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Introducing the XXX Bangla Handwriting Dataset and an Efficient Offline Recognizer of Isolated Bangla Characters

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Introducing the XXX Bangla Handwriting Dataset and an Efficient Offline Recognizer of Isolated Bangla Characters

***Abstract*—This paper presents a publicly accessible Bangla offline handwriting dataset, as well as benchmarking with a simple and robust isolated handwritten character recognition scheme. The dataset is named XXX Bangla Handwriting Dataset. The dataset contains 2 pages. The first has a 104 word/364 character essay. The essay uses 49 basic characters, all 11 vowel diacritics and 32 high frequency consonant conjuncts. The second page contains 84 isolated units containing all basic characters, numbers, vowel diacritics and several high frequency conjuncts. The initial release is based on the voluntary contribution of 100 different writers. One of the highlights and unique features of this database is that all of its contents are tagged with the associated ground truth information from different component hierarchies, such as characters, words and lines. It is expected to be useful for research on offline Bangla handwriting recognition, particularly with segmentation-based approaches. Furthermore, a basic character recognition method is presented where the features are extracted based on zonal pixel counts, structural strokes and grid points with U-SURF descriptors modeled with bag of features. The highest classification accuracy obtained with an SVM classifier based on a cubic kernel is 95.4% using the isolated characters from the XXX dataset together with 3 other datasets to ensure the versatility and robustness of this process.**

***Index Terms*—Bangla handwriting recognition, Bangla character recognition, Bangla handwriting database**

I. Introduction

This paper presents an offline Bangla handwriting dataset and an algorithm for recognition of isolated Bangla basic characters. Bangla (a.k.a. Bengali) is one of the most used languages in the world. With over 205 million people, it is the 7th most spoken native language. Bangla script, along with the Assamese alphabet is the 5th most widely used writing system in the world. It is the national and official language of the Peoples Republic of Bangladesh, and the official language of several states in India such as West Bengal, Tripura, Assam and Andaman.

Bangla basic isolated character recognition has its significance on two terms. First, often it serves as a core foundation block for unconstrained handwriting recognition specially with the segmentation-based approaches as seen from the development of handwriting recognition with other scripts. Second, the isolated basic characters (mostly in alphanumeric format) frequently appear in many regular places - such as document identifiers, forms, postal headers, house addresses, encrypted codes with confidential letters, handwritten flyers, posters, notices, banners, invitation cards, bank checks, tickets etc. in Bangladesh and a portion of India. Thus, the development of a decent recognizer has the potential to contribute in numerous ways to improve common tasks such as machine sorting, task automation, etc.

The Bangla writing system belongs to the Abugida writing class. It is written from left to right. The script consists of 11 vowels, 10 vowel diacritics, 39 consonants, several hundred consonant conjuncts, more than 10 consonant diacritics, 10 numeric digits and several punctuation marks. There is no upper or lower case distinction of characters when written. Bangla words are almost always connected by a distinctive horizontal line running along the tops of the letters, known as a Matra. Vowels appear as an attached diacritic if followed by a consonant, and adjacent consonants usually form either conjuncts or consonant diacritics. Consonant conjuncts can be formed by merging up to 4 characters. Some of the conjuncts and diacritics can be written in more than one way. All these notions make offline Bangla handwriting recognition quite a difficult task.

Databases are one of the fundamental components for training as well as benchmarking the statistics of handwriting recognition algorithms. Often, the development of any particular algorithm depends on the existence and availability of rich and useful datasets. The Center for Microprocessor Application for Training Education and Research in the Computer Science and Engineering Department of Jadavpur University has a repository (CMATERdb) of simple and compound Bangla characters, numerals, common words, mixed script, etc., [1], [4]–[7]. They have line and word level ground truth tagging, although unaccessible at the time of this writing. Bhattacharya et al. [2] presented a dataset (ISI db) of isolated basic and compound characters, numerals and vowel modifiers. This dataset is accessible by request through proper channels. Biswas et al. [3] also presented a publicly available dataset (BanglaLekha-Isolated) which consists of isolated basic characters, numerals and a few high frequency compounds. A highlight of these datasets are presented in Table I. Beyond these, several works indicate the existence of other datasets, but none of them are available for others to access. In this paper, a publicly accessible dataset is presented with aims to foster the development of offline Bangla handwriting recognition.

