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# Image classification using SURF and bag of LBP features constructed by clustering with fixed centers

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## Abstract

Image classification is the process of assigning a category/class to an image. It has gained much importance in the recent years because of its real-time applications in object tracking, medical imaging, image organizations for large datasets, image and video retrieval. For instance, in image retrieval, query image once classified to the correct category avoids the searching of similar images from the complete dataset. In the state of art approaches, the classification techniques are generally discussed for a single dataset having similar images such as Textures(Rock,trees, texture based images), Describable Texture dataset (clothing pattern), Oxford Dataset(building pattern), etc. Thus a common approach for classification of various types of images is lacking. This paper presents a common approach for the variety of datasets having different types of images. Four different types of dataset, Caltech-101(101 different categories of images eg. airplane, sunflower, bike, etc), ORL Face, Bangla Signature and Hindi Signature are used for testing the proposed classification approach. The proposed approach has three phases. Region of Interest(ROI) using SURF(Speed Up Robust Transform) Points is obtained in the first phase. Extraction of LBP(Local Binary Pattern) Features on ROI is done in the second phase. In the third phase clustering of LBP features are done with a new proposed approach as CFC(Clustering with Fixed Centers) to construct Bag of LBP Features. Through proposed CFC approach each image is annotated/tagged with a fixed Bag of Features to avoid the training of machine, again and again. SVM is used here for classification as it has been experimentally found to give the best performance when compared with Decision Tree, Random Forest, K Nearest Neighbor and Linear Method. The accuracy obtained for Caltech-101, ORL Face, and Signature(Bangla and Hindi) are 79.0%, 75.0%, 81.6% and 87.0% respectively. Thus the average accuracy obtained by the proposed approach is 81.7% in contrast to other state of art approaches having average accuracy as 64.15%, 76.47%, and 77.65%.

**Keywords** Bag of features · Polygon · Background suppression · Local binary pattern · SURF points · Clustering

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## 1 Introduction

Image classification is to assign a category/class to an image. Image classification plays a vital role in image understanding [10, 42]. It has gained much importance in the recent years because of its real time applications in object tracking [14, 37–41], object action recognition [16, 43–45] image , and video retrieval [7, 8] etc. Image classification is one of the most challenging task in computer vision as it faces both intra and inter-class challenges. Intra class challenge refers to the variations in shapes, styles, the illumination effect of the same object. For instance, a category of "chair" may have chairs of many shapes, sizes, shades, etc. Interclass refers to variations among different objects like car, airplane flower, etc., having some similarity in texture/color/shape, etc. The classifiers need to be trained thoroughly for the classification. The classification has two major tasks, first is the extraction of the suitable features describing the image in the best manner and the second is to train the classifiers using those features.

Researchers have used different features and different classifiers for image classification. Haralick, Robert et al. [12] used Texture features for classification of photomicrographs, aerial photographs, and satellite images. The accuracy obtained by him was 89 percent for the photomicrographs, 82 percent for the aerial photographs, and 83 percent for the satellite images. Porebski, Alice et al. [27] made a comparative study of the color histograms with color-texture features for the classification of color texture image set. The datasets used by them were OuTex-TC-00013 (OuTex) and Contrib-TC-00006 (VisTex). The result analysis by them showed that the color histogram yields a higher accuracy as compared to color texture features. Hirata, Kyoji et al. [13] used color and shape to classify selected primary objects from the web and obtained the accuracy of 73%. P. Perner, H. Perner et al. [28] had used texture features for the classification of $HE_p$-2 cells in medical imaging. The dataset used by him had 6 classes having a total of 321 images. The accuracy obtained by him was 75%. Chen, Haiyan et al. [2] proposed an improved feature encoding scheme called Locality-constrained Linear Coding Based on Histogram Intersection (HILLC) for scenery images. In the recent literature, several descriptors like SIFT, BRIEF, SIFT-PCA, etc have gained more attention for image analysis. P. Shivajee, Srivastava et al. [32] have proposed an efficient image classification approach using dynamic PCA filter selection in PCANet. Kamavisdar, Pooja et al. [29] survey paper have discussed various techniques for image classification. Among all the other local invariant feature descriptors SIFT [18] has been proved to be the most robust with respect to scaling, transformation and distortion [30].

The basic idea of SIFT [18] is to identify the interest points in an image which are generally corner points, blob points, etc in the scale space. These interest points are filtered to obtain the final keypoints. The orientation gradient of each keypoint is then computed with respect to its eight neighbors as $4 \times 4 \times 8$ vectors. A comparative study of SIFT and its variants PCA-SIFT(Principal Component Analysis SIFT), GSIFT (Global SIFT), CSIFT(Color invariant SIFT), SURF(Speed Up Robust Feature) and ASIFT(Affine SIFT) has been made by [36]. SURF [1] is an advancement of SIFT, that uses the approximation of Gaussian for the fast computation of keypoints. SURF descriptor has gained a good importance in the recent literature as it is robust towards scale, illumination, rotation effect and is also computationally fast [19]. Ali, Nouman et al. [22] have integrated SIFT and SURF for image classification. Dang, Quoc Bao et al. [5] has used the combination of SIFT, SURF and local descriptor for the classification of the camera-based documents and obtained the accuracy of 92.5%. Thus it is observed that state of art approaches for classification/categorization are confined to the specific types of dataset. For instance, LBP based classification is generally used for Faces and Texture datasets while Gray Level Co-occurrence Matrix for textile pattern dataset etc.

The approach proposed in this paper uses SURF instead of other keypoints descriptors as it is fast and robust towards various effects like scaling, rotation and illumination etc. Binary Robust Independent Elementary Features(BRIEF), Oriented FAST and Rotated BRIEF (ORB) keypoints detectors perform good for distorted and noisy images [9] whereas the proposed approach is meant for images having single object and are free from distortion. Experiments have been performed on following four different types of datasets having the variety of images having single object only. Dataset 1: Caltech-101, has 101 types of different categories (having single object in each image), for example, sunflower, faces, bikes, pizza, etc. Dataset 2: ORL Face formally known as "Dataset of Faces" is a collection of 40 categories of faces having 10 images in each category. The remaining two datasets $BHSig260_1$ and $BHSig260_2$ are of Bangla and Hindi Signatures. Both are offline datasets having 100 categories of Bangla Signatures with 54 signatures in each category and 160 categories of Hindi Signatures having 54 signatures in each category. All the images in the datasets mentioned above have a single object in each image. The results obtained for all the four different types of datasets are quite promising and outperforms the respective state of art approaches. Through proposed CFC approach each image is annotated/tagged with a fixed Bag of Features to avoid the training of machine, again and again. SVM used here for classification as it has been experimentally found to give the best performance when compared to Decision Tree, Random Forest, K Nearest Neighbor and Linear Method.

The rest of the paper is organized as follows: Section 2 discusses the Preliminaries. Section 3 is the Proposed Methodology. Section 4 gives Datasets used for Experiments. Results are analyzed in Section 5. Section 6 is the concluding section.

## 2 Preliminaries

A brief introduction to Speed Up Robust Transform (SURF), Local Binary Pattern(LBP), and Bag of Features (BoF) are given in following subsections.

### 2.1 Speed Up Robust Transform (SURF)

SURF [26], an advancement of SIFT is generally used for Image Matching. It is fast and robust that uses local similarity invariant features for matching of images. The initial step in SURF generates the key points. Next step determines the orientation invariant descriptors of these key points which are further for various applications: determining the correspondences between two images of the same object, image classification, image registration, camera calibration, etc.

#### 2.1.1 Interest point detection

A point at which the direction of the edge or the boundary of an object changes abruptly is considered as an interest point. Also, the intersection between two or more edge segments gives an interest point in an image. Interest points in synthetic images and real images are shown in Fig. 1a and b respectively.


