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On the Performance of Devnagari Handwritten Character Recognition

Rajiv Kumar, Kiran Kumar Ravulakollu and Sharda University

Department of Computer Science and Engineering

Abstract: This paper presents the offline handwritten character recognition for Devnagari, a major script of India. The main objective of this work is to develop a handwritten dataset (CPAR-2012) for Devnagari character and further develop a character recognition scheme for benchmark study. The present dataset is a new development in Devnagari optical document recognition. The dataset includes 78,400 samples collected from 2,000 heterogeneous strata of Hindi speaking persons. These dataset is further divided into 49,000 as training set and 29,400 as test set. The evaluated feature extraction includes: direct pixel, image zoning, wavelet transformation and Gaussian image transformation techniques. These features were classified by using KNN and neural network classifier. The experiment shows that Gaussian image transformation (level 1) using KNN classifier has achieved highest recognition 72.18 % than other feature extraction methods. Further classification result obtained from KNN classifier were combined, the combined result shows 84.03 % recognition accuracy with expense of 5.3 % rejection. Based on this result some shape similar character zones in Devnagari characters are highlighted in this paper.

Key words: Benchmark dataset · Character Recognition · Handwritten form processing · Neural network classifier and KNN classifier.

INTRODUCTION

Devnagari Optical Document Recognition (DODR) system for unconstrained handwritten character recognition is an active, yet challenging area of research [1]. With the increasing demand of computers in offices and homes, automatic processing of handwritten paper documents is gaining importance. Devnagari script is used for writing many official languages in India, e.g. Hindi, Marathi, Sindhi, Nepali, Sanskrit and Konkani, also Hindi is the national language of India. Hindi is the third most popular language in world [2].

Despite of tremendous advancements in automatic recognition processing system, there is still big challenges in unconstrained handwritten characters.

Many techniques have been proposed in the literature for recognizing unconstrained handwritten Devnagari character (D-Character) recognition. The techniques includes: Chain code [3, 4, 8], structural [5-7], gradient [10, 12-13] and Eigen deformation [11]. All the handwritten Devnagari character recognition system reported in literature (Table 1) shows the recognition accuracy lies between 80.36 % to 95.19 %. Many of the reported OCR techniques were experimented with small datasets [3-4, 6-8, 11] less than 12,000 samples.

Table 1: Progress on handwritten character recognition

Feature Extraction	Classifier	Dataset Size	Recognition Rate	Ref.
Chain code	Quadratic	11,270	80.36	[3]
Chain code	RE & MED	5,000	82	[4]
Structural approach	FFNN	50,000	89.12	[5]
Structural	Combined	1,500	89.58	[6]
Vector distance	Fuzzy sets	4,750	90.65	[7]
Shadow & CH	MLP & MED	7,154	90.74	[8]
Gradient	SVM	25,000	94.1	[9]
Gradient & Gaussian filter	Quadratic	36,172	94.24	[10]
Eigen deformation	Elastic matching	3,600	94.91	[11]
Gradient	SVM & MQDF	36,172	95.13	[12]
Gradient	MIL	36,172	95.19	[13]

There is no benchmark dataset available for researchers. The lack of this might be one reason to slow development in this field. There is a strong need of benchmark dataset in order to get uniform progress in this area. There is a strong need of this dataset for measuring the performance evaluation of

Corresponding Author: Rajiv Kumar, Department of Computer Science and Engineering.

अ	आ	इ	ई	उ	ऊ	ऋ	ए	ऐ	ओ	औ	अं	अः
A	AA	I	II	U	UU	RI	E	EI	O	OU	ANG	AH
क	ख	ग	घ	ङ	च	छ	ज	झ	ञ	ट	ठ	ड
KA	KHA	GA	GHA	NGA	CHA	CHHA	JA	JHA	NJA	TA	THA	DA
ढ़	ण	त	थ	द	ध	न	प	फ	ब	भ	म	य
DHA	NA	TA	THA	DA	DHA	NA	PA	PHA	BA	BHA	MA	YA
र	ल	व	श	स	ष	ह	क्ष	त्र	ज्ञ			
R	LA	VA	SHA	SA	SHH	HA	KSH	TRA	JNJA			

Fig. 1: Devnagari Characters

recognition tools and techniques and comparing the recognition accuracies of the character recognition systems.

