Off-line Nepali Handwritten Character Recognition Using Multilayer Perceptron and Radial Basis Function Neural Networks

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***Abstract*—An off-line Nepali handwritten character recognition, based on the neural networks, is described in this paper. A good set of spatial features are extracted from character images. Accuracy and efficiency of Multilayer Perceptron (MLP) and Radial Basis Function (RBF) classifiers are analyzed. Recognition systems are tested with three datasets for Nepali handwritten numerals, vowels and consonants. The strength of this research is the efficient feature extraction and the comprehensive recognition techniques, due to which, the recognition accuracy of 94.44% is obtained for numeral dataset, 86.04% is obtained for vowel dataset and 80.25% is obtained for consonant dataset. In all cases, RBF based recognition system outperforms MLP based recognition system but RBF based recognition system takes little more time while training.**

Index Terms: Off-line handwriting recognition, Neural Network, Nepali handwritten datasets.

I. INTRODUCTION

Handwriting Recognition is the mechanism for converting the handwritten text into a notational representation. It is a special problem in the domain of pattern recognition and machine intelligence. Automatic handwriting recognition have many application areas like postal addresses reading, bank check verification, ancient document digitalization, handwritten form verification, forensic and medical analysis, etc. The field of handwriting recognition can be split into two different categories: on-line recognition and off-line recognition. On-line mode deals with the recognition of handwriting captured by a tablet or touch-screen device, and use the digitized trace of the pen to recognize the symbol. In the on-line case we have the captured trajectory, pan up and pen down time, stroke orders, etc. of the written characters. Off-line mode deals with the recognition of the character or word present in the digital image of written text. In this case, we just have the holistic image of the written text.

Handwriting recognition is currently a hot topic in the research society. The early researches after the digital age were concentrated either upon machine-printed text or upon a small scale of well-separated handwritten symbols. Generally, template matching techniques were used for machine printed character recognition and statistical classification techniques were used for handwritten text recognition [1]. Due to lack of powerful computers and data perception tools, character recognition research is limited till $1980s$. In the period $1980-1990$, character recognition research takes a noticeable growth along with the development in information technology [2], [3]. Research progress on the off-line and on-line character recognition during this period can be found in [4] and [5]. After 1990, pattern recognition techniques and image processing techniques were combined using artificial intelligence. Modern steering of character recognition is handled by powerful learning tools like, Artificial Neural Networks, Support Vector Machines, Hidden Markov Models, Fuzzy Set Reasoning and Natural Language Processing Tools.

Character segmentation from cursive handwritten documents is a difficult task. So, in literature most of the researches were conducted on separated characters [2], [6]–[18]. Researches in the domain of word recognition are included in [3], [19], [20]. Handwriting recognition for Devanagari language and its continental variations can be found in [8], [10], [12], [13], [20]. Specially for the Nepali language there are very few researches in the domain of handwriting recognition [9], [21]. Mostly used recognition tools include statistical based recognition tools. Currently, neural network based recognition techniques are taking more attention of researchers. Template based and structural recognition techniques are not so widely used in this area of research.

II. SYSTEM OVERVIEW

Top level architecture of the proposed handwriting recognition system is show in Figure 1. The recognition system is divided into three sub-systems: preprocessing, feature extraction and recognition. Input images are preprocessed before passing into the feature extraction engine. Global feature vector is created in the feature extraction engine, using various feature extraction techniques, are then feed into the recognition engine. Recognition engine implements two neural network based recognition algorithms.

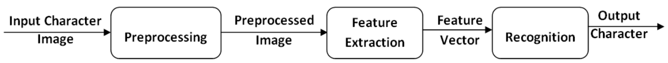

Fig. 1. Off-line handwriting recognition system architecture.

III. IMAGE PREPROCESSING

Image preprocessing is an important preliminary step of the recognition procedure. Raw images are fine grained before extracting features from them. In the preprocessing stage, scanning artifacts, noise and unnecessary markings are removed. Also, colour normalization, size normalization, slant correction, skew correction and image skeletonization are carried out in this stage. Main preprocessing techniques used are described in this section.

A. RGB to Grayscale Conversion

24 bit RGB image is converted into 8 bit grayscale image by taking the weighted summation of R, G and B components of RGB image. Weights are selected same as the NTSC color space selects for the luminance i.e. the grayscale signal used to display pictures on monochrome televisions. For the RGB image $f(x, y)$, corresponding grayslcae image is given by,

$$g(x, y) = 0.2989 * f_R + 0.5870 * f_G + 0.1140 * f_B \quad (1)$$

where, f_R, f_G, f_B are Red, Green and Blue components of the RGB image $f(x, y)$ respectively.

