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ORIGINAL RESEARCH

Language-based document image retrieval for Trilingual System

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Abstract Language-based document image retrieval (LBDIR) is an essential need for a multi-lingual environment. It provides an ease of accessing, searching and browsing of the documents pertaining to a particular language. This paper proposes a method for LBDIR using multi-resolution Histogram of Oriented Gradient (HOG) features. These features are obtained by computing HOG on the sub-bands of Discrete Wavelet Transform. The Canberra distance is used for matching and retrieval of the documents. The proposed scheme is investigated on the three datasets (Dataset1, Dataset2 and Dataset3) consisting of 1437 document images of Kannada, Marathi, Telugu, Hindi and English languages. The objective of this work is to provide an efficient LBDIR for the government and non-government organizations of Karnataka, Maharashtra and Telangana states with the context of the tri-lingual model adopted. An average precision (AP) of 96.2%, 95.4%, 94.6%, 99.4% and 99.6% for Kannada, Marathi, Telugu, Hindi and English language documents is achieved while retrieving top 50 documents with the proposed method. The proposed feature extraction scheme provided promising results compared to existing techniques.

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Keywords Document image retrieval · HOG · DWT · Similarity metric · Canberra distance

Abbreviations

HOG	Histogram of oriented gradients
DWT	Discrete Wavelet Transform
DCT	Discrete Cosine Transform
LBDIR	Language-Based Document Image Retrieval
LBP	Local Binary Pattern
RI-LBP	Rotation Invariant Local Binary Pattern
PCA	Principal Component Analysis
P	Precision
AP	Average precision
SVM	Support Vector Machine
KNN	K-Nearest Neighbor

1 Introduction

The rapid growth of technology has lead to digitization of documents in almost every part of the world. Many techniques have been developed for the retrieval of documents such as logo-based, signature-based, lay-out based, face-based, etc. But these techniques are independent of the language content of documents. When the repository includes documents of different languages, there is a need for LBDIR system.

India is a multi-lingual country and has 18 regional languages. The officially accepted languages of India are Assamese, Bangla, English, Guajarati, Hindi, Konkani, Kannada, Kashmiri, Malayalam, Marathi, Nepali, Oriya, Punjabi, Rajasthani, Sanskrit, Tamil, Telugu and Urdu [1]. Almost every state of India has adopted a three-language policy: A regional language, national language Hindi and a global language English. Hence in many of the Indian states, the documents generated may belong to one of these three languages. For example in the Karnataka state, the regional language-Kannada, the national language-Hindi and the global language-English are used as official languages.

Figure 1 shows sample of Kannada, Marathi, Telugu, Hindi and English document images. Kannada, Marathi and Telugu are the regional languages of Karnataka, Maharashtra and Telangana states. The electronically generated documents in these states would belong to a combination of Kannada-Hindi-English, Marathi-Hindi-English or Telugu-Hindi-English languages, respectively. The proposed work aims to provide an efficient LBDIR that would help the government and non-government organizations of the three states: Karnataka, Maharashtra and Telangana.

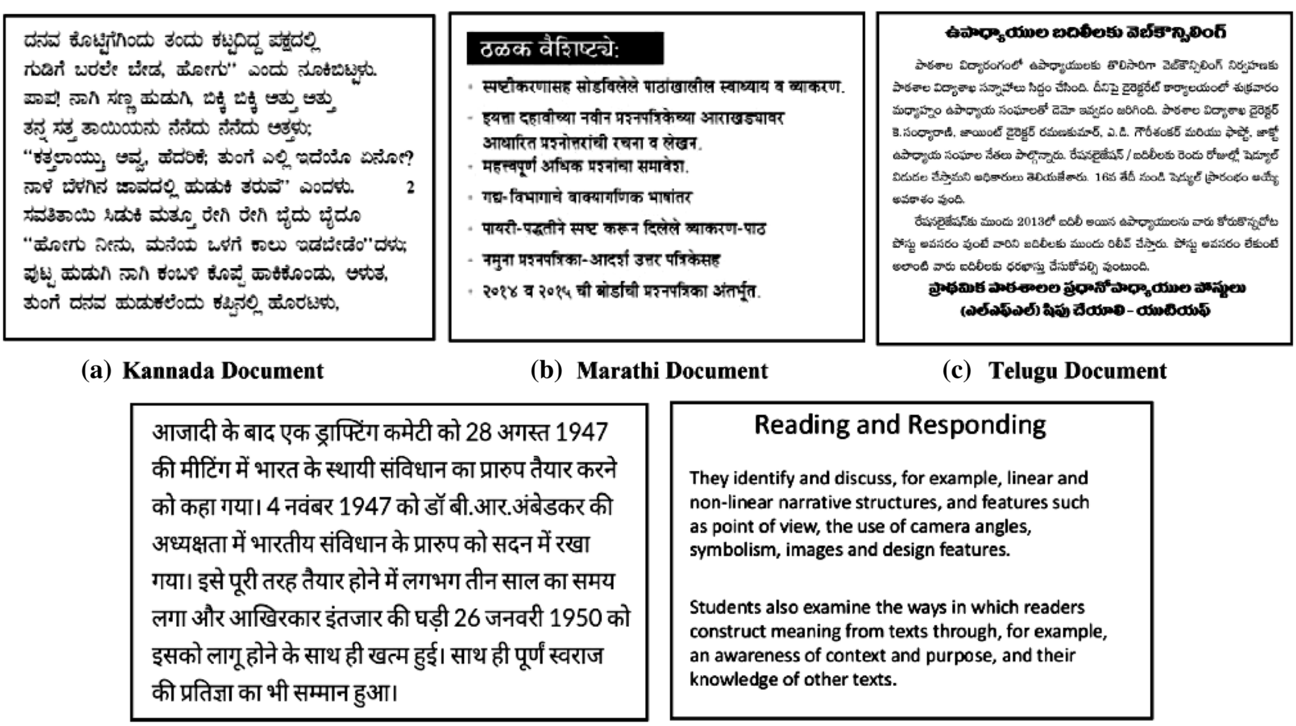
The document images of each language will have visually distinct textures. These texture features of the document images of different languages provide an opportunity for matching and retrieval. The main contribution of this work includes proposing a recognition-free LBDIR to improve the retrieval speed and accuracy using texture features. This paper presents multi-resolution HOG features, which are derived by computing HOG on four sub-bands of Discrete Wavelet Transform.