**Fig. 1** Interest points in Synthetic (**a**) and Real (**b**) image

Harris corner detector is one of the most widely used corner-detector, however, it is not scale invariant [1]. This scale invariant problem was overcome by T.Lindeberg [17] using Hessian matrix for automatic scale selection. SURF uses Hessian matrix approximation for the detection of interest points in an image as it is both scale and rotation invariant. It makes use of integral images that reduces the computational time drastically. The integral image of an image I is an intermediate representation, denoted by $I_{(x,y)}$ at a point(x,y). It is calculated by the sum of intensities between the point(x,y) and the origin as in (1). An integral image takes three additions and four memory access to calculate the sum of intensities of any rectangular area. Figure 2 shows the rectangle bounded by vertices P, Q, R and S and sum of its intensities is calculated by using (2f). This makes calculation time independent of image size. The use of integral image helps SURF to approximate Gaussian second order derivative at a very low computational cost [31].

$$I_{(x,y)} = \sum_{i=0}^{i<=x} \sum_{j=0}^{j<=y} I(i,j) \tag{1}$$

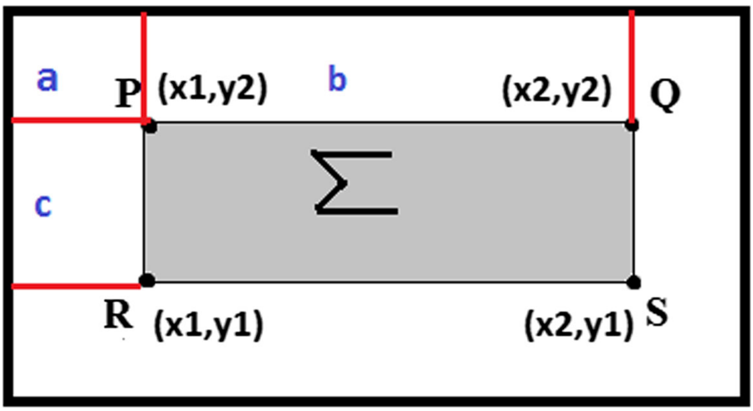



**Fig. 2** Using integral images, it takes only three additions and four memory accesses to calculate the sum of intensities inside a rectangular region of any size

where $I_{(x,y)}i$ is the integral image of the image I, at a location (x,y).

$$Q = a + b \tag{2a}$$
$$P = a \tag{2b}$$
$$R = a + c \tag{2c}$$
$$S = a + b + c + \sum \tag{2d}$$
$$\sum = S - a - b - c \tag{2e}$$
$$\sum = S - Q - R + P \tag{2f}$$

For the detection of Interest Points SURF detects local maxima in scale space using approximated Hessian Filter response. Around each interest point a rotated square region is determined and described as a 128- dimensional feature vector. The size of the square region and rotation angle are determined adaptively and automatically. This makes SURF invariant with respect to scale and rotation.

For a given point P=(x,y) in an image I, the Hessian matrix H(P,$\sigma$)at scale $\sigma$ is defined as

$$\begin{bmatrix} S_{xx}(P,\sigma) & S_{xy}(P,\sigma) \\ S_{yx}(P,\sigma) & S_{yy}(P,\sigma) \end{bmatrix} \tag{3}$$

where $S_{xx}$ (P,$\sigma$), $S_{xy}$(P,$\sigma$), $S_{yx}$(P,$\sigma$) and $S_{yy}$(P,$\sigma$) are the convolution of the Gaussian second order derivative of the image I at point P. The determinant of Hessian for each pixel in the image is calculated and values are used to find interest points [21].

## 2.2 Local Binary Pattern(LBP)

Local binary pattern (LBP) proposed by Ojala, Timo et al. [25] is based on the local pattern analysis of pixels in an image. The aim of LBP is to transform an image into array of integer labels that describes the local information of the neighboring pixels. Basic LBP considers all pixels of the image as center pixel and LBP operator works upon 3 x 3 block. The center pixel value acts as a threshold value for the other pixels in this block. Center pixel is subtracted from all the neighboring pixels and then 0/1 is assigned to neighboring pixels (Depending upon the difference) and then multiplied by the powers of two and summed to obtain a single value for the center pixel. A total of 8 neighbors are there for center pixel in a block of 3 x 3. Since 0/1 value is assigned to each neighboring pixels, a total of $2^8$= 256 different vales can be obtained. For an image I, let the gray level of center pixel(x,y) of a 3 x 3 block be $Z_c$ as in (4a), and $Z_n$ be the gray values of circular neighborhood points of (x,y) having P neighbors and R be the radius around (x,y) as in (4b) and (4c).

$$Z_n = I(x_n, y_n), n = 0, 1, 2....P - 1 \tag{4a}$$
$$x_n = x + Rcos(2\pi n/P) \tag{4b}$$
$$y_n = y + Rsin(2\pi n/P) \tag{4c}$$

Threshold function T(z) denotes the values (0/1) assigned to each neighboring pixels based on the difference $(Z_n - Z_c)$ as in (5)

$$T(z) = \begin{cases} 0, & \text{if } (Z_n - Z_c) < 0. \\ 1, & \text{otherwise.} \end{cases} \tag{5}$$

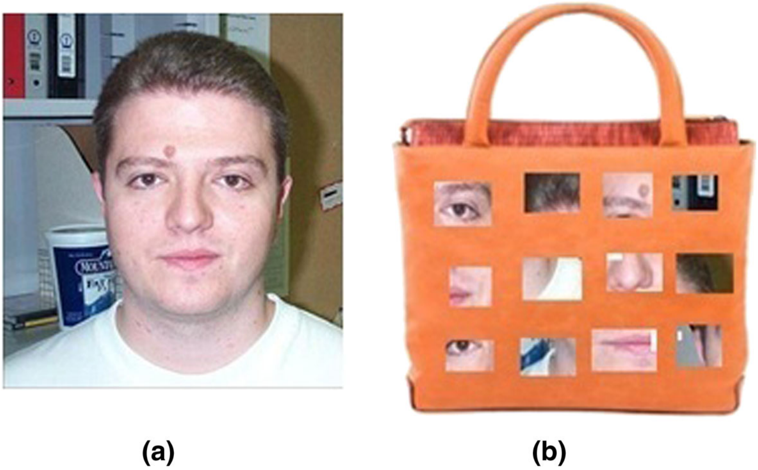



Fig. 3 Original Image (**a**), (**b**) Bag of features for image (**a**)

The LBP operator is computed as shown in (6):

$$LBP_{P,R}(x_c, y_c) = \sum_{n=0}^{P-1} T(Z_n - Z_c)2^n \tag{6}$$

## 2.3 Bag-of-Features(BoF)

Bag of Features [23] is an orderless collection of quantized local descriptors of an image as shown in Fig. 3. Construction of BoF is a multi-step process that clusters the features extracted from the whole image and constructs a visual vocabulary from them. The features extracted from the image represent the local information of the image irrespective of location. Clustering of the features extracted is then made to create a discrete vocabulary of the local features for the image. It is also known as Bag-of-Words (BoW) as it builds a vocabulary for an image. O'Hara, Stephen et al. [24] gave an introduction of BoF for image classification and retrieval. Cula, Oana G. et al. [4], gave a compact version of BoF for various texture features. In the recent literature it has gained much popularity in object detection, classification [3] and natural scene analysis [15], and etc. It is simple, free from location constraint and thus more popular. For image classification and image retrieval, BoF has shown better results and is computationally cheaper as compared to other methods [24]. A general approach for BoF is shown in Fig. 4.

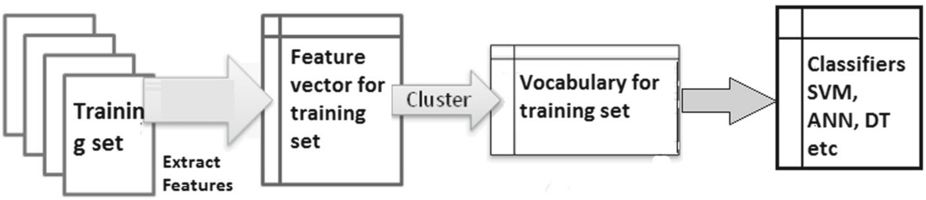



Fig. 4 General approach for bag-of-features model

## 3 Proposed methodology

In the work proposed, SURF and LBP are used for the classification of images. SURF is a very good and fast descriptor used for image matching. Although SURF gives good