B. Noise Removal

Noise removal is one of the important step of image preprocessing. Noisy image pixels are removed with the help of filtering. Here, Non-linear median filtering technique is used for noise removal. Median filter is an effective method of noise removal which can block isolated noise without blurring sharp edges. Median filter replaces a pixel with the median value of its neighbourhood. For the digital image $f(x, y)$, median filtered image is obtained as,

$$g(x, y) = median\{f(i, j) \,|\, (i, j) \in \; w\} \quad (2)$$

where, w is the neighbourhood centred around location (x, y) in the image.

C. Image Segmentation

Segmentation is the central problem of distinguishing object from the background. For the grayscale image $f(x, y)$, the segmented image $g(x, y)$ is obtained by the image binarization process as given below.

$$g(x, y) = \begin{cases} 1 & if \; f(x, y) \geq T \\ 0 & if \; f(x, y) < T \end{cases} \quad (3)$$

where, T is the threshold value and it can be obtained using the Otsu's threshold selection technique for grayscale image segmentation [22]. Otsu's graylevel threshold selection method for image binarization is a nonparametric and unsupervised method of automatic threshold selection. An optimal threshold is selected by the discriminant criteria i.e., by maximizing the interclass variance between white and black pixels.

D. Image Inversion

Handwritten documents are normally written in white paper with black pen. For the recognition system, we assume black pixels as a background and white pixels as the foreground. So, captured images are inverted before passing into the recognition engine. The inverted image of binary image $f(x, y)$ can be obtained by the negative transformation as,

$$g(x, y) = 1 - f(x, y) \quad (4)$$

E. Universe of Discourse

Determining universe of discourse of the character image is finding smallest rectangle that encloses the character object. It removes extra pixels outside the convex rectangle of the character image.

F. Size Normalization

Size normalization is the technique of converting all the variable size input images to fixed size images. Size normalization is done so that we do not require paddings of pixels at the time of feature extraction. All the input images are normalized to the predefined size of 36x36 pixels.

G. Image Skeletonization

Skeletonization is a process of reducing object regions in a binary image to a skeletal remainder that largely preserves the extent and connectivity of the original object while throwing away most of the original object pixels. It creates single pixel wide connected object boundary, that preserves Euler number of the original object.

Skeletonization calculates the medial axis skeleton so that points of this skeleton are at the same distance of its nearby borders [23]. A comprehensive survey of the thinning algorithms is described in [4]. Image skeletonization technique used for the binary image skeletonization is the medial axis transformation technique which iteratively delete boundary points of a region of the object [24].

IV. FEATURE EXTRACTION

After Pre-processing of the character image, the next stage of character recognition is feature extraction. Feature extraction step plays an important role in the recognition procedure. A good feature vector should represent characteristic of the class that helps distinguish it from other classes, while remaining discriminant to characteristic differences within the class. Hundreds of features are available in the literature [25], [26], [27], [17]. Different geometric and statistical features extracted from the preprocessed character image are described in this section.

A. Directional Features

Directional features are extracted from skeletonized image, based on the line types that form the character skeleton. For, image is zoned into 3x3 sub images and features are extracted from individual zones [28], [18].

B. Moment Invariant Features

Moment invariants are important tools in object recognition problem. These techniques grab the property of image intensity function. Moment invariants are pure statistical measures of the pixel distribution around the centre of gravity of the character and allow capturing the global character shape information [29], [24].

C. Euler Number

Euler number is the difference of number of objects and the number of holes in the image. It is invariant to affine transformation of image and extracted from the whole image. Euler number can be calculated by using local pattern information and does not require global connectivity information [30].

D. Centroid of Image

Centroid specifies the centre of mass of the object region in given image. Centroid coordinates of the binary image $f(x, y)$ of size MxN are given in equation 5.

$$x = \frac{\frac{1}{N}\sum_{i=0}^{M-1}\sum_{j=0}^{N-1} x_j f(i,j)}{\sum_{i=0}^{M-1}\sum_{j=0}^{N-1} f(i,j)}, \; y = \frac{\frac{1}{M}\sum_{i=0}^{M-1}\sum_{j=0}^{N-1} y_j f(i,j)}{\sum_{i=0}^{M-1}\sum_{j=0}^{N-1} f(i,j)} \quad (5)$$

E. Eccentricity

The eccentricity is the ratio of the distance between the foci of the ellipse that best fit the character object and its major axis length. It describes the rectangularity of the region of the object. The measure of eccentricity can be obtained by using the minor and major axes of such an ellipse [31].

F. Area of Character Skeleton

The area of the object within the binary image is simply the count of the number of pixels in the object for which f(x,y) = 1.

V. NEURAL NETWORKS

Artificial neural network is a non-linear, parallel, distributed, highly connected network having capability of adaptivity, self-organization, fault tolerance and evidential response, which closely resembles with physical nervous system. Physical nervous system is highly parallel, distributed information processing system having high degree of connectivity with capability of self-learning. In this research, two neural network based learning algorithms are used, namely, MLP and RBF.