The rest of the paper is organized as follows: Sect. 2 provides a literature review, Sect. 3 discusses the proposed method, Sect. 4 describes the experimental results and finally, Sect. 5 concludes the work.

2 Literature review

A technique for detecting languages of document images is reported by Spitz [2]. Initially, he classifies the script as Han-based or Latin-based using upward concavities and then employs shape features of the characters to distinguish the language. Thanuja and Shreedevi [3] presented a method for recognition and retrieval of Kannada documents by matching the image at word level. Visual discriminating features of the languages are employed for recognition and retrieval in their work. Chandrakala [4] proposed recognition-free content-based document image retrieval for collection of Kannada document images using correlation method.

Script identification for Indian languages using different classifiers is proposed by Chaudhury et al. [5]. They used Gabor filter-based features of connected components in their scheme for identification. Kulkarni et al. [6] developed a method for script identification for multi-lingual documents using eight different features formed by combining different attributes of the word images. Zhu et al. [7] used shape-based features with multi-class SVM for identification of Arabic, Chinese, English and Hindi scripts.



ದನವ ಕೊಟ್ಟಿಗೆಗಿಂದು ತಂದು ಕಟ್ಟಿದಿದ್ದ ಪಕ್ಕದಲ್ಲಿ
ಗುಡಿಗೆ ಬರಲೇ ಬೇಡ, ಹೋಗು'' ಎಂದು ನೂಕಿಬಿಟ್ಟಳು.
ಪಾಪ! ನಾಗಿ ಸಣ್ಣ ಹುಡುಗಿ, ಬಿಕ್ಕಿ ಬಿಕ್ಕಿ ಅತ್ತು ಅತ್ತು
ತನ್ನ ಸತ್ತ ತಾಯಿಯನು ನೆನೆದು ನೆನೆದು ಅತ್ತಳು;
"ಕತ್ತಲಾಯ್ತು, ಅವ್ವ, ಹೆದರಿಕೆ; ತುಂಗೆ ಎಲ್ಲಿ ಇದೆಯೊ ಏನೋ?
ನಾಳೆ ಬೆಳಗಿನ ಜಾವದಲ್ಲಿ ಹುಡುಕಿ ತರುವೆ'' ಎಂದಳು. 2
ಸವತಿತಾಯಿ ಸಿಡುಕಿ ಮತ್ತೂ ರೇಗಿ ರೇಗಿ ಬೈದು ಬೈದೂ
"ಹೋಗು ನೀನು, ಮನೆಯ ಒಳಗೆ ಕಾಲು ಇಡಬೇಡೆಂ''ದಳು;
ಪುಟ್ಟ ಹುಡುಗಿ ನಾಗಿ ಕಂಬಳಿ ಕೊಪ್ಪೆ ಹಾಕಿಕೊಂಡು, ಅಳುತ,
ತುಂಗೆ ದನವ ಹುಡುಕಲೆಂದು ಕಪ್ಪಿನಲ್ಲಿ ಹೊರಟಳು,

(a) Kannada Document

ठळक वैशिष्ट्ये:

- स्पष्टीकरणासह सोडविलेले पाठांखालील स्वाध्याय व व्याकरण.
- इयत्ता दहावीच्या नवीन प्रश्नपत्रिकेच्या आराखड्यावर आधारित प्रश्नोत्तरांची रचना व लेखन.
- महत्त्वपूर्ण अधिक प्रश्नांचा समावेश.
- गद्य-विभागाचे वाक्यागणिक भाषांतर
- पायरी-पद्धतीने स्पष्ट करून दिलेले व्याकरण-पाठ
- नमुना प्रश्नपत्रिका-आदर्श उत्तर पत्रिकेसह
- २०१४ व २०१५ ची बोर्डाची प्रश्नपत्रिका अंतर्भूत.

