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Comparison of the Classifiers in Bangla Handwritten Numeral Recognition

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***Abstract*— Handwritten Bangla numeral recognition has great prospects in Writer Identification, Postal Automation, Bangla OCR (Optical Character Recognizer) etc. In this paper we have presented the detailed comparison of classifiers for Bangla handwritten numeral recognition. For this work we have used our own database (WBSUCS character database) which consists of total 517 documents and ISI Bangla Numeral database which consists of more than 12000 numerals. For our database each writer was asked to write predefined filled in forms five times. After collecting and extracting characters from filled in forms, 400 dimensional feature vectors is computed based on gradient of the images. The feature and classifier selection is one of the most challenging tasks in the field of Pattern Recognition. As the performance of 400 dimensional feature is already established in numeral recognition field, for the present work we have focused on performance evaluation of classifiers in handling complex real time Pattern Recognition problems like Numeral Recognition. Here we have selected Support Vector Machine (SVM), Library for Large Linear (LIBLINEAR), Multilayer Perceptron (MLP), Fuzzy Un-ordered Rule Induction Algorithm (FURIA), Modified Quadratic Discriminant Function (MQDF) as the classifiers for recognition of the numerals and comparison of the results. Though all these classifier are suitable for this work but LIBLINEAR is found to be the fastest in terms of convergence criteria while MQDF outperform others in terms of recognition result for our WBSUCS character database.**

***Index Terms*— Bangla numeral Recognition, SVM, MLP, FURIA, MQDF, LIBLINEAR, WEKA.**

I. INTRODUCTION

Bangla Handwritten Numeral recognition has been an active area of research for a decade or two in document level Image processing. It has such potential that it can be used in applications like Writer verification and Identification, Optical Character recognition (OCR), Postal Automation etc. Though various pieces of works are exists in literature on handwritten numeral recognition of Roman, Chinese and Arabic numeral recognition [1-6]. There also exists works towards different Indian scripts' numeral recognition, like the work of T. K. Bhowmick et al. on Oriya numeral recognition [7], U. Pal et al. on Kannada Numerals [8], on Devnagari numerals, the works of S. Chaudhury et al. and U. Bhattacharya et al. [9, 10]. Few works on Bangla handwritten numeral recognition are exist in literature like the work of Y. Wen et al., K. Roy et al., A. K. Dutta et al., Chaudhuri et al. [11-14].

Wen et al. used support vector machine (SVM) classifier combined with extensive feature extractor using principal component analysis (PCA) and Kernel principal component analysis (KPCA) [11]. K. Roy et al. used a widely used neural network (NN) based approach for Bangla handwritten numeral recognition [12]. Dutta et al proposed a two stage feed-forward NN based scheme for the same [13]. Chaudhuri et al. proposed a structural feature based approach for Bangla handwritten numeral recognition [14].

In our work we have used our own datasets for recognition of numerals. Here 400 dimensional feature has been used for numeral recognition. We have used 4 sets for training and 1 set for testing. Here we have used Support Vector Machine (SVM), Multi Layer Perceptron (MLP), Library for Large Linear (LIBLINEAR), Fuzzy Un-ordered Rule Induction Algorithm (FURIA) of WEKA and Modified Quadratic Discriminant Function (MQDF) as the classifiers for numeral recognition and classifier comparison. The compared results show that the rule based classifier like FURIA is not so much suitable for complex real time problems without discrete features. Here we have used WEKA tool for classifiers LIBSVM, LIBLINEAR, MLP, and FURIA.

II. PROPERTIES OF BANGLA NUMERALS

By population Bangla stands second in the list of most popular languages in India. It also ranks sixth in the list of most popular languages internationally. The source of this language is an ancient Indo-Aryans language. Bangla script alphabet is used in texts of Bangla, Assamese and Manipuri languages. Bangla is also the national language of Bangladesh. Also Bangla is the official language of the state West Bengal in India [15]. To get an idea of Bangla numerals and their variability in handwriting, five sets of handwritten Bangla numerals of different writers are shown in Fig.1.