In the field of Bangla isolated basic character recognition, several approaches are present at this moment. One of the best recognition results with a single stage classification scheme was obtained by Roy et al. [8] with an Artificial Bee Colony (ABC) optimization using directional gradient features and a Support Vector Machine (SVM) as the classifier. Since this

TABLE I
EXISTING PUBLIC BANGLA HANDWRITING DATASETS
(NUMBERS USED HERE ARE CLOSE ESTIMATES)

Attributes	**CMATER Database [1]**	**ISI Database [2]**	**BanglaLekha Isolated [3]**	**XXX Bangla Handwriting Dataset [X]**
Basic Characters	15,000	30,000	98,000	5,000
Numbers	6,000	23,000	19,000	1000
Characters with Vowel Diacritics	None	Present*	None	1000
Consonant Conjuncts	42,000	Present*	47,000	1100
Essay (# pages)	150**	None	None	100
Ground Truth Metadata	Line and Script Level Information**	N. A.	N. A.	Character, Word, Line and Essay Level Information
Accessibility	Open	On Request	Open	Open

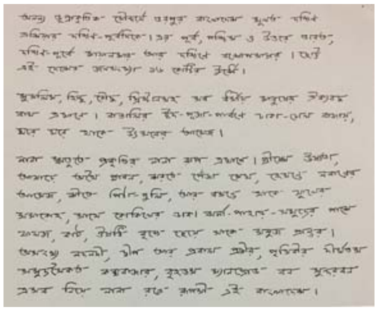
*Exact numbers couldn't be found.
**Couldn't be accessed during the time of writing

is a 50 class problem, most of the leading recognition results come from classifiers that use multiple stages. Rahman et al. [9] compiled several high level features through a number of individual classifier, such as Template Matching Scheme (TMS), Binary Weighted Scheme (BWS), Frequency Weighted Schemes, Moment-based Pattern Classifier (MPC) etc. in a fusion form for classification. Bhowmik et al. [10] presented a hierarchical learning architecture using MLP, Radial Basis Function (RBF) and SVM classifiers with wavelet features extracted from the Daubechies transformation. They obtained their best result by using a pre-classifier to identify a confusion group. From the confusion matrix 13 overlapping groups were formed during training and applied the best suited classifiers to each group. Bhattacharya et al. [2] used gradient directions and regional pixel counts with a Modified Quadratic Discriminant Function (MQDF) classifier at their first stage. Later, they created a list of character pairs with similar shape attributes and exploited the knowledge of shape difference in the second stage of feature extraction. With a simple 2-class problem fed into a 3 layer MLP classifier, the second stage resulted in one of the best recognition accuracies. In a recent work, Alif et al. [11] reported the highest recognition accuracy on Bangla isolated characters using a Convolutional Neural Network (CNN) with a modified Residual Network (ResNet-18) architecture. A list with some of these notable achievements is presented in Table II. A script like Bangla with hundreds of consonant conjuncts, variants of writing, complex vowel and consonant diacritic attributes etc. requires a multiple pass classification scheme for a robust handwriting recognition platform. It is advantageous and computationally efficient if a small set like the basic characters can be recognized through a single stage classifier. Here, a simple and efficient single stage classification scheme with carefully chosen features is proposed which achieves results comparable to top recognizers using multiple pass architectures.

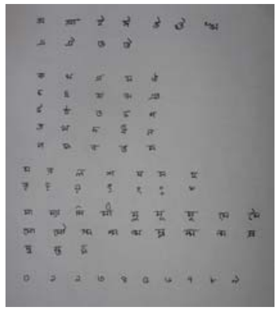
II. DATASET DESCRIPTION

The dataset about to be released is presented here as the XXX Bangla Handwriting Dataset developed and hosted by X University. This is an open access dataset aiming to help researchers who are working on offline Bangla handwriting recognition. Participants from different ages and professions were asked to contribute two types of content. The first is a sample essay of 104 words/364 characters. The essay was carefully prepared using mostly common and frequently used Bangla words. It contains all Bangla basic characters (except 'ঙ', which rarely appears in its basic form), all possible vowel diacritics (with 'ম') and 32 high frequency conjuncts. The second is a page containing isolated characters consisting of all 50 basic characters, 10 numbers, all 11 vowel diacritics with a consonant and 10 high frequency conjuncts. The target content was provided in machine printed form. Contributors copied both the essay and the isolated units on blank paper. These were digitized using cellphone cameras. The images were cropped and basic skew correction was applied. No color alteration, resizing or filtering was done to the images. Although the participation was anonymous, the gender, age, profession and left/right handedness information was preserved and tagged along with their writing samples. The type of pen, pencil, paper or the photographing device was not specified.