To support research and benchmarking this research work will facilitate collection, compilation and storage of handwriting data, along with writer's attributes, over a long period of time. This, in turn, will help in knowledge extraction from handwriting samples for medical, forensic, writer identification, personality assessment and similar applications that require handwriting samples collected over a long period of time.

The section 2 of the paper shows the dataset development, the feature extraction and classification techniques were discussed in section 3, the various experimental results are explained in section 4 and finally section 5 concludes the paper.

Dataset for Handwritten Characters: In this research work we present an important contribution of the development and organization of offline handwritten Character (CPAR-2012) dataset.

There are 13 vowels, 33 consonants, 3 composite consonant commonly used characters in Devnagari. Fig. 1 shows *Devnagari* Character shapes. Although, these shapes are unique but *Devnagari* characters shows similar shape characteristics.

The CPAR-2012 dataset contains images of constrained, semi-constrained and unconstrained handwritten numerals; isolated characters; unconstrained and constrained pangram text; digitized data collection forms. The pangram text has 13 most frequently used vowels, 14 modifiers and 36 consonants. This pangram is developed to study handwriting variations. Also writer creditials are also provided for writer identification, a requirement for handwriting analysis research.

The novelty of the dataset is that it is the largest test dataset for *Devnagari* script based document recognition research. The data reflects the maximum handwriting variations as it is sampled from writers belonging to diverse population strata. The dataset comprises of different dimensions like age groups (from 6 to 77 years), gender, educational backgrounds (from 3rd grade to post graduate levels), professions (software engineers, professors, students, accountants, housewives and retired persons) and regions (Indian states: Bihar andhra Pradesh, Uttar Pradesh, Haryana, Punjab, National Capital Region (NCR), Madhya Pradesh, Karnataka, Kerala, Rajasthan and countries: Nigeria, China and Nepal). Almost two thousand writers participated in dataset acquisition process.

We designed a form to collect the isolated digits, characters and writer's information.Data were collected from 2,000 writers where each writer filled the forms. The duly filled forms were digitized using HP Cano LiDE 110 scanner at resolution 300 DPI in color mode and from these forms extracted the desired data using a defined software application [14].

Form Processing: The extraction ofisolated characters (digits and alphabet) along with writer information from Form-1 (Fig. 2) begins with skew correction operation, if required. To reduce preprocessing time, an automatic image skew correction (Radon transformation [15]) is performed before segmentation of images to extract the images of individual characters. Later, in skew-free images of form-1, the process locates the machine printed character block, hand written character block followed by writer's information block.

To extract the isolated characters the following steps are carried out:

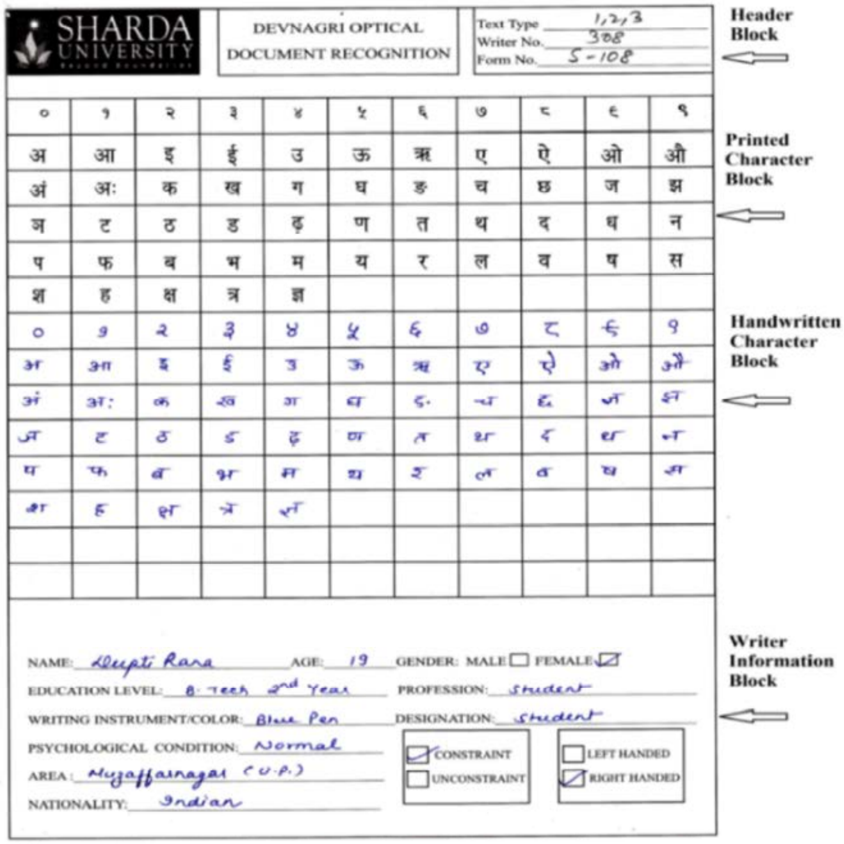


Fig. 2: Design of Form usedinisolatedcharactersextraction

- Binarize Form-1 image using Otsu Method [16].
- Remove noise (impression of other forms, salt and pepper noise, corner folding, physically damaged paper, extraneous lines, stapler pins marks) that occurs during the digitization process.
- Perform hole filling morphological to obtain the uniform connected component on digitalized image.
- Perform the labeling operation on the connected components obtained in step-3 to find the bounding box (top-left point, width and height) for each labeled region.
- Locate and filter out all labeled components in the handwritten character block.

An acceptance of 1700 forms is obtained from 2000 during extraction. From each accepted form 154 bounding boxes were detected, cropped, stored and displayed for verification. Finally, an acceptable dataset of 15000 numerals and 78400 characters of handwritten samples is obtained. A small portion of poor quality samples (1,400 samples) are denied. These samples have also been stored in the database for further investigation.

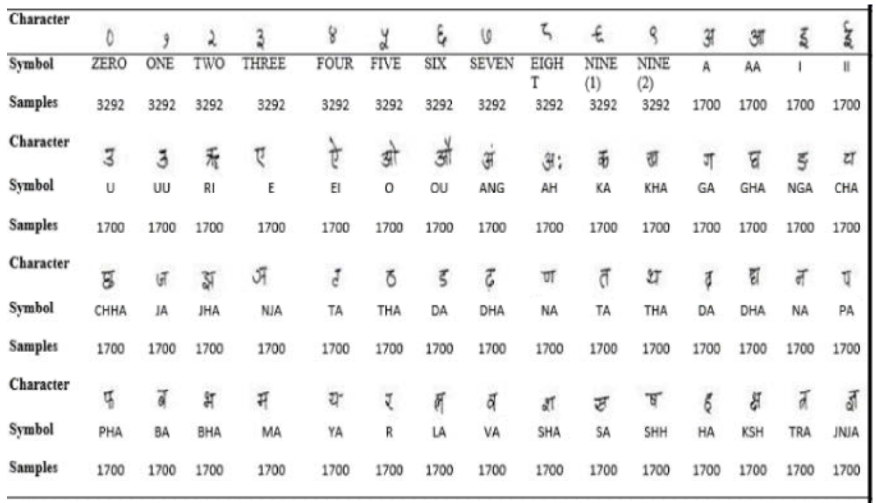
Out of 15000 unconstrained and 5000 constrained handwritten numerals, some samples are lost due to overwritten on either side of guidelines especially with constrained numerals. The final dataset consists of: 83,300 isolated characters; 35,000 numerals; 2,000 constrained pangrams and 2,000 unconstrained pangrams; Writer's Information; 2,000 Form-1 images and 2,000 Form-2 images. For processing these colour images are preprocessed for noise elimination, binarization and size normalize into 32 x 32 pixels as shown in Fig. 3.