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III. DATA COLLECTION

As we are interested in numeral recognition, we have designed a sample document consisting of all Bangla alphabets (vowel and consonants), numerals and vowel modifiers. Each participant (writer) was required to copy-out the printed characters in the particular box area of the sample document form for each given set and 5 sets are given for each writer. For this work we have collected data from different individuals of different age groups. Our WBSUCS character database consists of more than 120 writers. Where most of them are in between age group 17-25 and we also have writers in between age group 30-45 and even 50-60. Most of the writers are right handed. Out of 120 writers until now we have managed to collect full 5 sets of data from 90 writers (used for current work purpose) and for remaining writers we have collected 2-3 sets of data. Each set contains 10 Bangla numerals and 51 Bangla alphabets and 10 Bangla vowel modifiers. We have a total of 26367 Bangla alphabets, 5170 numerals and 5170 vowel modifiers. An example of our designed character sample collection document form is shown in Fig 2. There exists no boundary for writers regarding the type of pen and ink they use. We scanned these documents using a flatbed scanner for digitization. The images are in gray tone and digitized at 300/600 dpi and stored in Tagged Information File Format (TIFF). Only the numerals have been used for this work. In our current work we have used the 300 dpi gray toned TIFF format image.

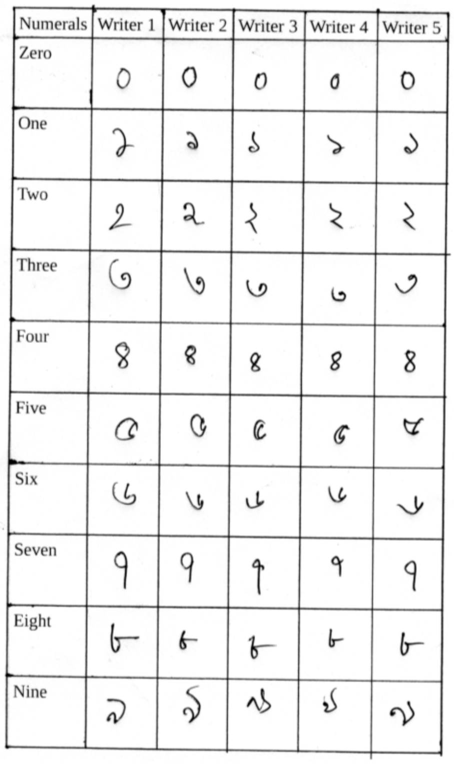

Fig. 1. Sample of all Bangla handwritten numerals of 5 different writers.

IV. PRE-PROCESSING

The digitized images are firstly binarized using a global binirization method [15]. Then a character extraction technique has been used to extract the characters from the digitized form and they are being stored in gray mode.

A. Character extraction technique

This technique is used for extraction of each individual character from the document form of handwritten characters. The steps are:

Firstly, the global binirization of the whole document has been carried out. Then maximum run length has been computed on horizontal and vertical histogram of that document form. Using the maximum run length of horizontal and vertical histogram, we have identified the horizontal lines and vertical lines of the document form. After the identification of vertical and horizontal lines we have deleted those lines from the document form image to get an image which contains only the suggestive characters and the original handwritten characters. Then using the horizontal and vertical line information we have calculated the top corner point values of each block and then we have removed the suggestive characters. After this, bounded box for each handwritten character has been calculated and these information have been stored for further processing.

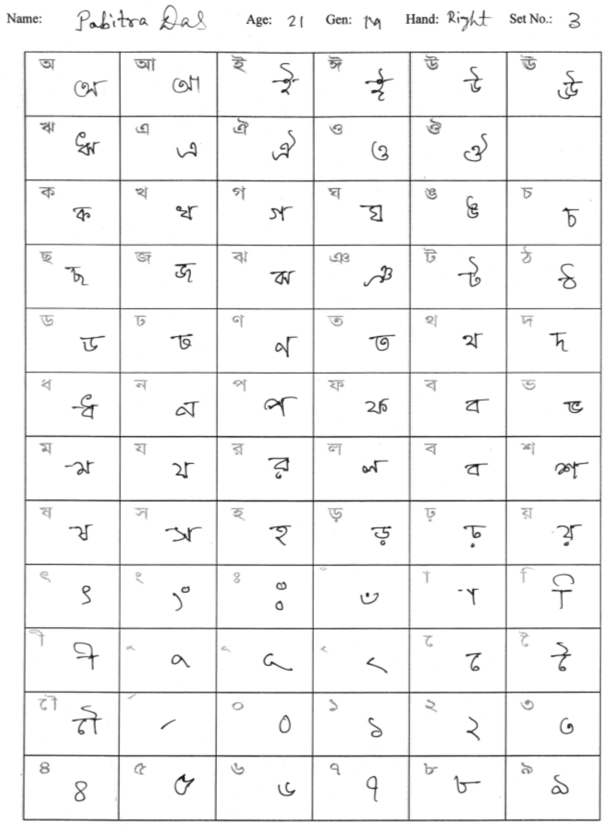

Fig. 2. Sample document form for collection of Bangla Handwritten Alphabet, Numerals, Vowel modifires

V. FEATURE EXRACTION

In this work 400 dimensional feature extraction technique [16] is used. We have used this feature extraction technique as it has given some encouraging results for different Indic script numeral recognition for the work of U. Pal et al. [17]. To obtain 400 dimensional features we have applied the following steps:

STEP 1—At first the input gray image is binarized.