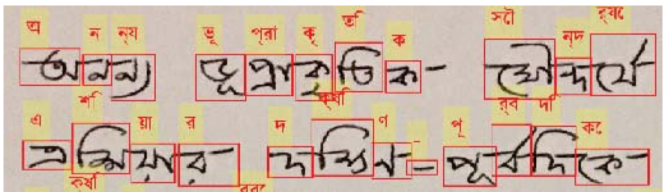
The essay images were tagged with ground truth information. All characters, words and lines are tagged with a bounding box represented with x_{min}, y_{min}, height and width values. The same was done with the images of the isolated characters and numbers. Specific tools were developed to tag and verify the data. The classical or traditional approach to handwriting recognition involves a step of segmenting the characters and many researchers [12], [13] achieved great results for segmenting unconstrained Bangla handwritten scripts. With the character level ground truth information tagging, the XXX dataset aims to provide such segmentation-based approaches a nice amount of data to work and verify with. Sample sections of both kinds of documents, tagging data and an overlay illustration are presented in Fig. 1. This initial release of the XXX Bangla Dataset contains the contribution of 100 individuals. That makes this first release have over 10,000 words or 35,000 characters in the form of essay scripts and over 8000 isolated units, all tagged with their ground truth information. The data and the tagging were thoroughly inspected and scrutinized before the release. This dataset is



(a) Essay document sample page



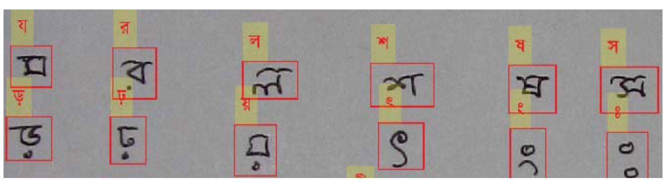
(b) Isolated element sample page



(c) Sample section from the essay document with tagging labels and bounding boxes

```
Line001 Word001 Char001 অ – 98,133,55,35
Line001 Word001 Char002 ন – 154,133,32,35
Line001 Word001 Char003 ন্য – 185,129,49,58
Line001 Word002 Char004 ভূ – 288,129,56,70
```

(d) Sample ground truth from the essay document



(e) Sample section from the isolated character document with tagging labels and bounding boxes

```
Char044 ড় – 2091,1043,117,124
Char045 ঢ় – 2329,1033,107,124
```

(f) Sample ground truth from the isolated character document

Fig. 1. (a), (b) Sample sections, (d), (f) ground truth tag files and (c), (e) ground truth overlay of the essay and isolated character documents from XXX dataset.

freely available at doi:XXXX.

III. Isolated Basic Character Recognition

The aforementioned dataset was created to aid the development of Bangla offline handwritten text recognition. To benchmark this dataset the results of this research is tested on this new dataset and the publicly accessible Bangla datasets. Here, the result for isolated basic character recognition is reported.

A. Feature Extraction

Three categories of features were used for recognition. These are referred to as Zonal, Pattern and Gradient features and are discussed in the following sections.

1) Zonal Features: Here the images were split into equal 8×8 zones. With the binary images formed where 1 represents the dark or object pixel and 0 represents the white or background, the features are computed as

$$R_{ij} = \frac{Sum\ of\ all\ Pixels}{Area\ of\ the\ block} \qquad i/j = 1, 2, ..., 8. \qquad (1)$$

This creates a 64-bit vector mapping different zonal footprints of the characters. This approach with different zone dimensions was also used by Bhattacharya et al. [2] to recognize basic Bangla characters.

2) Pattern Features: Processing was done to extract stroke directions for the samples. At the first stage, using a morphological operation the interior pixels of the object were removed leaving a thin outline of the connected border pixels [14]. All the connected objects in a column are replaced by only one center element of that object. The top- and left-most pixel is counted as the first key point and a column-wise search operation traces the stroke edge. The character boundary contour is followed. Points where the direction transitions from left to right, right to left, up to down or down to up are considered as other key points. If the boundary leads to a dead-end or a branch with a length less than $1/4$ of the image height, the trail is removed. If two key points are very close (measured by a Euclidean distance less than $1/25$ of the image height), the later one from (the tracking direction) is removed. After these stages, a minimal clean outlined version of the characters are found with the highlighted key points. Next, the angles of the straight line connecting adjacent key points are calculated. These angles are quantized in 45° intervals (8 compass directions). Then the Euclidean distances between interconnected adjacent key points are computed. Adjacent lines having the same angle (after the quantization) were merged and any connection less than a threshold ($1/5$ of the image height) was ignored. The resulting connections, which represent the stroke direction pattern feature of the sample characters, are represented using a numeral string.