(b) Marathi Document

ఉపాధ్యాయుల బదిలీలకు వెబ్‌కౌన్సిలింగ్

ప్రాథమిక పాఠశాలల ప్రధానోపాధ్యాయుల పోస్టులు (ఎల్‌ఎఫ్‌ఎల్) షిఫ్టు చేయాలి - యుటీయఫ్

(c) Telugu Document

आजादी के बाद एक ड्राफ्टिंग कमेटी को 28 अगस्त 1947 की मीटिंग में भारत के स्थायी संविधान का प्रारुप तैयार करने को कहा गया। 4 नवंबर 1947 को डॉ बी.आर.अंबेडकर की अध्यक्षता में भारतीय संविधान के प्रारुप को सदन में रखा गया। इसे पूरी तरह तैयार होने में लगभग तीन साल का समय लगा और आखिरकार इंतजार की घड़ी 26 जनवरी 1950 को इसको लागू होने के साथ ही खत्म हुई। साथ ही पूर्ण स्वराज की प्रतिज्ञा का भी सम्मान हुआ।

(d) Hindi Document

Reading and Responding

They identify and discuss, for example, linear and non-linear narrative structures, and features such as point of view, the use of camera angles, symbolism, images and design features.

Students also examine the ways in which readers construct meaning from texts through, for example, an awareness of context and purpose, and their knowledge of other texts.

(e) English Document

Fig. 1 Sample document images of Kannada, Marathi, Telugu, Hindi and Marathi Languages

Padma and Vijaya [8] used profile based features for identification of script from a tri-lingual document image. They used K-NN classifier in the proposed system and reported encouraging results. Pal and Chaudhuri [9] presented the system that identifies Roman, Chinese, Arabic, Devanagari and Bangla text lines from a single document comprising of multi-lingual text. Shape-based and water reservoir based features are used in the proposed method. Shirdhonkar and Kokare [10] proposed a handwritten document image retrieval technique using contourlet transform based features. They used the Canberra distance metric for similarity matching in their work.

Obaidullah et al. [11] developed a system for handwritten script identification for Indian documents using mathematical, structural and script independent features. Script identification for the printed multi-lingual document using different classifiers is reported in [12]. Word level hand-written script identification scheme for Indian documents was proposed by Pardeshi et al. [13]. They used Radon transform, DWT, Statistical filters and Discrete Cosine Transform (DCT) to obtain multi-resolution features with K-NN and SVM classifiers.

Kokare and Shirdhonkar [14] presented an overview of document image retrieval and described the applications and challenges involved. A detailed survey on Devanagari script identification techniques for the Indian postal system is reported by Wanchoo et al. [15]. A detailed survey of script identification algorithms and their comparison is presented in [16]. Li and Lin [17] developed a face recognition technique using HOG features. They applied Principal Component Analysis (PCA) for reducing the feature vector size. Lakshmi [18] presented a method for identifying Telugu palm leaf characters using the depth of 3D features.

From the literature, we learned that,

- Lot of research work is carried out towards script identification at word level and line level.
- Shape, structure and statistical features of the characters are employed for script or language recognition at the word or line level.
- There is a need to develop LBDIR to retrieve documents of a particular language from a repository of multi-language documents.

The texture-based features provided good results for content-based image retrieval. This motivated us to use the texture features of document images for LBDIR. The HOG provides good texture features; but fail in capturing minute details such as horizontal, vertical and diagonal, when applied directly on the image. These minute details are vital in discriminating the characters, words and lines of document images of different language. Hence in this work, to prevail the minute details mentioned above, a multi-resolution approach for extracting HOG features is proposed. Since script/language recognition is computationally expensive; we developed a recognition-free scheme for LBDIR to improve the speed. The proposed multi-resolution HOG features provided better retrieval results.

3 Proposed method

The scripts used in different languages are visually distinctive and provide unique texture features. This paper employs a global approach for the extraction of the texture features. The texture features of the query document image are compared with the texture features of documents stored in the database using similarity measure. Depending on the similarity metrics obtained, the top ‘N’ numbers of documents are retrieved. The framework of the proposed LBDIR system is depicted in Fig. 2. It includes preprocessing, feature extraction, similarity measure and document retrieval as the important building blocks.