STEP 2—Next the binary image is normalized into 73x73 pixels.

STEP 3—The Normalized image is then converted into gray-scale image. This is done by applying a 2×2 mean filtering five times.

STEP 4—The mean gray scale value is converted to zero and the maximum to 1 by normalizing the gray-scale image.

STEP 5—Next the normalized image with mean 0 and maximum 1 is then segmented into blocks of size 9x9.

STEP 6—To obtain gradient of the input image we have applied Roberts filter. We have quantized the arc tangent of the gradient (strength of gradient) into 16 directions. Thus, the strength of the gradient has been computed and accumulated in each direction.

STEP 7—Next histograms are computed in each of 9 x 9 blocks of the above processed image.

STEP 8—At last the above computed histograms are down sampled into 5×5 blocks. For the down sampling we have applied a Gaussian filter and obtained 400 ($5 \times 5 \times 16$) dimensional feature [16].

VI. WEKA AND CLASSIFIERS

WEKA is one of the widely used tools in the area of for machine learning [17]. The built in tools can be called from own Java code or using the weka.jar file of the package or directly from GUI interface. It contains tools for various applications like data pre-processing, classification, clustering, regression, association rules, visualization etc. For the evaluation purpose in our work we have used common classifiers like SVM, LIBLINEAR, FURIA, MLP and RBF NET.

A. LIBSVM

The LIBSVM is the SVM classifier in WEKA tool. LIBSVM is integrated software for support vector classification using C-SVC, nu-SVC; regression using epsilon-SVR, nu-SVR and distribution estimation using one-class SVM. Multi-class classification can also be performed using this. We have used the C-SVC as the SVM Type parameter, radial basis function as the kernel type for our work purpose. The parameters COEF0, COST, DEGREE, EPS (the tolerance of the termination criterion) and all the other parameters are set to their default values. For more details see [23].

B. LIBLINEAR

LIBLINEAR is a good linear classifier for data with large number of instances or features. It has converged faster for our dataset than other classifiers of WEKA. We have used the L2-Loss Support Vector Machine (dual) as the SVM Type parameter of the LIBLINEAR. Both the Bias and Cost parameters are 1.0. The EPS (the tolerance of the termination criterion) is 0.01. For more details see [24].

C. FURIA

Fuzzy Unordered Rule Induction Algorithm (FURIA) is a fuzzy-rule-based classifier, used to obtain fuzzy rules. FURIA has recently been developed as an extension of the well-known RIPPER algorithm. Instead of conventional rules and rule lists it learns fuzzy rules and unordered rule sets. Furthermore it uses an efficient rule stretching scheme to deal with uncovered examples [22].

All the parameters for FURIA classifier of WEKA tool are set to its default values for this work like the MINNO (minimum total weight of the instances in a rule) has been set to 2.0.

D. MLP

The MLP is a layered feed forward network, pictorially represented with a directed acyclic graph. Each node represents an artificial neuron of the MLP, and the labels in each directed arc denote the strength of synaptic connection between two neurons and the direction of the signal flow in the MLP. For pattern classification, the number of neurons in the input layer of an MLP is determined by the number of features selected for representing the relevant patterns in the feature space and the output layer is chosen by the number of classes in which the input data belongs. The neurons in hidden and output layers compute the sigmoidal function on the sum of the products of input values and weight values of the corresponding connections to each neuron. Training process of an MLP involves tuning the strengths of its synaptic connections so that it can respond appropriately to every input taken from the training set. The number of hidden layers and the number of neurons in a hidden layer should be determined during training process. For this work, as the feature is 400 dimensional and the numerals are 10, so the number of neurons in input layer and output layer are 400 and 10 respectively. The number of neurons for the hidden layer is chosen automatically (the default value) by the MLP classifier of the WEKA tool.

Most of the parameters for MPL classifier of WEKA tool are set to its default values for this work like the learning rate has been set to 0.3 and momentum to 0.2. Only the training time is reduced to 300 from default value 500 for the same.