Fig. 2 shows the various stages for obtaining these stroke direction pattern features and a few samples of the strings obtained for particular classes. Afterwards, a histogram of the unit elements and bigrams of these representative strings were taken as features. A total of 64 features were obtained in this process. These were normalized before being used as the second portion of the feature vector.

Lastly, the length of all the combined strokes of vertical lines (2s and 8s), positive slants (3s and 7s) and negative slants (1s and 9s) are calculated, normalized and used as a 3 dimensional feature vector along with the pattern features. The horizontal strokes (4s and 6s) are ignored in this case, because the majority of these strokes usually belong to the Matra. The usage of the Matra varies significantly depending on handwriting style and never impacts the basic characters

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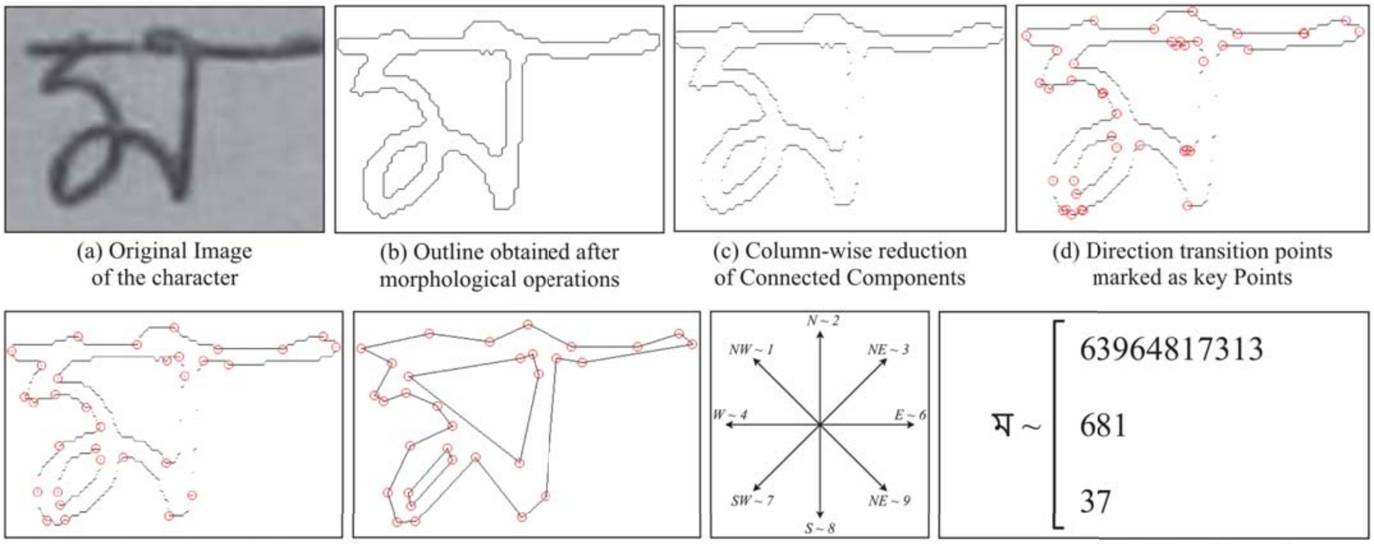

(a) Original Image of the character
(b) Outline obtained after morphological operations
(c) Column-wise reduction of Connected Components
(d) Direction transition points marked as key Points
(e) After key Points elimination based on proximity threshold
(f) Estimation of connected key Points as straight lines
(g) Compass direction encoding
(h) Obtained pattern after angle quantization and encoding

Fig. 2. From (a) to (h) different stages of obtaining pattern feature for a sample character

to be misclassified. Some conjuncts and numbers have some conflicting attributes with the basic characters based solely upon the presence of this Matra, but since this work deals with the basic characters only, the horizontal stroke contributions are totally ignored in this stage.