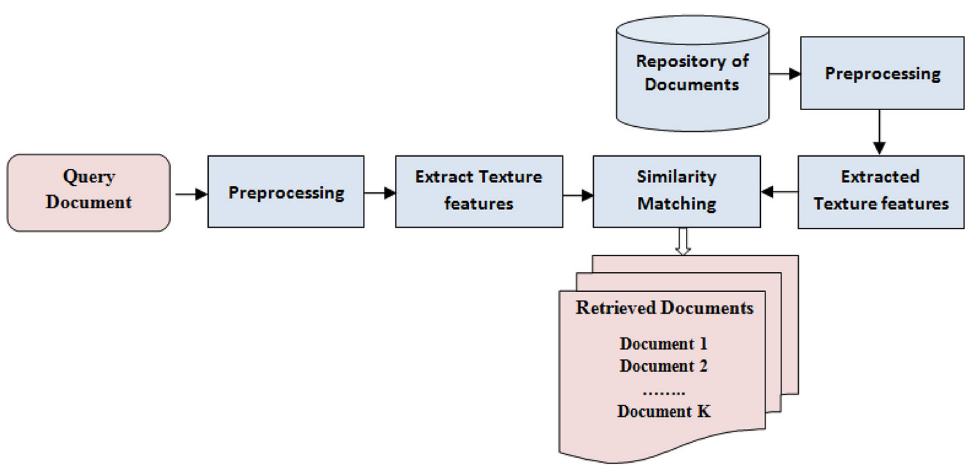


Fig. 2 Framework of the proposed document image retrieval

3.1 Preprocessing

Document images suffer from various types of degradations due to the process used in scanning, conversion and transmission [19]. The quality of such degraded images needs to be improved to obtain meaningful features. Initially, a median filter of size 3 × 3 is used to remove the pepper and salt noise. To enhance the quality of the document, the proposed method uses a low-pass filter followed by an un-sharp filter on the query document image [20]. The un-sharp filter enhances the edge details of the document text and the application of low pass filter improves the quality of the text. Algorithm 1 enlists the sequence of steps used for preprocessing.

Algorithm 1: Preprocessing

1. **Begin**
   Input: Document image D(x,y).
   Output: Preprocessed Image $D_P(x,y)$.
2. Apply a 3×3 median filter to eliminate salt and pepper noise.
3. Convolve D(x,y) with $H_1(x,y)$ using equation (1).

$$D'(x,y) = D(x,y) * H_1(x,y) \tag{1}$$

   Where $H_1(x,y)$ is the 3×3 mask used for un-sharp filtering with the following elements.

$$H_1(x,y) = \{1,-1,-1;-1,8,-1;-1,-1,-1\} \tag{2}$$

4. Convolve D'(x,y) with $H_2(x,y)$ using equation (3).

$$D_P(x,y) = D'(x,y) * H_2(x,y) \tag{3}$$

   Where $H_2(x,y)$ is a 3×3 mask used for low-pass filtering with the following elements.

$$H_2(x,y) = \{1,1,1;1,1,1;1,1,1\} \tag{4}$$

5. **End**

3.2 Multi-resolution feature extraction

Histogram of Oriented Gradient features represent local shape information of the regions in an image. They are widely used for the purpose of detection and classification in image processing. The proposed work is inspired by the method described by Dalal and Triggs [21]. The general method of obtaining HOG features includes dividing the image into cells of suitable size, organizing the cells into blocks, computing histogram of oriented gradients of these blocks and finally combining the histograms together to generate the features. The dimension of the HOG feature vector is given by Eq. (5).

$$\text{Number of HOG features} = \text{BS} \times \text{NBPI} \times \text{NBINS} \tag{5}$$

where 'BS' is the size of the block, 'NBPI' is a number of overlapping blocks per image and 'NBINS' is the number of bins used to obtain histogram. The sequence of steps used in the proposed feature extraction scheme is listed in Algorithm 2.

Algorithm 2: Multi-resolution HOG feature extraction

1. **Begin**
   Input: Preprocessed document image $D_P(x,y)$,
   Output: Multi-resolution HOG features (HFV)
2. Resize $D_P(x,y)$ to 256×256 pixels.
3. Apply DWT on $D_P(x,y)$ to obtain approximate (CA), Horizontal (CH), Vertical (CV) and Diagonal (CD) coefficients. This results in 4 sub-bands of size 128×128.
4. Divide each sub-band into cells of size 64×64 and organize a group of four cells as a block. This leads to a total of 4 blocks per image.
5. Compute HOG features of each sub-band using 9 bins in the histogram. Equations (6) and (7) are employed for computing the gradient of pixels in horizontal ($G_H(x,y)$) and vertical directions ($G_V(x,y)$). The magnitude of the gradient M(x,y) and its direction Θ(x,y) are computed using equations (8) and (9) respectively.

$$G_H(x,y) = D_P(x+1,y) - D_P(x-1,y) \tag{6}$$

$$G_V(x,y) = D_P(x,y+1) - D_P(x,y-1) \tag{7}$$

$$M(x,y) = \sqrt{G_H(x,y)^2 + G_V(x,y)^2} \tag{8}$$

$$\Theta(x,y) = \tan^{-1}\frac{G_H(x,y)}{G_V(x,y)} \tag{9}$$

   Let H_1, H_2, H_3 and H_4 are the histogram of oriented gradients computed on the sub-bands CA, CH, CV and CD respectively.