We observed the following discrepancies while checking acceptance or rejection of samples.

- Voilation in writing guidelines or the amount of content in the boundaries considered, converts samples from one character to other as show in

Fig 4. Some samples of AA,OU,ANG and AH became A, II became I, EI became E.

- We also observed Overwriting and discontinuity in shapes see Fig 5(a) and (b).



Character															
Symbol	ZERO	ONE	TWO	THREE	FOUR	FIVE	SIX	SEVEN	EIGHT	NINE (1)	NINE (2)	A	AA	I	II
Samples	3292	3292	3292	3292	3292	3292	3292	3292	3292	3292	3292	1700	1700	1700	1700
Character															
Symbol	U	UU	RI	E	EI	O	OU	ANG	AH	KA	KHA	GA	GHA	NGA	CHA
Samples	1700	1700	1700	1700	1700	1700	1700	1700	1700	1700	1700	1700	1700	1700	1700
Character															
Symbol	CHHA	JA	JHA	NJA	TA	THA	DA	DHA	NA	TA	THA	DA	DHA	NA	PA
Samples	1700	1700	1700	1700	1700	1700	1700	1700	1700	1700	1700	1700	1700	1700	1700
Character															
Symbol	PHA	BA	BHA	MA	YA	R	LA	VA	SHA	SA	SHH	HA	KSH	TRA	JNJA
Samples	1700	1700	1700	1700	1700	1700	1700	1700	1700	1700	1700	1700	1700	1700	1700

Fig. 3: Handwritten character samples obtained from the forms.

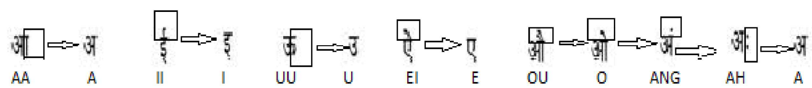
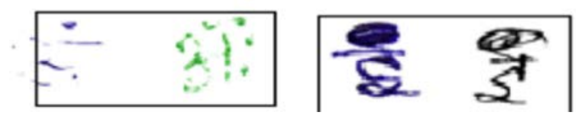


Fig. 4: Samples converted from one shape to other shapes



(a) (b)

Fig. 5: (a) discontinuity and (b) overwritten samples

Due to these we lost 10-20 % samples in from each groups. Finally we obtained 78,400 correct character samples. These samples were further divided into training and test set.

Experimental Details: Now handwritten D-character dataset is ready to feed for recognition techniques, a series of experiments has to be conducted for analyzing performance. The objective of these experiments is to provide recognition results for benchmark studies.

Feature Extraction: Feature extraction is the primary step during recognition process. A discriminative feature vector is essential for high recognition results at comparable cost. In this experiment feature extraction technique is applied on, preprocessed and sizenormalized image of 32 x 32. The feature performance is measured with features ranging from the simple most features to more complex features explained below.

Direct Pixel: Experiments are initiated with simple feature definition - the pixel value [14]. Feature vectors are formed by storing the size normalized two-dimensional digit images into one-dimensional (in column major) feature vectors where each feature element is pixel value. For this images are resized into 1024 pixels in column major. Thus obtained recognition results are used as a baseline of comparison, assuming that it represents the worst recognition scenario.

Profile Based Features: For comparative study simple profile[17] features are used, for effective feature extraction. Due to their simplicity and usefulness, several variations, like features from left, right, top and bottom profiles are being used. Experiments are conducted considering all four profiles forming 128 pixels (32 x 4) to define feature vectors. Each feature element that depicts the profile value, is formed by combining the above mentioned profiles respectively.