3) Gradient Features: In this stage a uniform 8×8 grid was created on the sample. Upright Speed Up Robust Features (U-SURF) [15] were extracted from the intersection of the grid lines. U-SURF is a high performing scale invariant interest point detector and descriptor, although here only the descriptor was used to obtain the feature vector. Patch sizes for multi-scale extraction were selected as blocks of 32, 64, 96 and 128 square-pixels around the center. The upright version of SURF is not invariant to image rotation which makes it computationally faster and better suited for the cases where the camera remains more or less horizontal. The feature descriptor is based on the sum of the Haar wavelet response around the point of interest. The responses are then weighted by a Gaussian function with the interest point at its center and addressed as points in a 2D space with abscissa and ordinate as the horizontal and vertical responses. The summation of the horizontal and vertical responses forms a local orientation vector. To describe the point, a square region around that point is extracted, divided into 4×4 square sub-regions, and for each the Haar wavelet responses are approximated at 5×5 regularly spaced sample points. 80% of the strongest features from each samples were kept and fed into a bag of features model.

Bag of features representation have become very popular for their simplicity and great performance, and have been used in different challenges regarding handwriting recognition in recent times [16]–[18]. The basic idea of this approach is to take a set of local image patches (in this case U-SURF descriptor) and convert the vector-represented patches into codewords, which can be considered as representative of several similar patches. The collection of all the codewords is referred to as a codebook. This terminology is analogous to the concept of words and dictionary from a document corpus. Afterwards, using K-means clustering, a 500 word visual vocabulary was prepared. Each patch in an image was mapped to a certain codeword and the image was represented by the histogram of the codewords.

From the zonal, pattern and gradient features a combined 631 dimension feature vector is prepared and fed into the classifier.

B. Classifier

A Support Vector Machine (SVM) was used on the feature vector obtained. SVM is designed for two-class pattern recognition problems. Multi-class SVMs are realized by combining several two-class SVMs. Two popular strategies for this are OVO (One Versus One) and OVA (One Versus All). Here, OVO was used as it offers better accuracy over OVA. Although, OVA operates faster as it requires $c(c-1)/2$ binary classifiers compared to c classifiers with OVO for a c-class problem. The classifier was tuned with a cubic kernel. A cubic kernel is generalized by

$$K(x,y) = (x^T y + c)^3 \quad (2)$$

where x and y are the feature vectors in input space. The higher degree polynomial allows a more flexible decision boundary. Although, non-linear SVMs are expensive to train, they performed significantly better than the linear SVMs in this case. All the features are standardized prior to the classifier input. The Classification Learner app from the MATLAB Statistics and Machine Learning Toolbox was used for training and validation.

TABLE II

SOME NOTABLE RESEARCH WORKS ON BANGLA ISOLATED HANDWRITTEN BASIC CHARACTER RECOGNITION

Researchers	# Classes	Feature	Classification	Dataset Used	Test Set	Max Accuracy
Roy et al. [8]	50	Directional Gradient features with ABC optimization	SVM	CMATER	3,000	86.40%
Rahman et al. [9]	49	Various Structural Attributes	TMS, BWS, FWS, MLP, MPC in a multistage	Private	N. A.	88.38%
Bhowmik et al. [10]	45	Wavelet Decomposition	Two stage HLA with SVM	Private	5000	89.22%
Bhattacharya et al. [19]	50	Shape Feature Vectors modeled with HMM	MLP	ISI	9,481	90.42%
Bhattacharya et al. [2]	50	Gradient Directions, Regional Pixel Counts	MQDF and MLP in two stage	ISI	12,858	95.84%
Alif et al. [11]	84.	NA	Convolutional Neural Network ResNet-18	BanglaLekha	33,221	95.10%*
Proposed Work	50	Zonal Pixel Counts, Stroke Patterns and SURF	SVM with Polynomial Kernel	CMATER, ISI, BanglaLekha, XXX	4,844	96.80%

* Reported 95.99% on CMATERdb, # classes, training and test set information weren't explicit

C. Dataset Used

Several experiments were conducted based on the publicly available datasets discussed in Table I. First, three training sets were obtained from the 1) training set of CMATERdb 3.1.2 (12,000 samples, 240 per class), 2) training and validation set of ISI handwritten basic Bangla characters (25,000 samples, 500 per class) and 3) a selected set of BanglaLekha database (60,000 samples, 1,200 per class). These were tested on the 1) test set of CMATERdb 3.1.2 (3,000 samples, 60 per class), 2) test set of ISI handwritten basic Bangla characters (12,858 samples, unevenly distributed), 3) a selected set of BanglaLekha database (5,000 samples, 100 per class). Afterwards, classifiers based on each of these three training sets were tested on the XXX isolated character dataset (4,844 samples, unevenly distributed). Finally, a combined dataset was formed from the three training sets (97,000 samples, 1,940 per class) and tested on the XXX isolated character dataset.