6. Combine H_1, H_2, H_3 and H_4 to form the final feature vector HFV using Equation (10).

$$\text{HFV} = \{H_1, H_2, H_3, H_4\} \tag{10}$$

7. **End**

In the proposed feature extraction technique, the preprocessed document image is initially resized to 256 × 256 pixels to reduce the number of features. The resized image is then decomposed into four sub-bands: approximate (CA), Horizontal (CH), Vertical (CV) and Diagonal (CD) by applying DWT [22]. The size of each sub-band is now 128 × 128 pixels. The approximate band consists of the original image with a reduced number of samples and the other three sub-bands contain horizontal, vertical and diagonal details of the document text. These sub-bands are then used to generate multi-resolution HOG features.

To obtain multi-resolution HOG features, the four sub-bands are further divided into cells of size 64 × 64 pixels, yielding a total of (4 × 4) 16 cells. Cell size plays an important role in extracting HOG features. In this work, the size of the cell is chosen empirically by conducting experiments. A group of four cells (2 × 2) are then organized as a block, which results in four non-overlapping blocks per image. Histograms of oriented gradients of the pixels in each block are computed and combined together to obtain the feature vector. Since nine bins per histogram are used, it leads to a total of 144 HOG features. The conceptual view of multi-resolution HOG feature extraction used in this paper is shown in Fig. 3. The plot of the features for a sample document image is shown in Fig. 4.

3.3 Similarity matching

The retrieval techniques need a suitable similarity metric to obtain the best matches. Canberra distance is found to yield best matches in content-based image retrieval applications when the texture features are used [23]. Hence in the proposed algorithm, Canberra distance is employed for finding the similarity between the features of query-document image and database of documents. The Canberra distance can be computed by using Eq. (11).

$$\mathrm{Canberra}(X, Y) = \sum_{i=1}^{N} \frac{|X_i - Y_i|}{|X_i| + |Y_i|} \tag{11}$$

where ‘X’ and ‘Y’ refers to the feature sets to be matched. The ‘N’ in the equation indicates the size of ‘X’ and ‘Y’.

3.4 Retrieval of documents

The sequence of steps used for matching and retrieval of the documents is shown in Algorithm 3.

Algorithm 3: Matching and Retrieval of documents

1. **Begin**
   HFDB: Multi-resolution HOG features of database documents.
   HFQ: Multi-resolution HOG features of the query document.
   K: Number of documents to be retrieved.
   N: Total number of documents
2. Calculate Canberra distance between HFDB and HFQ

```
for i =1 to N
    D(i)=CanberraDistance(HFDB(i),HFQ)
endfor
```

3. Sort the documents based on similarity distance.
4. Display top-K documents on the screen.
5. **End**

The document images are pre-processed, and their extracted multi-resolution HOG features are made readily available, to improve the speed of retrieval process. Canberra distance between the query image features and the extracted features of document images is computed to identify the closest matches. The lowest distance value indicates the closest match with the query document and vice versa. The documents are then sorted based on the Canberra distance. The ‘K’ number of top-matching documents are retrieved and displayed on the computer screen. Value of ‘K’ can be specified by the user and it needs to be less than the total number of documents in the database.

4 Experimental results

The proposed LBDIR is implemented on Core i3/4 GB RAM/windows8 machine using MATLAB software. Our implementation took approximately 0.5625 s to retrieve

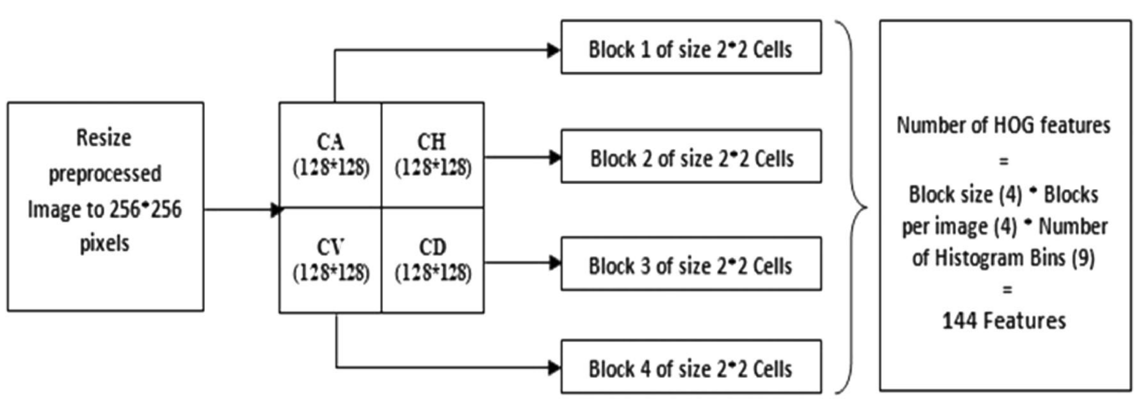
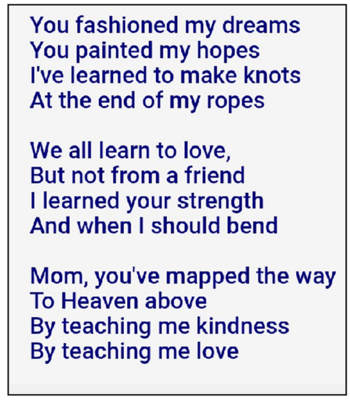