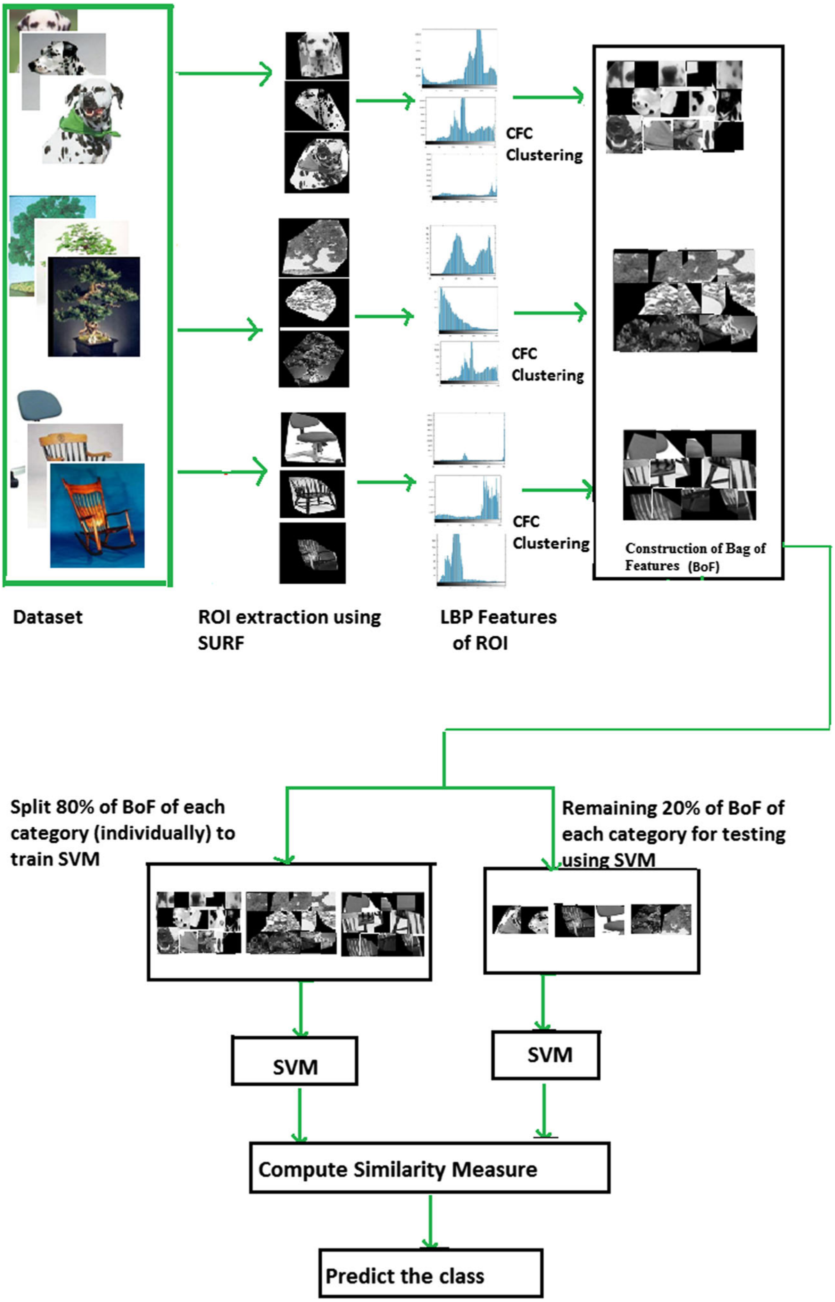



**Fig. 5** Proposed methodology overview

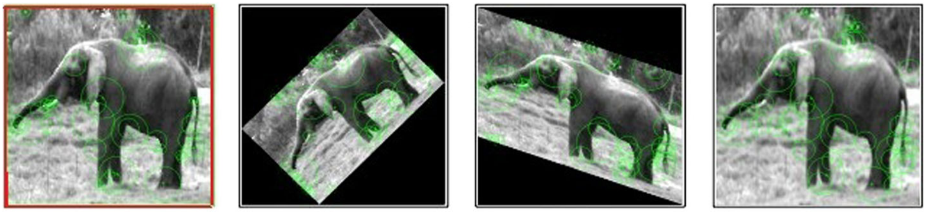
accuracy for exact matching, but it might/might not perform well for similar images. In the case of image classification, similar images need to be categorized into one class. Thus in the proposed approach SURF and LBP have been used for image classification. The complete procedure is shown in Fig. 5. The proposed approach is explained through 3 algorithms. Algorithm 1, selects the SURF Points ($St_i^j$) of every $i^{th}$ image of $j^{th}$ category, and passes it to Algorithm 2 for the extraction of Region of Interest($ROI_i^j$). Thereafter, LBP feature vector is computed for $ROI_i^j$ only and is then passed to Algorithm 3 for Clustering With Fixed Centers (CFC). CFC is a new modified proposed k-means clustering algorithm to find the Bag of Features(BoF) ($B_i^j$) for $i^{th}$ image of $j^{th}$ category. For all the images i of $j^{th}$ category, ($B_{i's}^j$)BoF's are combined to form a single $CD_B^j$ of $j^{th}$ category. These constructed Bag Of Features$CD_B^1$, $CD_B^2$, ..., $CD_B^{10}$ for all the 10 categories are used to train SVM to form Trained Category ($TC$). Steps are explained in detail in the following subsections.

**Algorithm 1** Training

**Input**: Categorized Dataset CD
**Output**: Trained Category TC
**for** $j \leftarrow 1$ ***to*** $N$ **do**
    **for** $i \leftarrow 1$ ***to*** $M$ **do**
        $St_i^j \leftarrow$ Strongest 40 points of $i^{th}$ image of $j^{th}$ category
        $L \leftarrow ROI(St_i^j)$
        $ROI_i^j \leftarrow$ construct polygon on L points
        $[ROI_{in}]_i^j \leftarrow ROI(IN)_i^j$
        $[ROI_{on}]_i^j \leftarrow ROI(ON)_i^j$
        $F_i^j \leftarrow LBP(ROI_{in}, ROI_{on})$
        $B_i^j \leftarrow CFC(F_i^j, K)$
    $CD_B^j \leftarrow [B_i^j, j]$
$TC \leftarrow CD_B^j$
**return** (TCD)

### 3.1 Algorithm 1(Training): detection of interest-points using SURF

A point at which the direction of an edge or the boundary of an object changes abruptly is considered as an interest point. There are several descriptors to detect the interest points in an image. In the proposed approach SURF has been selected for generating the interest



(a) (b) (c) (d)

**Fig. 6** SURF Points on **a** Original Image **b** Rotated Image **c** Affine Image **d** Scaled Image points as it is robust to geometrical transformation (rotation, scale, affine) [20] as shown in Fig. 6. In the proposed methodology, 40 top SURF Points have been selected for an image. Through performing several experiments, it was observed that the contour of these top 40 SURF points cover the prominent part of the image. In Algorithm 1, $M_j$ denote the number of images in $j^{th}$ category where j=1 to N(Total no. of categories). For every $i^{th}$ image of $j^{th}$ category top 40 SURF Points are denoted as the set: $St_i^j$. $St_i^j$, are later used for the extraction of respective Region of Interest ($ROI_i^j$).

### 3.2 Algorithm 2: extraction of region of interest extraction

$ROI_i^j$ is constructed using $St_i^j$. Algorithm 2 generates the convex hull (https://slideplayer.com/slide/5087104/) of the set $St_i^j$. Points lying inside(IN)/on(ON) the boundary of the convex hull form the $ROI_i^j$ of $i^{th}$ image of $j^{th}$ category. Figure 7 shows the ROI obtained for 3 images as an example.

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**Algorithm 2** Extraction of Region of Interest$(ROI)_i^j$

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**Input**: Set of points in each image $St_i^j$

**Output**: A list (L) containg the verices for Region of Interest based on $St_j^i$

1 Sort the points $St_i^j$ in a sequence $St_1^j 1$, $St_i^j 2$,.....$St_i^j M_j$

2 Put the points $St_i^j 1$, $St_i^j 2$ in the list $l_{up}$ with $St_i^j 1$ in the first position

3 **for** $i \leftarrow 3$ ***to*** $j$ **do**

4     Append $St_i^j$ to $l_{up}$

5     **while** *$l_{up}$ contains more than 2 points and last three points in $l_{up}$ doesnot make a right turn* **do**

6         delete the middle of the last three points from $l_{up}$

7         Repeat step 2 to 6 for opposite direction to make $l_{low}$

8         remove the first and the last point from $l_{up}$

9         Append $l_{up}$ and $l_{low}$ to make L

10 **return** (L)

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#### 3.2.1 LBP features of ROI

LBP features are computed for ROI's taking 8 neighbors (P=8) and radius of 2(R=2) using (6). An example is shown in Fig. 8. LBP Features for every $i^{th}$ image of $j^{th}$ category is saved in $F_i^j$. Thereafter CFC is applied on $F_i^j$ to construct $B_i^j$(Bag of Features of $i_{th}$ image of $j_{th}$ category).

### 3.3 Algorithm 3: k-means Clustering with Fixed Centers (CFC)

Algorithm 3 is a proposed modified k-means Clustering with Fixed Centers. In the proposed approach k has been taken as 10 for k-means clustering. Histograms of $F_i^j$ (Hist($F_i^j$)) are constructed for j=1 to 10 categories. Each Hist($F_i^j$) is partitioned into 10 equal bins with respect to intensity values. From each bin, LBP Feature value having the highest peak(maximum