There are two major benefits of using datasets from different sources in this case. Firstly, a sufficiently large amount of training and test data could be used which ensures the classification process to be solid and robust. Secondly, this ensures that the pattern of the data is diverse. People from different regions of the two major Bangla-speaking countries, of different ages, genders, professions, educational status, handedness and under different acquisition environments are the contributors of this combined dataset. Therefore, the recognition results can be claimed to be pretty versatile with minimum to no bias towards any particular demographics.

D. Pre-Processing

Before the features were extracted, all the sample images were preprocessed. First, a 2D Gaussian smoothing filter with standard deviation of 0.3 was applied. Then the color and grayscale images were converted to binary images using a threshold obtained using Otsu's method. The data received from the BanglaLekha dataset [3] were originally binarized, therefore they were used without these two steps. Afterwards, an area filtering was done to remove any isolated small objects which have area less than 80 square pixels. The images were cropped to leave one blank or background pixel row and column on each side. At the last stage, these were resized into a fixed height of 128 pixels, with a variable width to preserve the original aspect ratio.

E. Results

The experiments were designed to compare the proposed recognition procedure with other results reported on the three other publicly accessible datasets, Table II, matching both the training and test sets very closely. Further experiments were run to compare the new dataset with the other datasets by holding the training set constant and comparing testing results on the XXX dataset with results on other datasets. The results obtained are presented in Table III.

Roy et al. [8] reported 86.40% accuracy on the CMATERdb 3.1.2 dataset. Alif et al. [11] reported 95.99% accuracy on the same dataset, although the number of classes, training and test sets were not explicit. The proposed approach achieves 92.87% accuracy this dataset. One of the best reported accuracies on the ISI dataset, reported by Bhattacharya et al. [2], is 95.84% using a two stage classification scheme. The proposed method results in 93.10% accuracy with a single stage classification. On the BanglaLekha-Isolated dataset the highest reported accuracy was 95.10% by Alif et al. [11] using a convolutional neural network. This dataset is significantly larger than the others. The obtained accuracy from a portion of this dataset with the proposed architecture is 96.80%.

Afterwards, the results using these same training datasets were compared where the XXX dataset was used for testing. The recognition accuracies were consistently lower. The similarity to the training datasets is lost, and the XXX dataset is cell phone camera acquired, where the others were all scanned on a flatbed scanner in 300/600 dpi. Finally, a combination of the these three dataset was tested on the XXX dataset. The recognition result rose to 96.42%.

TABLE III
RESULTS FROM DIFFERENT TRAINING AND TESTING SETS

Dataset used for Training	Dataset used for Testing	Recognition Accuracy
CMATERdb 3.1.2 Training Set	CMATERdb 3.1.2 test set	92.87%
	XXX Bangla db	91.39%
ISI db Training and Validation Set	ISI db test set	93.10%
	XXX db	89.24%
BanglaLekha db (Selected Samples)	BanglaLekha db	96.80%
	XXX Bangla db	95.78%
Combined	XXX Bangla db	96.42%

IV. CONCLUSION

In the research field of Bangla handwriting recognition, here the XXX Bangla Handwriting dataset is released and presented with isolated characters, diacritics, high frequency conjuncts, numbers and a rich script with ground truth tagged at the character, word and line levels. This easy to use and openly accessible dataset aims to help the development of isolated character, number, consonant conjuncts, characters with diacritics recognition, character segmentation from handwritten words, line identification, word spotting, etc. Demographic information can help research into handwriting variations based on age group, sex, profession and left/right handedness. For the isolated basic character recognition, a basic simple stage classification scheme based on features extracted from different perspectives and classification with Support Vector Machines with a cubic kernel is presented which exceeds all other similar approaches in terms of recognition accuracies and competes with those with multi-stage classification schemes. A sufficiently large volume of data collected from four different datasets was used for this, which ensures the recognition scheme to be robust and free from any specificity. This approach is quite generic and is expected to work with other similar Indo-Aryan scripts as well. Also, a second pass of classification can always be added with this approach to further improve the results if needed.

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