Fig. 3 Conceptual view of Multi-resolution feature extraction scheme

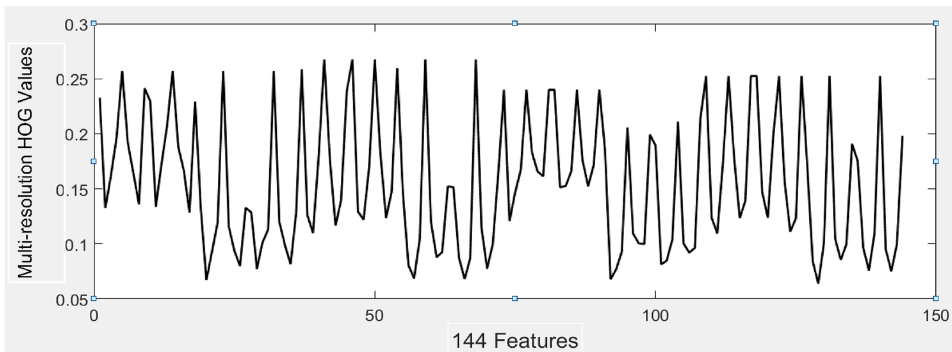
Fig. 4 Plot of Multi-resolution HOG features for a sample document


You fashioned my dreams
You painted my hopes
I've learned to make knots
At the end of my ropes

We all learn to love,
But not from a friend
I learned your strength
And when I should bend

Mom, you've mapped the way
To Heaven above
By teaching me kindness
By teaching me love

(a) Sample Document



(b) Plot of Multi-resolution HOG features

Table 1 Details of 3 datasets

Sl. no	Dataset	Number of document images					
		Kannada	Marathi	Telugu	Hindi	English	Total
1	Dataset1	94	–	–	196	191	481
2	Dataset2	–	110	–	196	191	497
3	Dataset3	–	–	72	196	191	459
Total number of document images with different languages							1437

top 50 matched document images after submission of the query. Retrieval time depends on the size of the database, quality of images and many other factors.

The algorithm is tested on three datasets. These datasets are developed by collecting images from the internet, newspapers, books, etc. The images of these documents comprise of printed text and graphics with different fonts and size. Table 1 shows the details of three datasets. These datasets consist of a combination of Kannada-Hindi-English, Marathi-Hindi-English and Telugu-Hindi-English documents. The reason behind testing these combinations is to evaluate the performance of the proposed method for tri-lingual system adopted in the states of Karnataka, Maharashtra and Telangana.

The precision is used as an evaluation parameter for comparison of the results, which is computed using Eq. (12). It is defined as a ratio of the number of relevant documents retrieved to the total number of retrieved documents.

$$\text{Precision (P)} = \frac{\text{Relevant documents retrieved}}{\text{Total number of retrieved documents}} \tag{12}$$

For each dataset, we computed an average precision (AP) for top 10, top 20, top 30, top 40 and top 50 matched documents by selecting a random query. As shown in Table 1, each dataset has three classes of documents. From each class, we executed ten queries leading to 30 queries/dataset and a total of 90 queries for three datasets. Thus an exhaustive set of experiments are conducted for evaluating and comparing the results of the proposed method with rotation-invariant LBP [24] and HOG features [21]. Figure 5 shows the sample result of retrieval for dataset1 with Kannada query document image. It can be observed