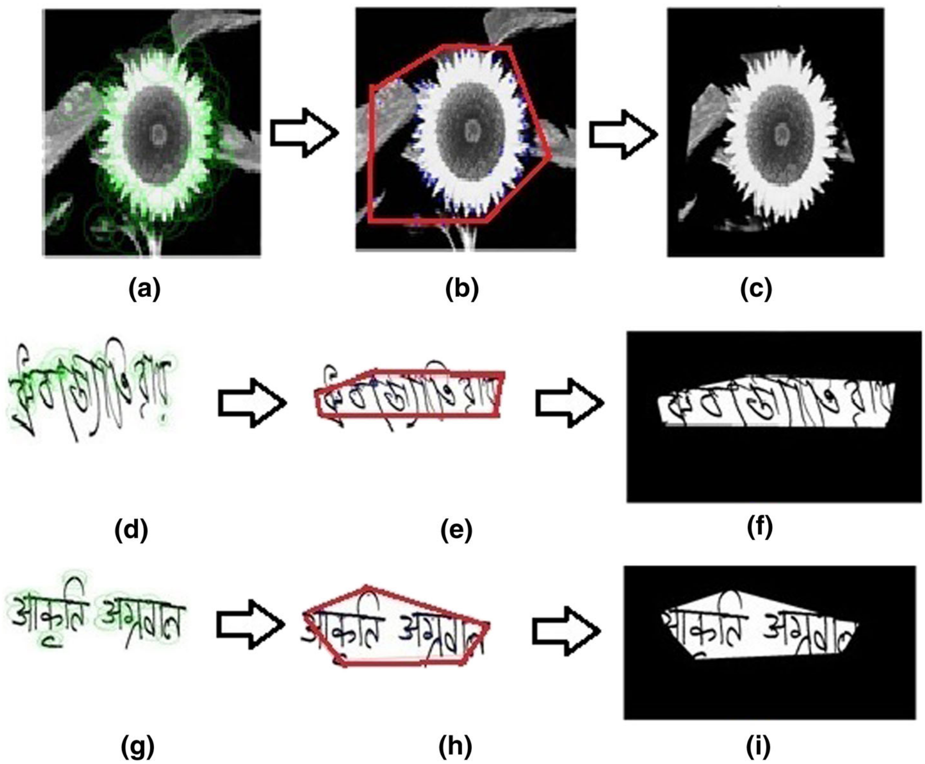


**Fig. 7** ROI extraction of images (**a**) (**d**) and (**g**) from 3 different datasets. (**b**) (**e**) and (**h**) convex hulls using algorithm 2 determined on (**a**), (**d**) and (**g**) respectively. (**c**), (**f**) and (**i**) are the ROI's of (**a**), (**d**) and (**g**) respectively

count) is taken as a center for that bin. These peak values from each bin are fixed as centers for k-means clustering. BoF of the image is constructed using these 10 fixed centers. In general k-means clustering ends up with the different set of centers affecting BoF. Thus the proposed CFC solves a major problem of different clusters formation using standard k-means. For every i$^{th}$ image of j$^{th}$ category BoF $B_i^j$ is constructed. Once $B_i^j$ for all the

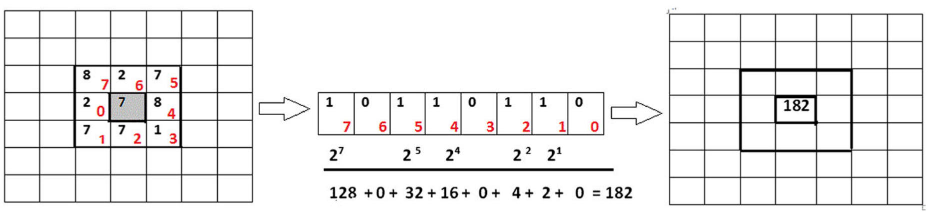


**Fig. 8** Calculation of LBP Values at center 7

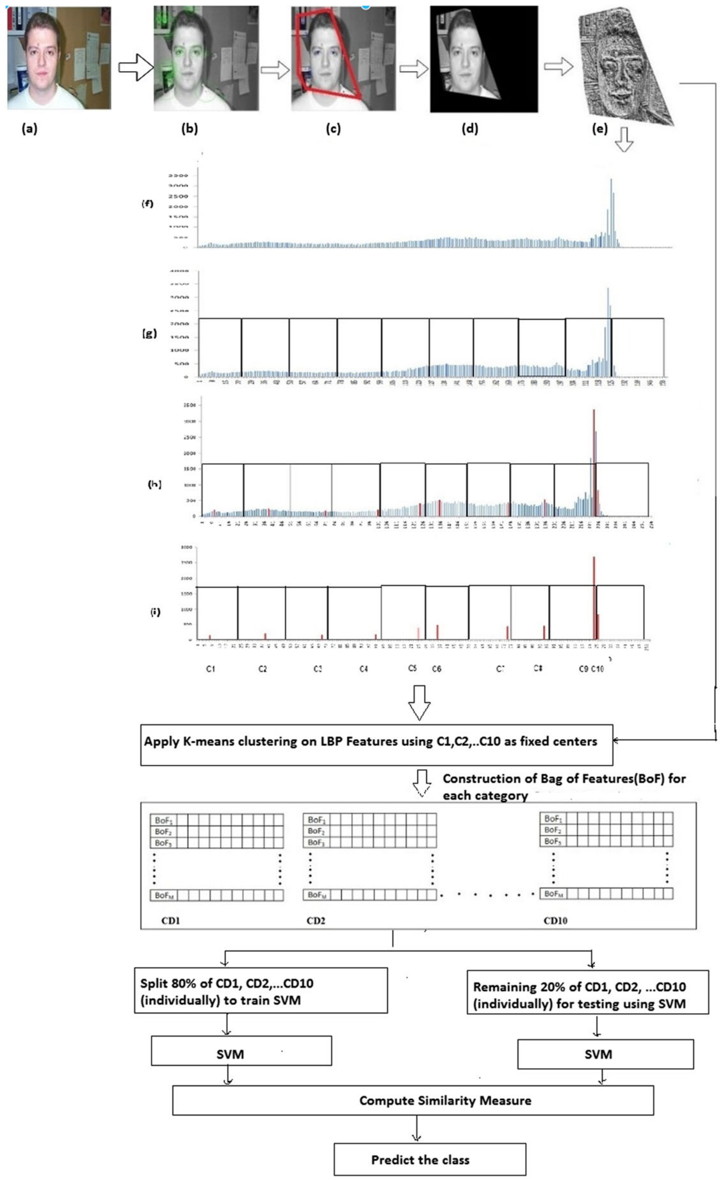


**Fig. 9** **a** Original Image **b** Detection of SURF points on (**a**) **c**)Convex hull based on SURF points on (**a**) **d**)Region of Interest(ROI) of (**a**) **e**)LBP Feature of ROI **f**)LBP Histogram **g**)Histogram divided into 10 bins h)Peak Value selected from each bin i)Peak values taken as centers C1,C2,..C10

'M' images in j$^{th}$ category (M$_j$) are formed, a complete BoF for j$^{th}$ category $CD_B^j$ is constructed. SVM is then trained on $CD_B^j$: j=1 to 10. The complete procedure is shown in Fig. 9.

**Algorithm 3** CFC: Clustering with Fixed Centers

**Input**: $F_i^j$, K
**Output**: Bag of features $B_i^j$
K $\leftarrow$ 10
intervel $\leftarrow$ (254/K);
start $\leftarrow$ 1;
stop $\leftarrow$ intervel;
y$\leftarrow$ 0
[$lbphist$] $\leftarrow$ Hist($F_i^j$)
**for** $i \leftarrow 1$ ***to*** 10 **do**
    [count C] $\leftarrow$ max[$lbphsit(start : stop)$]
    **if** *i==1* **then**
        CENTS(i) = C **else**
            CENTS(i) = (start-1) + C
        start $\leftarrow$ stop +1
        stop $\leftarrow$ stop + intervel
[$Cluster_K$, $count_K$] $\leftarrow$ K-menas($F_i^j$, CENTS)
$B_i^j$ $\leftarrow$ [$Cluster_K$, $count_K$]
**return** ($B_i^j$)

## 4 Datasets used for experiments

Four categorized datasets have been used for the experiments: Caltech-101[1], ORL Face[2], BHSig260[3]$_1$(Bangla Signatures) and BHSig260[3] $_2$(Hindi Signatures) . All these datasets are different in nature as Caltech-101 is a collection of 101 categories of images like airplane, bonsai, camera, dalmatian and etc. Each category contains about 40-400 images. A sample of Caltech-101 is shown in Fig. 10. ORL Face dataset formally known as "Database of Faces" is a collection of 40 categories of faces having 10 images in each category, a sample is shown in Fig. 11. BHSig260$_1$ and BHSig260$_2$ , are an offline Bangla and Hindi signatures respectively. There are 100 categories in Bangla Signature having 54 Signatures in each. Hindi Signature dataset has 160 categories, having 54 signatures in each category. Samples for both Bangla and Hindi signatures have been shown in Figs. 12 and 13 respectively.

The efficiency of the proposed approach has been tested using above mentioned datasets. From each dataset, 10 categories have been taken for experiment. A total of five experiments are performed. Experiment 1 has been performed on Caltech 101 and the 10 categories taken are:Airplane, Bonsai, Camera, Dalmatian, Electric Guitar, Euphonium, Face, Pizza, Soccer Ball and Sunflower. Experiment 2 has been performed on ORL Face dataset taking first 10 categories(s1, s2,...,s10). Experiment 3 and 4 are performed on Bangla and Hindi signatures respectively. For both the signatures dataset, first 10 categories(001, 002,...,010) are taken.