E. RBF net

In Radial basis function (RBF) networks for hidden layer processing elements the static Gaussian function has been used as the nonlinearity. The function works in a small centered region of the input space [19]. The implementation of the network depends on the centers of the Gaussian functions [20, 21]. The main functionality depends on how the Gaussian centers are derived and they act as weights of input to hidden layer. The widths of the Gaussians are calculated depending on the centers of their neighbours. The faster convergence criterion is one of the advantages of this network. This is because it only updates weights from hidden to output layer.

All the parameters for RBF NETWORK classifier of WEKA tool are set to its default values for this work like the MINSTDDEV (minimum standard deviation) has been set to 0.1.

F. MQDF

The Modified Quadratic Discriminant Function (MQDF) is a successful statistical approach for handwritten numeral recognition. To achieve high recognition accuracy in statistical pattern recognition, the distribution of patterns must be precisely estimated. For more details on MQDF see [16]. For this work we have considered the Eigen value upto 70.

VII. Results

In our work we have used our own WBSUCS character database and ISI Bangla numeral database [18] for numeral recognition and classifier comparison. Here 4 sets are used for training of the classifiers and 1 set for testing of the classifier for our database and same for ISI Bangla Numeral database also.

We have computed 400 dimensional feature on both the databases to compute the results of numeral recognition. The comparative result of different classifiers for two different numeral databases has been shown in Table I and also the chart of these results is shown in Fig. 3. We can see that the MQDF and SVM classifiers give the best result for any of the two databases. But for WBSUBCS character database the MQDF gives a slightly better result than SVM. But in case of ISI Bangla Numeral database SVM scores slightly better than MQDF. The recognition accuracy of MQDF classifier increases to 96.71% (97.8%) if we consider first 2 (3) top choices in case of our WBSUCS character database. The numerals 8 gave highest recognition accuracy followed by 1 and 7 for our database. The recognition accuracy of MQDF (91.89%, 98.10%), SVM (91.48%, 98.25%), MLP (90.10%, 97.80%); LIBLINEAR (84.46%, 96.40%); RBF Network (81.02%, 90.70%); FURIA (80.60%, 93.30%) are being achieved for our and ISI Bangla Numeral database respectively.

So, it can be concluded that for handwritten Bangla numeral recognition both MQDF and SVM are best suitable and give pretty much same recognition results. We have also tried the classifiers like J48, JRIP and FLR for recognition. But the results of these classifiers are not suitable compared to the highest recognition result. Only FURIA have shown some respective results for both the databases.

VIII. Conclusion

In this paper we have proposed a comparison of different classifiers using handwritten Bangla numeral recognition. We have analyzed all the classifiers and found that the MQDF, SVM and MLP classifiers are more suitable than others in terms of accuracy for the complex real time Pattern Recognition problems like handwritten Bangla numeral recognition. But in terms of convergence criteria the LIBLINEAR classifier is faster than others classifiers.

We intend to increase the number of data for our latter works. Results in this proposed work are encouraging and we will try to use different features and classifiers combinations for our future works.

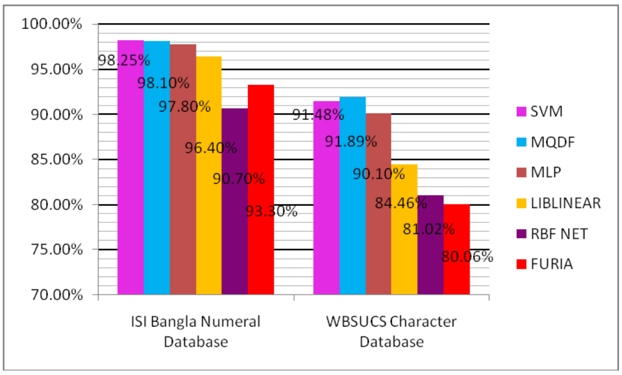

Fig. 3. Numeral recognition result chart of different classifires on both WBSUCS character database and ISI Bangla Numeral database.

Table I. Table for comparative numeral recognition result on WBSUCS character database and ISI Bangla Numeral Database

Classifiers	*Accuracy*	
	WBSUBCS Character Database	*ISI Bangla Numeral Database*
SVM	91.48%	98.25%
MQDF	91.89%	98.10%
MLP	90.10%	97.80%
LIBLINEAR	84.46%	96.40%
RBF Network	81.02%	90.70%
FURIA	80.60%	93.30%

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