The profile feature values range from 1 to 32 pixels which is length and width of each image. Fig. 6 shows profiles of handwritten character ‘A’ from CPAR-2012 dataset.

Image Zoning: The image zoning (IZ) [18] value feature is the average pixel intensity value in a specified region or zone. In order to determine the region size we studied the distribution of these features in zone of varying size.

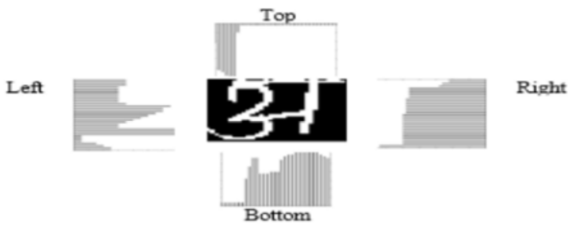


Fig. 6: Left, right, top and bottopm profile of character 'A'.

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

Fig. 7: (a) original image (b) Wavelet transform (level 1) (c) Gausian pyramid (level 1) and (d0 Gausian pyramid (level 2)

We defined these zones by partitioning the size normalized image into equal number of rows and columns. In order to estimate the optimal zone size we experimented with zone size: 2x2, 3x3, 4x4, 5x5, 6x6 and 8x8 and discovered the best zone size of 5x5. In this manner we extracted 36 features from 36 zones from the size normalized 30 x 30 image.

Wavelet Transform: Wavelet transform (WT) [19] provides multi resolution analysis of an image. The transform leads to decomposition of an image into four components: the approximation (LL) and the details in three orientations (horizontal: LH, vertical: HL and diagonal: HH). Wavelet transforms are available in many varieties. However Daubechies (db) wavelets are compactly supported in the image processing and provides good spatial-frequency localization. For this reason in this work Daubechies wavelet pyramid was applied.

In this case we applied the wavelet transform (db-1) level -1 on the original image that produced the transformed image of 16x16 containing four wavelet coefficients. We resized the transformed image (approximation coefficient- LL) into 256x1 pixels feature vector. Fig. 7(a) and Fig 3(b) shows the original image and their wavelet transformed image.

Gaussian Pyramid: The Gaussian pyramid (GP) [20] is a multi-level and multi-resolution representation of images. In this approach we first smooth the image and then subsample the smoothed image successively. The expression given in Eq. (2) below is suggested to be used to compute Gaussian pyramid coefficients *Gl*(*i*) at subsampling level l.

$$G_l(i,j) = \sum_m \sum_n W(m,n) G_{l-1}(2i+m, 2j+n) \qquad (1)$$

Where l indexes the level of the pyramid and w (m, n) is the Gaussian weighted function.

In this case we applied the Gaussian pyramid level -1 on original image that produced the transformed image of 16x16 containing Gaussian pyramid coefficients. As before we resizedthe transformed image into 256x1 pixels to form a feature vector Fig. 7(a) and Fig 3(c) show the original image and their Gaussian transformed image at level -1. In order to reduce feature length we experimented this with Gaussian pyramid -level 2 transformation as shown in Fig 3 (d).

Classifier: In this section a brief description of classification techniques, that can be applied to classify the feature components are introduced. They are:

Neural Network [21] Classifiers:

- Pattern Recognition (PR),
- Feed forward (FFN),
- Fitness Function (FFT),
- Cascade Neural Network (CCN) and

Statistical Classifier:

- KNN (k-nearest neighbor) classification
- Linear discriminant analysis (LDA)

Neural Network Classifier: An N-layered feed-forward multilayer neural network containing a input layer, an output layer and N- hidden layers is considered. Starting from the first layer, neurons of every pairs of layers (k-1, k), are connected with each other via a weight matrix $W^k_{m_k, m_{k-1}}$ where m_k and $m_{k-1}$are the total number of neurons in the k^{th} and $(k-1)^{th}$ layers respectively. The element $W^k_{m_k, m_{k-1}}(i,j)$, where 1 = i = m_k and 1 = j = m_{k-1}, denotes the weight between the i^{th} neuron of the k^{th} layer and the j^{th} of neuron of the $(k-1)^{th}$ layer.