[1]The dataset is available at http://www.vision.caltech.edu/Image$_D$atasets/Caltech101/
[2]The dataset is available at http://www.cl.cam.ac.uk/research/dtg/attarchive/facedatabase.html
[3]The dataset is available at https://goo.gl/9QfByd

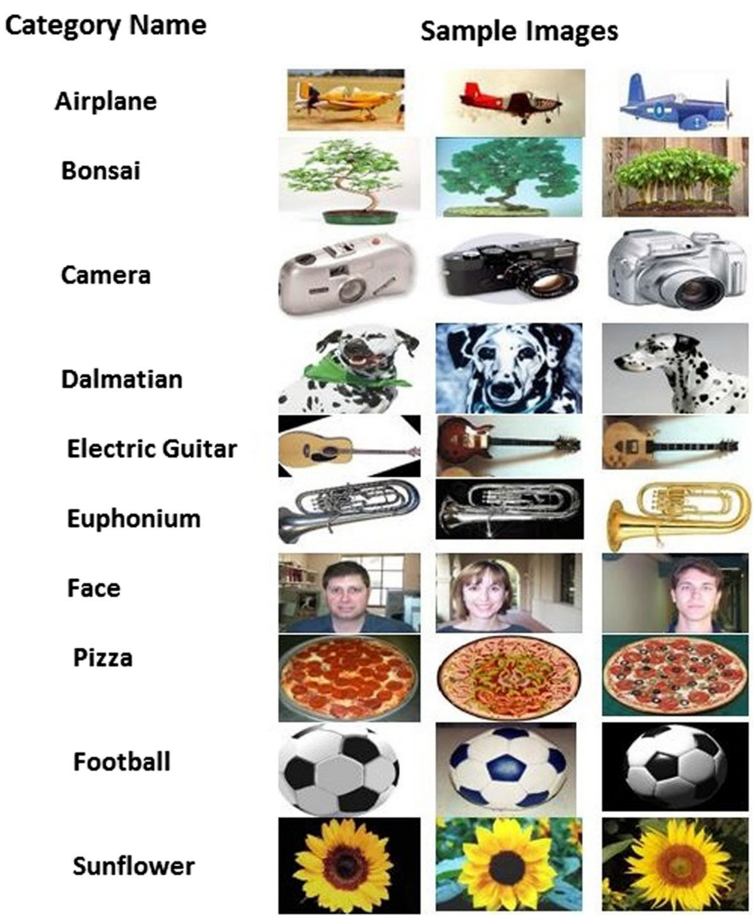


**Fig. 10** 3 Sample images of each 10 categories from Caltech-101 Dataset

Experiment 5 is for justifying the selection of SVM as a classifier. Each dataset has been randomly divided in the ratio of 80% (training) and 20% (testing).

## 5 Results analysis

Tables 1, 2, 3 and 4 are confusion matrices obtained for Caltech-101, ORL Face, Bangla Signatures and Hindi Signatures respectively. The diagonal gray highlighted elements in Tables 1, 2, 3 and 4 represent elements represent the number of images correctly identified for respective category. Following metrics are used for measuring the performance of the proposed approach.

$$Precision = \frac{Tp}{(Tp + Fp)} \tag{7}$$

$$Recall/Sensitivity = \frac{Tp}{(Tp + Fn)} \tag{8}$$

$$Specificity = \frac{Tn}{(Tn + Fp)} \tag{9}$$

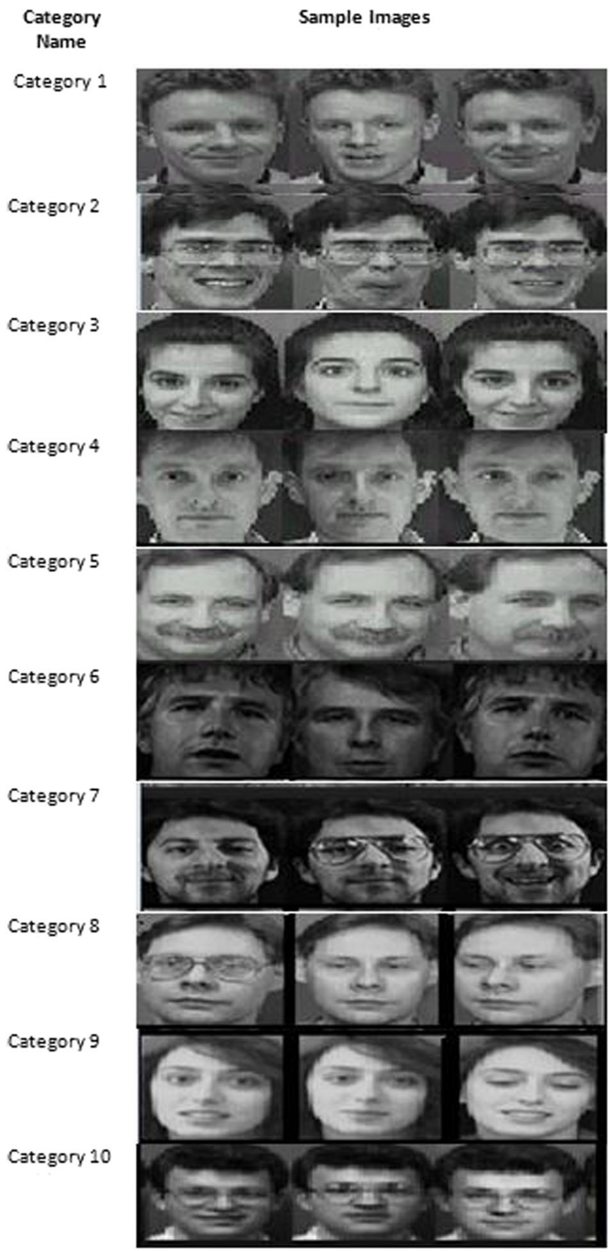


**Fig. 11** 3 Sample images of each 10 categories from ORL Dataset

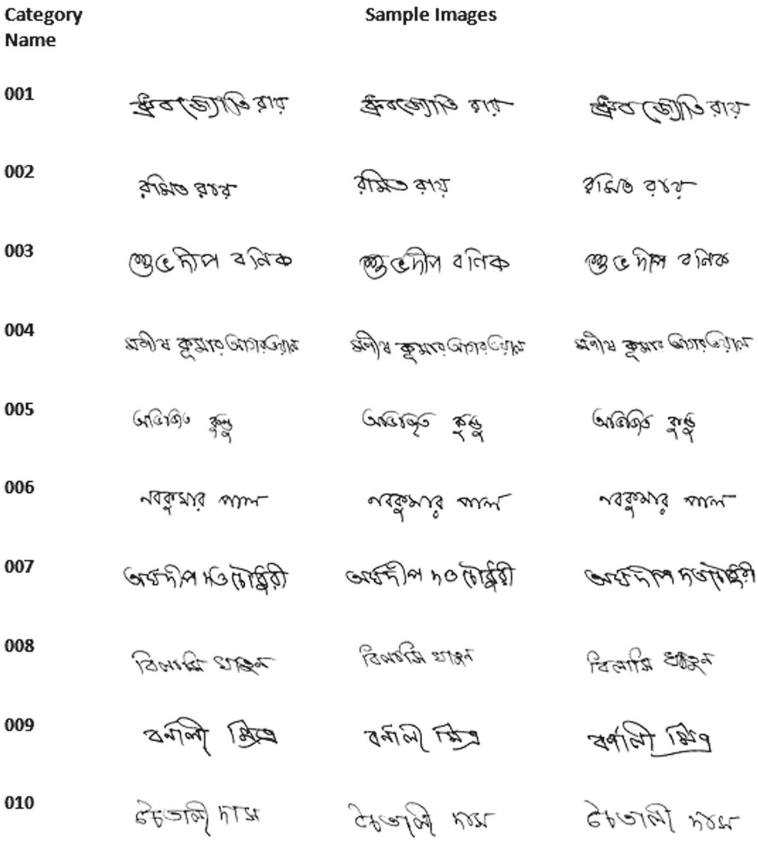


**Fig. 12** 3 Sample signatures of 10 each categories from Bangla Signature ($BHSig260_1$) Dataset

$$F - measure = \frac{2 * (Precision * Recall)}{(Precision + Recall)} \tag{10}$$

$$Accuracy = \frac{Tp + Tn}{N} \tag{11}$$

where Tp, Tn, Fp, Fn, N are true positive, true negative, false positive and false negative respectively and N is the total number of images taken in the experiment.

### 5.1 Experiment 1: dataset used- caltech 101

Table 5 show the performance metrics for Caltech-101. The average Precision, Recall, Specificity, F-measure and Accuracy are 0.63, 0.61, 0.48, 0.61 and 79% respectively. The highest accuracy is obtained for the category of face having accuracy of 96.3% and the lowest accuracy of 36% is obtained for the category of pizza.