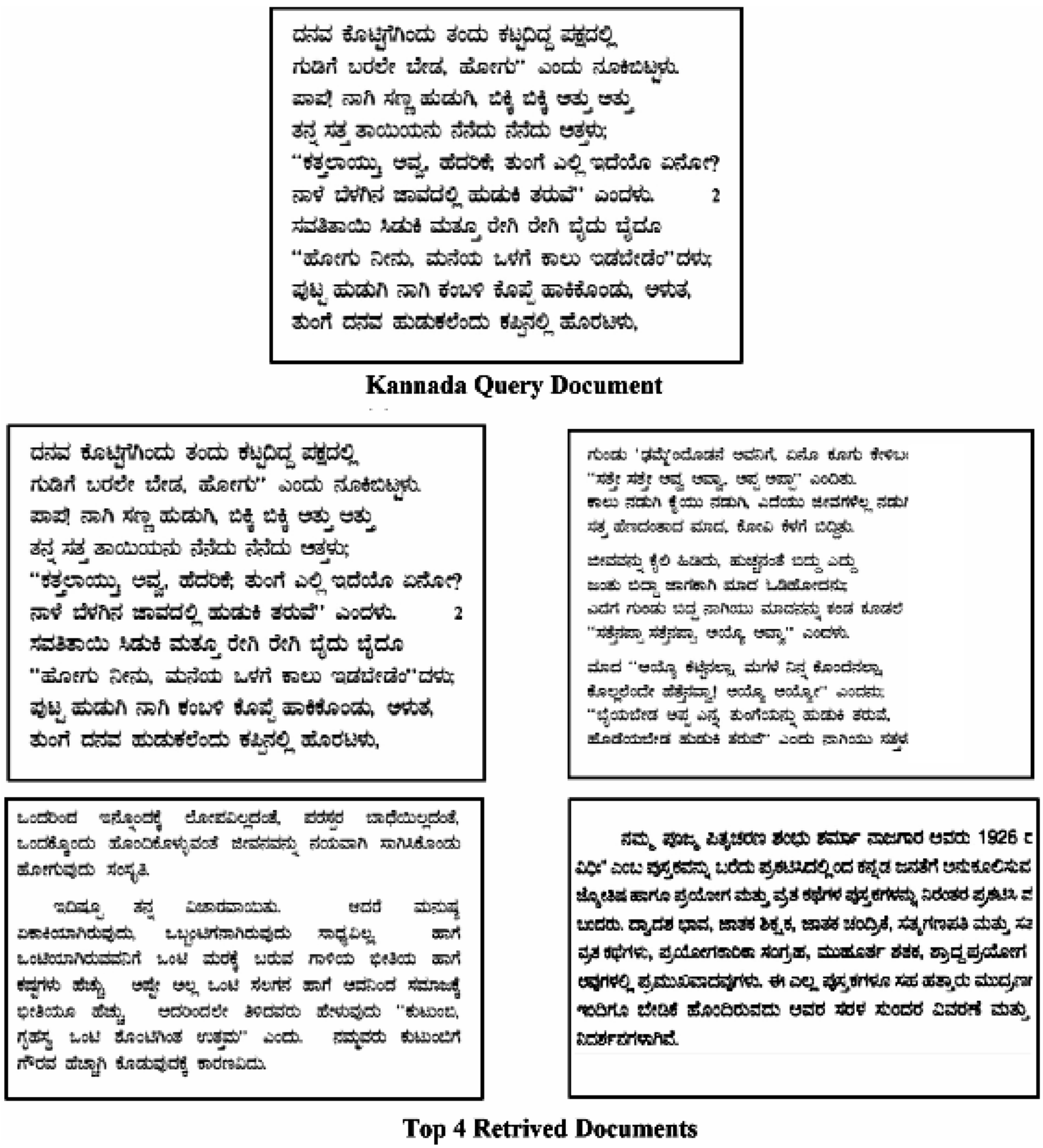


Fig. 5 Sample result of document retrieval

that all the four retrieved documents are of Kannada language.

Tables 2, 3 and 4 shows the results obtained for dataset1, dataset2 and dataset3, respectively. These tables provide average precision for combinations of Kannada–Hindi–English, Marathi–Hindi–English and Telugu–Hindi–English documents. The average precision (AP) is computed using the Eq. (13).

$$\text{Average Presicion (AP)} = \frac{1}{N}\sum_{i=1}^{N} P_i \qquad (13)$$

where ‘P_i’ is the precision of ith query and ‘N’ is the total number of queries executed. In this work, a total of ten

Table 2 Average precision for dataset1

Number of top matches	Percentage AP using rotation-invariant LBP features			Percentage AP using HOG features			Percentage AP with proposed multi-resolution HOG features		
	Kannada	English	Hindi	Kannada	English	Hindi	Kannada	English	Hindi
10	86	96	98	88	91	99	**99**	**100**	**100**
20	68	97	97.5	81.5	78.5	87.5	**97.5**	**100**	**100**
30	60.67	93.66	94.33	75.33	80	89.33	**97.33**	**99.75**	**100**
40	57.25	93.5	94.75	73	76.75	87.25	**96.25**	**99.75**	**99.75**
50	53.4	86.8	88.6	72.4	69.2	82.6	**96.2**	**99.6**	**99.8**

AP average precision, *LBP* local binary pattern, *HOG* histogram of oriented Gradient

Table 3 Average precision for dataset2

Number of top matches	Percentage AP using rotation-invariant LBP features			Percentage AP using HOG features			Percentage AP with proposed multi-resolution HOG features		
	Marathi	English	Hindi	Marathi	English	Hindi	Marathi	English	Hindi
10	78	82	86	88	94	100	**97**	**100**	**100**
20	71	76	82.5	81.5	88	93.5	**97**	**100**	**100**
30	66.33	73.33	79.33	77	82.67	91	**96.67**	**100**	**100**
40	64.25	71.5	75.75	75	77.5	87.25	**96**	**99.75**	**99.75**
50	61.8	69.4	72	73.4	75.4	83.14	**95.4**	**99.4**	**99.8**