The output of i^{th} neuron of the k^{th} layer is a function of the i^{th}row of $W^k_{m_k, m_{k-1}}$ and the output O^{k-1} $1 \le j \le m_{k-1}$ of the $(k-1)^{th}$ layer neurons, the output of the i^{th} neuron of the k^{th} layer is as shown in below Eq. (2).

$$O_i^k = f\left(net_i^k\right) \quad (2)$$

Where $net_i^k = \sum_{j=1}^{m_{k-1}} w_{i,j}^k \times O_i^{k-1} + b_i^k$, O^{k-1} is a column vector of size m_{k-1} where each element is an output of the (k-1)th layer neurons, b^k is a column vector of size m_k where each element is a bias for kth layer neurons.

Initial classifer is developed using logsig transfer function on feedforward nerual network basis. This functions calculate the layers output from its input. The output layer of feedforward neural network is given by Eq. (3).

$$O_i^k = f\left(net_i^k\right) = \text{logsig}\ (net_i^k) = 1/\ 1 + e^{-net_i^k} \quad (3)$$

The second classifier uses tansig function on pattern recognition classifier basis. The output layer of pattern recognition classifier is given in Eq. (4).

$$O^{k-1} = \text{tansig}\ (net_i^k) = 2/(1 + (e^{2*-net_i^k})) - 1 \quad (4)$$

This network is more commonly used for pattern recognition purposes. This function is good where speed is important and the exact shape of the transfer function is not important.

The third classifier uses cascade forward neural network. This classifier uses function that is similar to feedforward networks but include a fully connected weights for layers 1 to n. The additional connection improves the speed at which the network learns the desired outcome.

The fourth classifier used were function-fitting neural network. This classifier uses feedforward neural network function to fit input-output relationship and returns a fitting neural network.

Statistical Classifier: Statistical classifier [22] predicts the class label of given test pattern from predefined class. The classifier finds the closest neighbor of test pattern and determines the class label using majority voting. The performance of K-Nearest Neighbour classifier depends on the choice of 'k' and distance metric used to measure the neighbor distances. In this research, experiments are carried out using Euclidean distance metric (as shown in Eq. 5).

$$dist\left(X_i, Y_i\right) = \left|\sum\nolimits_{i=n}^{k}\left(X_{in}, Y_{in}\right)^2\right. \quad (5)$$

Linear Discriminant Analysis Classifier: Linear discriminant analysis [23] is a statistical classification technique used to classify objects based on measurable set of features. In this analysis an object k is assigned to group i that has maximum f_i see Eq. 6)

$$f_i = \mu_i c^{-1} x_k^t - \frac{1}{2}\mu c^{-1}\mu_i^t + \ln\left(\mathrm{p_i}\right) \quad (6)$$

Where μ_i is vector mean and c_i is a covariance matrix of group I, p_i is the probability of occurance of event I and x is the set of measurement.

RESULTS

This section discusses the validity of our newly developed dataset. We conducted recognition experiments using MATLAB-2013 on Intel Core 2 Duo 2.00GHz based system with 4 GB internal memory. Fig xx summarizes the experimental results. The results indicate that the recognition rate varies from 35% to 72.18%. The results further indicate that among all neural network based classifiers the PR network using SCG yielded the best result. It is noticeable that the KNN classifier has yielded the best recognition result but at the expense of a set of a large number of class prototypes. Linear discreminat analysis classifiere yielded poor results in almost cases. Table 2 shows the execution time taken by various feature extraction and classification methods. Column of this table represents classification time and rows represents their corresponding features. From this table it is clear that as we increase the feature length it takes more time to classify the samples. LDA classifier took less execution time than other classifiers. Among all neural network classifier PR classifier took less time. All other classifier lies in between. It is widely claimed that use of a classifier ensemble should improve the recognition accuracy. To verify the claim, we conducted an experiment by combining the classifiers decisions given by KNN classifiers using majority voting strategy.