### 5.2 Experiment 2: dataset used-ORL Face

First 10 categories(s1, s2,...,s10) of ORL Face dataset are taken for experiment. Table 6 show the performance metrics for ORL Face dataset. The average Precision, Recall, Specificity, F-measure and Accuracy are 0.22, 0.75, 0.05, 0.31 and 75% respectively. Categories

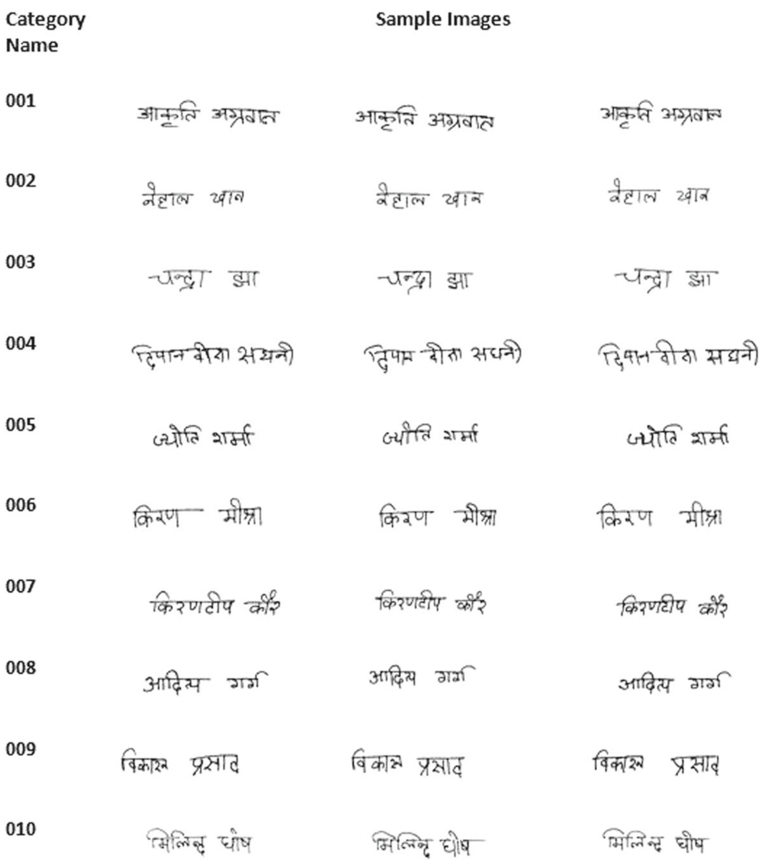


**Fig. 13** Sample signatures of 10 categories from Hindi Signature (BHSig260$_2$) Dataset

**Table 1** Confusion Matrix for 10 categories of Caltech-101 Dataset with k=10

| | airp. | bons. | came. | dalm. | elec. | euph. | face. | pizz. | socc. | sunf. |
|---|---|---|---|---|---|---|---|---|---|---|
| airp. | 79.8 | 0 | 0 | 1 | 4 | 0 | 0 | 0 | 1 | 0 |
| bons. | 0 | 17 .8 | 1 | 2 | 2 | 0 | 2 | 1 | 0 | 0 |
| came. | 0 | 0 | 8.8 | 2 | 0 | 0 | 0 | 4 | 0 | 0 |
| dalma. | 1 | 0 | 1 | 7.8 | 0 | 0 | 0 | 0 | 0 | 1 |
| elec. | 0 | 0 | 0 | 2 | 5 .8 | 0 | 0 | 1 | 0 | 1 |
| euph. | 0 | 1 | 0 | 0 | 0 | 4.8 | 1 | 2 | 0 | 0 |
| face. | 0 | 0 | 0 | 0 | 0 | 1 | 77.8 | 0 | 2 | 0 |
| pizz. | 0 | 4 | 2 | 0 | 0 | 1 | 4 | 9.8 | 3 | 3 |
| socc. | 0 | 0 | 0 | 1 | 0 | 1 | 1 | 0 | 5.8 | 0 |
| sunf. | 0 | 3 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 7.8 |

**Table 2** Confusion matrix for 10 categories of ORL FACE dataset with k=10

| | s1 | s2 | s3 | s4 | s5 | s6 | s7 | s8 | s9 | s10 |
|---|---|---|---|---|---|---|---|---|---|---|
| s1 | 2 .8 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| s2 | 0 | 1 .8 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| s3 | 0 | 0 | 1.8 | 0 | 0 | 1 | 0 | 0 | 0 | 0 |
| s4 | 0 | 0 | 0 | 1.8 | 0 | 0 | 0 | 0 | 0 | 0 |
| s5 | 0 | 0 | 0 | 0 | 2 .8 | 0 | 0 | 0 | 1 | 0 |
| s6 | 0 | 0 | 0 | 0 | 0 | 1.8 | 0 | 0 | 0 | 0 |
| s7 | 0 | 0 | 0 | 0 | 0 | 0 | 2.8 | 0 | 0 | 0 |
| s8 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 2.8 | 0 | 0 |
| s9 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1.8 | 0 |
| s10 | 0 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 2.8 |

s1, s2, s4, s6, s7 and s9 have the highest accuracy of 100% whereas s3 and s10 obtained the lowest accuracy of 50%.

### 5.3 Experiment 3: dataset used- Bangla Signatures

First 10 categories(001, 002,...,010) of $BHSig260_1$(Bangla Signatures) are taken for experiment. Table 7 show the performance metrics for Bangla Signatures. The average Precision, Recall, Specificity, F-measure and Accuracy are 0.53, 0.85, 0.13, 0.65 and 86.1% respectively. Highest accuracy of 100% are obtained for categories 003,007 and 009 and the lowest accuracy of 66.7% is obtained for the category 005.

### 5.4 Experiment 4: dataset used- Hindi Signatures

First 10 categories(001, 002,...,010) of $BHSig260_2$(Hindi Signatures) are taken for experiment. Table 8 show the performance metrics. The average Precision, Recall, Specificity, F-measure and Accuracy are 0.55, 0.86, 0.13, 0.66 and 87.0% respectively. Categories 004,

**Table 3** Confusion Matrix for 10 categories of Bangla Signatures Dataset with k=10

| | 001 | 002 | 003 | 004 | 005 | 006 | 007 | 008 | 009 | 010 |
|---|---|---|---|---|---|---|---|---|---|---|
| 001 | 7 .8 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 |
| 002 | 0 | 11 .8 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 |
| 003 | 0 | 0 | 9.8 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 004 | 0 | 0 | 1 | 10.8 | 0 | 0 | 0 | 0 | 0 | 0 |
| 005 | 2 | 0 | 0 | 0 | 10 .8 | 1 | 2 | 0 | 0 | 0 |
| 006 | 2 | 0 | 0 | 1 | 0 | 9.8 | 0 | 0 | 0 | 0 |
| 007 | 0 | 0 | 0 | 0 | 0 | 0 | 9.8 | 0 | 0 | 0 |
| 008 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 10.8 | 2 | 0 |
| 009 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 7.8 | 0 |
| 010 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 11.8 |

**Table 4** Confusion Matrix for 10 categories of Hindi Signature Dataset with k=10

| | 001 | 002 | 003 | 004 | 005 | 006 | 007 | 008 | 009 | 010 |
|---|---|---|---|---|---|---|---|---|---|---|
| 001 | 11 .8 | 0 | 0 | 1 | 0 | 0 | 1 | 0 | 0 | 0 |
| 002 | 0 | 9 .8 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 |
| 003 | 0 | 1 | 9.8 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 004 | 0 | 0 | 0 | 9.8 | 0 | 0 | 0 | 0 | 0 | 0 |
| 005 | 0 | 0 | 2 | 0 | 10 .8 | 0 | 1 | 0 | 0 | 0 |
| 006 | 0 | 0 | 0 | 0 | 0 | 11.8 | 0 | 1 | 1 | 0 |
| 007 | 0 | 0 | 0 | 0 | 0 | 0 | 8.8 | 0 | 0 | 0 |
| 008 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 9.8 | 0 | 0 |
| 009 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 7.8 | 0 |
| 010 | 0 | 1 | 0 | 0 | 1 | 0 | 1 | 0 | 1 | 11.8 |

**Table 5** Performance Metrics for Caltech-101

| | Caltech-101 | | | | |
|---|---|---|---|---|---|
| Categories | Precision | Recall | Specificity | F-measure | Class Accuracy(%) |
| airp. | 0.90 | 0.98 | 0.42 | 0.93 | 92.9 |
| bons. | 0.73 | 0.77 | 0.57 | 0.74 | 68.0 |
| came. | 0.66 | 0.50 | 0.60 | 0.56 | 57.1 |
| dalma. | 0.70 | 0.46 | 0.50 | 0.55 | 70.0 |
| elec. | 0.45 | 0.41 | 0.40 | 0.42 | 55.6 |
| euph. | 0.40 | 0.57 | 0.40 | 0.47 | 50.0 |
| face. | 0.93 | 0.90 | 0.37 | 0.91 | 96.3 |
| pizz. | 0.64 | 0.52 | 0.77 | 0.57 | 36.0 |
| socc. | 0.45 | 0.45 | 0.33 | 0.45 | 62.5 |
| sunf. | 0.53 | 0.58 | 0.45 | 0.55 | 58.3 |
| Average | 0.63 | 0.61 | 0.48 | 0.61 | 79.0 |