AP average precision, *LBP* local binary pattern, *HOG* histogram of oriented Gradient

Table 4 Average precision for dataset3

Number of top matches	Percentage AP using rotation-invariant LBP features			Percentage AP using HOG features			Percentage AP with proposed multi-resolution HOG features		
	Telugu	English	Hindi	Telugu	English	Hindi	Telugu	English	Hindi
10	89	98.3	100	94	91	100	**98**	**100**	**100**
20	86.5	96	100	81	86	96.5	**97**	**100**	**100**
30	80.67	96	99.67	78.33	85.33	95.33	**96.33**	**100**	**100**
40	79.75	96	99.5	77	82	93	**96.25**	**100**	**100**
50	77	96	97.8	76.6	80.2	90.2	**94.6**	**99.6**	**99.8**

AP average precision, *LBP* local binary pattern, *HOG* histogram of oriented Gradient

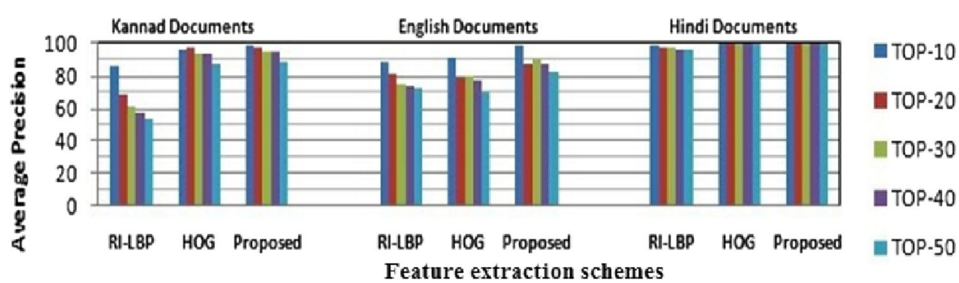


Fig. 6 Graphical comparison of results for dataset1

queries from each class are considered for computing AP. Figures 6, 7 and 8 shows the graphical comparison of results obtained using the proposed feature extraction scheme and other schemes. It can be observed that the proposed method provides promising results for all the three datasets in comparison with existing methods.

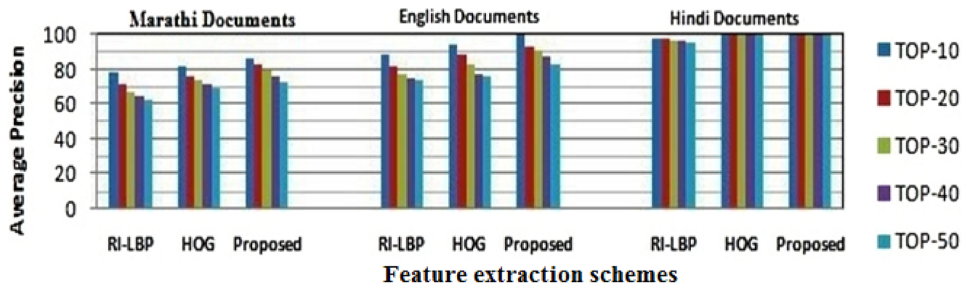


Fig. 7 Graphical comparison of results for dataset2

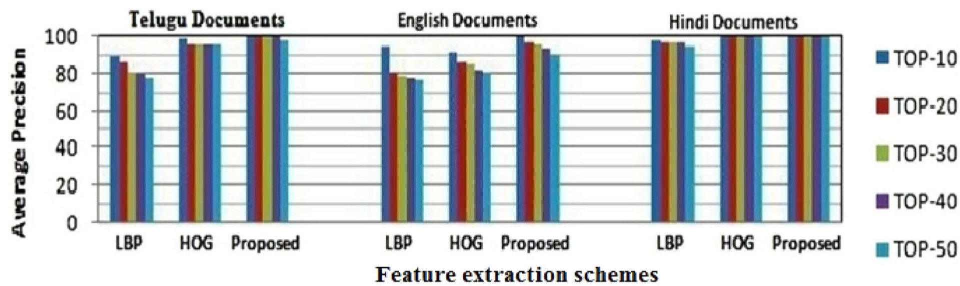


Fig. 8 Graphical comparison of results for dataset3

5 Conclusion

In this paper, we presented a recognition-free method for language-based document image retrieval using multi-resolution HOG features. These features are obtained by applying HOG on vertical, horizontal, diagonal and approximate sub-bands of the document image. Canberra distance is used as a similarity metric for matching and retrieval of document images. The proposed method is evaluated on three datasets consisting of 1457 documents images and compared with the existing state of the art. The multi-resolution HOG feature extraction scheme provided promising results for all the three datasets.

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