	Our Method	36,172

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