**Table 6** Performance metrics for ORL face

| | ORL Face | | | | |
|---|---|---|---|---|---|
| Categories | Precision | Recall | Specificity | F-measure | Class Accuracy(%) |
| s1 | 0.18 | 1 | 0 | 0.30 | 100 |
| s2 | 0.11 | 0.50 | 0 | 0.18 | 100 |
| s3 | 0.11 | 0.50 | 0.11 | 0.18 | 50.0 |
| s4 | 0.11 | 0.50 | 0 | 0.18 | 100 |
| s5 | 0.20 | 1 | 0.11 | 0.33 | 66.7 |
| s6 | 0.11 | 0.50 | 0 | 0.18 | 100 |
| s7 | 1 | 1 | 0 | 1 | 100 |
| s8 | 0.18 | 1 | 0.10 | 0.30 | 66.7 |
| s9 | 0.11 | 0.50 | 0 | 0.18 | 100 |
| s10 | 0.18 | 1 | 0.18 | 0.30 | 50.0 |
| Average | 0.22 | 0.75 | 0.05 | 0.31 | 75.0 |

**Table 7** Performance Metrics for Bangla Signature

| | Bangla Signature | | | | |
|---|---|---|---|---|---|
| Categories | Precision | Recall | Specificity | F-measure | Class Accuracy(%) |
| 001 | 0.50 | 0.63 | 0.12 | 0.55 | 87.5 |
| 002 | 0.55 | 1 | 0.10 | 0.70 | 91.7 |
| 003 | 0.52 | 0.90 | 0 | 0.66 | 100 |
| 004 | 0.55 | 0.90 | 0.11 | 0.68 | 90.9 |
| 005 | 0.55 | 0.90 | 0.38 | 0.68 | 66.7 |
| 006 | 0.56 | 0.81 | 0.30 | 0.66 | 75.0 |
| 007 | 0.52 | 0.81 | 0 | 0.63 | 100 |
| 008 | 0.52 | 1 | 0.25 | 0.68 | 76.9 |
| 009 | 0.53 | 0.63 | 0 | 0.57 | 100 |
| 010 | 0.55 | 0.55 | 0.10 | 0.70 | 91.7 |
| Average | 0.53 | 0.85 | 0.13 | 0.65 | 86.1 |

007 and 008 obtained the highest accuracy of 100% and the lowest accuracy of 73.3% is obtained for the category 010.

### 5.5 Scalability of the proposed approach

Experiments 1 - 4 have been performed using 10 categories from each dataset. By varying the number of categories taken from each dataset in the experiment, it is found that the overall accuracy is not affected much as shown in Table 9. All the results are computed by keeping k=10 in k-means clustering as experimentally it was found that k=10 is sufficient for constructing Bag of Features.

### 5.6 Experiment 5: selection of suitable classifier for the proposed approach

In machine learning there is a theorem called "No Free Lunch" [34], which in simple terms states that no classifier works best in every situation. For instance, the complexity of algorithm depends upon the type of data structure used. Similarly, the selection of classifier

**Table 8** Performance Metrics for Hindi Signature

| | Hindi Signature | | | | |
|---|---|---|---|---|---|
| Categories | Precision | Recall | Specificity | F-measure | Class Accuracy(%) |
| 001 | 0.55 | 1 | 0.18 | 0.70 | 84.6 |
| 002 | 0.56 | 0.81 | 0.12 | 0.66 | 90.0 |
| 003 | 0.52 | 0.81 | 0.11 | 0.63 | 90.0 |
| 004 | 0.56 | 0.81 | 0 | 0.66 | 100 |
| 005 | 0.55 | 0.90 | 0.27 | 0.68 | 76.9 |
| 006 | 0.55 | 1 | 0.81 | 0.70 | 84.6 |
| 007 | 0.61 | 0.72 | 0 | 0.66 | 100 |
| 008 | 0.52 | 0.90 | 0 | 0.65 | 100 |
| 009 | 0.53 | 0.70 | 0.14 | 0.60 | 87.5 |
| 010 | 0.55 | 1 | 0.30 | 0.70 | 73.3 |

**Table 9** Scalability of the proposed method

| | Caltech-101 | |
|---|---|---|
| No. of Categories | Total no. of images | Accuracy(%) |
| 5 | 802 | 78.05 |
| 10 | 1386 | 79.0 |
| 15 | 1848 | 76.8 |
| 20 | 2206 | 75.7 |
| Average | | 77.3 |
| | ORL Face | |
| No. of Categories | Total no. of images | Accuracy(%) |
| 5 | 50 | 80.0 |
| 10 | 100 | 75.0 |
| 15 | 150 | 73.3 |
| 20 | 200 | 76.7 |
| Average | | 76.25 |
| | Bangla Signature | |
| No. of Categories | Total no. of images | Accuracy(%) |
| 5 | 270 | 88.01 |
| 10 | 540 | 86.1 |
| 15 | 810 | 86.3 |
| 20 | 1080 | 83.49 |
| Average | | 85.9 |
| | Hindi Signature | |
| No. of Categories | Total no. of images | Accuracy(%) |
| 5 | 270 | 90.89 |
| 10 | 540 | 87.0 |
| 15 | 810 | 86.04 |
| 20 | 1080 | 84.12 |
| Average | | 87.01 |

highly depends upon how the features are organized/stored especially in case of supervised learning. Histograms are very frequently used in computer vision, image processing, image classification, etc. Most of the descriptors are based on the histogram of features. In the proposed approach also, histogram of LBP features is constructed using CFC. Since SVM classifiers are very effective in dealing with the histograms [35], therefore the proposed approach has preferred. The experimental results also confirm that SVM performs best on same feature vectors when compared to other classifiers: Decision Tree, Random Forest, Linear Method and K- Nearest Neighbor.

Experiment 5 was performed to justify the use of SVM as a classifier. Table 10 shows the results for the experiment using classifiers: Decision Tree(DT), K Nearest Neighbor(KNN), Linear Method(LM), Random Forest(RF) and Support Vector Machine(SVM). SVM obtained the highest average accuracy of 81.7% and is thus preferred over other classifiers for the proposed approach. Figure 14 shows the ROC plot for Table 10.

**Table 10** Selection of suitable classifier for the proposed approach

| | Different Classifiers | | | | |
|---|---|---|---|---|---|
| Datasets | DT | KNN | LM | RF | SVM |
| Caltech-101 | 62.9 | 61.0 | 79.3 | 76.0 | 79.0 |
| ORL Face | 25.0 | 71.5 | 50.0 | 70.0 | 75.0 |
| Bangla Signature | 53.9 | 71.5 | 80.5 | 83.4 | 86.4 |
| Hindi Signature | 58.4 | 65.1 | 85.2 | 87.0 | 87.0 |
| Average Rate | 50.0 | 67.3 | 73.7 | 79.1 | 81.7 |

## 5.7 Effectiveness of the proposed methodology

The results of the proposed approach have been compared with the recent state-of art approaches: [6, 11, 33] through Table 11. Ferraz, Carolina Toledo et al. [11] proposed the classification of an object using various local descriptors like: M-LMP(Mean local mapped pattern), CS-LMP(Center Symmetric Local Mapped Pattern), SIFT, and Local Intensity Order Pattern (LIOP). The experiments were performed on Caltech-101 dataset. The overall average accuracy obtained for various descriptors is 77.65% whereas the proposed approach achieves the accuracy of 79% for the same dataset. Manisha, B. Raman [33] proposed the

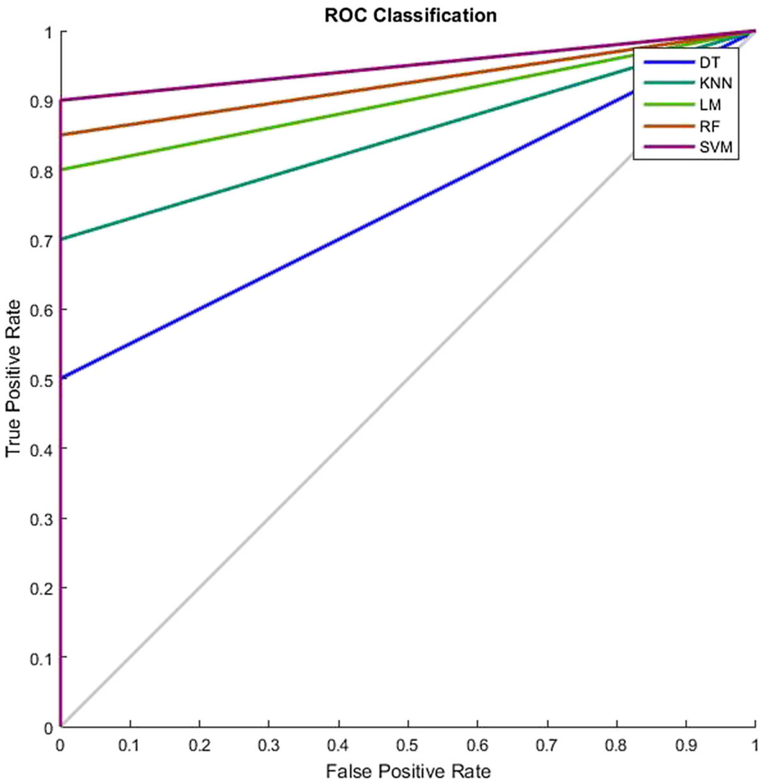


**Fig. 14** ROC plot for various classifiers

**Table 11** Comparison with state of art approaches (Accuracy (%))

| Dataset | Deng et al. [6] | Ferraz et al. [11] | Manisha et al. [33] | Proposed Approach |
|---|---|---|---|---|
| Caltech-101 | – | 77.65 | – | 79.0 |
| ORL | – | – | 73.9 | 75.0 |
| Different objects (chairs, dogs, etc) | 76.47 | – | – | 79.0(Caltech-101) |
| Bangla Signature | – | – | – | 86.1 |
| Hindi Signature | – | – | – | 87.0 |

image classification for ORL Face dataset the accuracy obtained by [33] is 73.9% whereas the proposed approach has the accuracy of 75% for the same dataset.