For majority voting scheme, four best class ifier values were selected from the features wavelet trans form (level 1), Gaussin pyramid (level 1), Gausian pyramid (level 2) and image zoning. We have not considered poor resulting classified values. The classified values of these classifiers formed the bas is for majority voting. An unknown digit is recognized as the one which is recognized by the majority of classifiers. Incase of a tie,aweighted voting mechanismwasfollowed. The tie was resolved by aggregating the weights of each group of

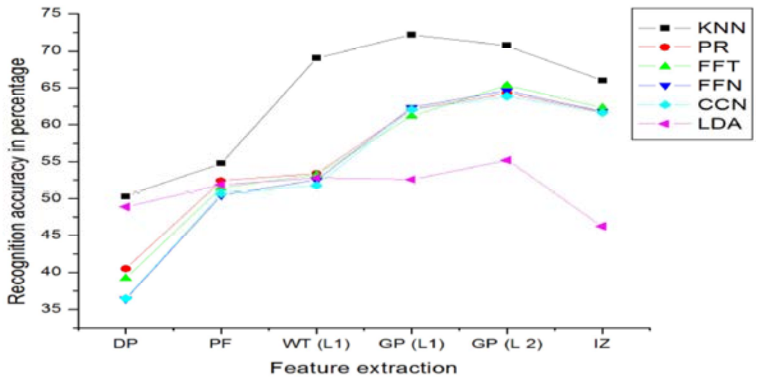


Fig. 8: Recognition accuracy with features - classification techniques.

Fig. 9: Shape similarity in Devnagari characters.

Table 2: Execution time with various features - classification techniques.

Classifier Feature	KNN	PR	FFT	FFN	CCN	LDA
DP	930.18	577.64	378.26	189.76	4173.47	192.07
PF	495.67	681.34	374.65	573.67	5134.67	50.27
WT	951.43	579.61	571.78	438.33	5176.89	126.37
GP	937.51	757.11	686.41	632.44	5311.31	121.39
GP (level 2)	301.46	561.61	570.09	581.88	4180.11	21.4
IZ	118.95	452.17	468.77	471.44	3154.78	8.06

classifiers and applying the rule: Recognize the unknown digit as the one supported by the group having the greater weight, otherwise recognize as the one that is supported by the classifier that has the maximum weight among all the classifiers. If all the classifier doesn' tagreeon common con sensus then in that case the sample is rejected. The majority voting classifier yielded 84.03 % which is higher than 72.18% recognition rate yielded by the best performing classifier which is KNN classifier as shown in fig xx. We rejected 5.3 % samples based on this rejection crieteria. We have studied the shape similarity in Devnagari alphabets from the obtained confusion matrix. These samples are highlighted in Fig 9.

CONCLUSION

In this paper, we have presented a benchmark study on handwritten *Devnagari* character recognition that we have collected from a large heterogeneous writers' groups. The dataset contains digits, characters and words for recognition and text for handwriting analysis. It is the largest dataset that has been collected in a real life writing environment for research in Devnagari optical document recognition research. The salient features of the dataset are: it has 35,000 digits; 78,400 characters; 2,000, constrained handwritten pangram images; 2,000 unconstrained handwritten pangram images; writer's information; and original images of data collection forms. The CPAR-2012 dataset is available in the public domain. The dataset can be accessed through the Integrated Research Environment for Devnagari optical Document Recognition. This study exhibits the analysis of the character recognition considering direct pixel, profile feature, wavelet transform, gaussian pyramid and image zoning feature extraction techniques with KNN and neural network classifiers. The Gaussian pyramid (level 1) when classified with KNN yielded best result among all feature - classifier combinations. We have also highlighted the shape similarity in Devnagari alphabets.

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