## 6 Conclusion

State of art approaches for classification/categorization are confined to the specific type of dataset. For instance, LBP based classification is generally used for Face, Texture datasets. Gray Level Co-occurrence Matrix for textile pattern dataset and etc. This paper presented a common approach for classification of variety of datasets. Proposed method uses SURF and LBP both for image classification. Here SURF has been used for the extraction of Region of Interest(ROI) in an image and LBP is used for feature extraction. The LBP Features obtained are then clustered by using CFC approach to construct the BoF. Through proposed CFC approach each image is annotated/tagged with a fixed Bag of Features to avoid the training of machine, again and again. The accuracy obtained for Caltech-101, ORL Face, and Signature(Bangla and Hindi) are 79.0%, 75.0%, 81.6% and 87.0% respectively. Thus the average accuracy obtained by the proposed approach is 81.7% in contrast to other state of art approaches having average accuracy as 64.15%, 76.47%, and 77.65%.



## References

1. Bay H et al (2008) Speeded-up robust features (SURF). Comput Vis Image Underst 110(3):346–359
2. Chen H et al (2017) Scene image classification using locality-constrained linear coding based on histogram intersection. Multimed Tools Appl 3:1–12
3. Csurka G et al (2004) Visual categorization with bags of keypoints. In: Workshop on statistical learning in computer vision, ECCV, vol 1, pp 1–22
4. Cula OG, Dana KJ (2001) Compact representation of bidirectional texture functions. In: Proceedings of the 2001 IEEE computer society conference on computer vision and pattern recognition, 2001. CVPR 2001, vol 1. IEEE
5. Dang QB et al (2015) Camera-based document image retrieval system using local features-comparing SRIF with LLAH, SIFT, SURF and ORB. In: 2015 13th international conference on document analysis and recognition (ICDAR). IEEE
6. Deng J et al (2014) Large-scale object classification using label relation graphs. In: European conference on computer vision. Springer, Cham
7. Divya S, Goel S, Agarwal S (2017) Pipelined technique for image retrieval using texture and color. In: 2017 4th international conference on power control & embedded systems (ICPCES). IEEE
8. Divya S et al (2018) Pattern-based image retrieval using GLCM. Neural Comput & Applic. Special issue: India Intl. Congress on Computational Intelligence, pp 1–14

9. Ebrahim K, Prasad S, Shehata M (2017) Image matching using SIFT, SURF, BRIEF and ORB: performance comparison for distorted images. arXiv:1710.02726
10. Felzenszwalb PF, Girshick RB, McAllester D, Ramanan D (2010) Object detection with discriminatively trained partbased models. IEEE Trans Pattern Anal Mach Intell 32(9):1627–1645
11. Ferraz CT, Gonzaga A (2017) Object classification using a local texture descriptor and a support vector machine. Multimed Tools Appl 76(20):20609–20641
12. Haralick RM, Shanmugam K (1973) Textural features for image classification. IEEE Trans Syst Man Cybern 6:610–621
13. Hirata K et al (2000) Integration of image matching and classification for multimedia navigation. Multimed Tools Appl 11(3):295–309
14. Lan X, Ma AJ, Yuen PC, Chellappa R (2015) Joint sparse representation and robust feature-level fusion for multi-cue visual tracking. IEEE Trans Image Process 24(12):5826–5841
15. Li F-F, Perona P (2005) A bayesian hierarchical model for learning natural scene categories. In: IEEE computer society conference on Computer Vision and Pattern Recognition CVPR 2005. vol 2, IEEE, 2005
16. Li L et al (2016) Recognizing complex activities by a probabilistic interval-based model. AAAI 30:1266–1272
17. Lindeberg T (1998) Feature detection with automatic scale selection. IJCV30 2(2):79–116
18. Lowe DG (1999) Object recognition from local scale-invariant features. ICCV 2:1150–1157
19. Luo J, Gwun O (2009) A comparison of sift, pca-sift and surf. International Journal of Image Processing (IJIP) 3(4):143–152
20. Ma J et al (2014) A method of protein model classification and retrieval using bag-of-visual-features. In: Computational and mathematical methods in medicine 2014
21. Mikolajczyk K, Schmid C (2001) Indexing based on scale invariant interest points. ICCV 1:525–531
22. Nouman A et al (2016) A novel image retrieval based on visual words integration of SIFT and SURF. PloS One 11(6):e0157428
23. Nowak E, Jurie F, Triggs B (2006) Sampling strategies for bag-of-features image classification. Comput Vis ECCV 2006:490–503
24. O'Hara S, Draper BA (2011) Introduction to the bag of features paradigm for image classification and retrieval. arXiv:1101.3354
25. Ojala T, Pietikäinen M, Harwood D (1996) A comparative study of texture measures with classification based on featured distributions. Pattern Recog 29(1):51–59
26. Oyallon E, Rabin J (2015) An Analysis of the SURF method. Image Process Line 5:176–218
27. Porebski A et al (2014) A new benchmark image test suite for evaluating colour texture classification schemes. Multimed Tools Appl 70(1):543–556
28. Perner P, Perner H, Muller B (2002) Mining knowledge for HEp-2 cell image classification. Artif Intell Med 26:161–173
29. Pooja K, Saluja S, Agrawal S (2013) A survey on image classification approaches and techniques. Int J Adv Res in Comput Commun Eng 2(1):1005–1009
30. Schmid C, Mikolajczyk K (2003) A performance evaluation of local descriptors. ICPR 2:257–263
31. Shivakumar BL, Baboo LDSS (2011) Detection of region duplication forgery in digital images using SURF. IJCSI International Journal of Computer Science Issues 8:4
32. Shivajee P, Srivastava D, Agarwal S (2017) An efficient approach for dynamic PCA filter selection in PCANet for image classification. In: 2017 4th IEEE Uttar Pradesh section international conference on electrical, computer and electronics (UPCON). IEEE, pp 139–144
33. Verma M, Raman B (2015) Center symmetric local binary co-occurrence pattern for texture, face and bio-medical image retrieval. J Vis Commun Image Represent 32:224–236
34. Wolpert DH (2002) The supervised learning no-free-lunch theorems. In: Soft computing and industry. Springer, London, pp 25–42
35. Wu J (2012) Efficient HIK SVM learning for image classification. IEEE Trans Image Process 21(10):4442–4453
36. Wu J et al (2013) A comparative study of SIFT and its variants. Meas Sci Rev 13(3):122–131
37. Xiangyuan L, Ma AJ, Yuen PC (2014) Multi-cue visual tracking using robust feature-level fusion based on joint sparse representation. In: Proceedings of the IEEE conference on computer vision and pattern recognition, pp 1194–1201
38. Xiangyuan L, Zhang S, Yuen PC (2016) Robust joint discriminative feature learning for visual tracking. In: Proceedings of twenty-fifth international joint conference on artificial intelligence. IJCAI, pp 3403–3410
39. Xiangyuan L, Yuen PC, Chellappa R (2017) Robust MIL-based feature template learning for object tracking. In: Proceedings of 31 AAAI conference on artificial intelligence. AAAI, pp 4118–4125

40. Xiangyuan L et al (2018) Robust collaborative discriminative learning for rgb-infrared tracking. AAAI
41. Xiangyuan L et al (2018) Learning common and feature-specific patterns: a novel multiple-sparse-representation-based tracker. IEEE Trans Image Process 27(4):2022–2037
42. Yang J, Yu K, Gong Y (2009) Linear spatial pyramid matching using sparse coding for image classification. In: Proceedings IEEE Conf. Comput. Vis. Pattern Recog., pp 1794–1801
43. Ye L et al (2015) Action2activity: recognizing complex activities from sensor data. IJCAI 2015:1617–1623
44. Ye L et al (2016) From action to activity: sensor-based activity recognition. Neurocomputing 181:108–115
45. Ye L et al (2016) Fortune teller: predicting your career path. In Proceedings of 30th AAAI conference on artificial intelligence, vol 2016. AAAI, pp 201–207

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