A. Multilayer Perceptron

A multilayer feedforward neural network consists of a layer of input units, one or more layers of hidden units, and one layer of output units. The output from each layer is the weighted linear summation of all input vectors along with the bias term, passed through some activation function. The network weight adjustment is done by back-propagating the error of the network. The learning algorithms used for learning weights in the network are Gradient Descent with Momentum & Adaptive Learning Rate (GDMA) [32] and Levenberg-Marquadt (LM) Learning Algorithm [33].

Fig. 2. Sample image of Nepali handwritten Numerals.

Fig. 3. Sample image of Nepali handwritten Vowels.

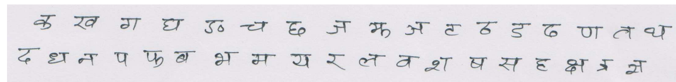

Fig. 4. Sample image of Nepali handwritten Consonants.

B. Radial Basis Function Network

A radial basis function network consists of a layer of input units, one or more layers of hidden units, and one layer of output units. Hidden layer units implement the radial basis function. The output of the hidden layer unit is product of difference of all input vectors form predefined centers to bias term, passed through radial basis function. The computation of output layer is similar to the computation of output layer of MLP. The basis vector selection and network weight adjustment is done by using Orthogonal Least Square (OLS) Training Algorithm [34].

VI. NEPALI HANDWRITTEN CHARACTER DATASETS

Nepali language belongs to Devanagari script which is invented by Brahmins around 11th century. It consist of 36 consonant symbols, 12 vowel symbols and 10 numeral symbols along with different modifiers and half forms. According to current census research, 17 million people worldwide speaks Nepali language.

For the experimentation with the proposed model, three datasets for Nepali Handwritten Characters are created; namely for numerals, vowels and consonants. Handwritten samples are taken from 45 different writers from different fields. Collected documents are than scanned and cropped for individual characters. Nepali handwritten numeral dataset contains 288 samples for each class of Nepali numeral family, Nepali handwritten vowel dataset contains 221 samples for each class of Nepali vowel family and Nepali handwritten consonant dataset contains 205 samples for each class of Nepali consonant family. Figures 2, 3 and 4 shows sample images of Nepali handwritten numerals, vowels and consonants respectively.

VII. EXPERIMENTS AND RESULTS

The aim of this research is to evaluate the complete MLP and RBF neural network based handwriting recognition systems on self-created off-line Nepali handwritten corpus. First of all, system is trained in each corpus by taking some samples,

TABLE I
NEURAL NETWORK CONFIGURATIONS.

Dataset Name	Dataset Size	Recognition Algorithm	Train/Test Samples	Hidden Layer Neurons	No. of Epochs
Numeral	10x288	MLP (LM)	2016/432	30	9
Dataset	=2880	RBF	2304/576	580	580
Vowel	12x221	MLP (LM)	1857/397	30	12
Dataset	=2652	RBF	2122/530	840	840
Consonant	36x205	MLP (GDMA)	5411/891	100	1000
Dataset	=7380	RBF	5166/891	1025	1025

TABLE II
RECOGNITION RESULTS.

Dataset Name	Recognition Algorithm	Training Time (min.)	Recognition Accuracy (%)	Miss-classification Rate (%)
Numeral	MLP	16.66	87.50	12.50
Dataset	RBF	69.91	**94.44**	5.55
Vowel	MLP	24.36	79.15	20.85
Dataset	RBF	113.23	**86.04**	13.96
Consonant	MLP	13.92	71.72	28.28
Dataset	RBF	308.4	**80.25**	19.75

TABLE III
RECOGNITION RESULTS FOR EACH CLASS OF NUMERALS.

Class	Recognition Algorithms	Recognition Accuracy (%)	Class	Recognition Algorithms	Recognition Accuracy (%)
०	MLP	97.7	१	MLP	94.1
	RBF	98.6		RBF	98.4
२	MLP	85.1	३	MLP	82.1
	RBF	93.0		RBF	90.4
४	MLP	82.5	५	MLP	82.5
	RBF	98.0		RBF	81.1
६	MLP	82.9	७	MLP	86.7
	RBF	95.0		RBF	96.2
८	MLP	97.8	९	MLP	80.4
	RBF	100		RBF	90.9

in supervised manner. And then, system is tested against new samples and accuracy is measured. In each datasets, data is partitioned into three exclusive parts, for training, validation and testing. Network configurations and recognition results for MLP and RBF based recognition systems for each datasets are described in this section.

Table I shows neural network configurations for MLP and RBF recognition systems on all three datasets.

Table II shows performance matrices for MLP and RBF based off-line handwriting recognition systems on each dataset.

Table III shows recognition results for each class of Nepali handwritten numeral dataset. The corresponding Confusion Matrix (CM) corresponding to RBF based recognition system is given in table IV. Here, CM is an 10 x 10 dimensional matrix with $CM(i,j)$ is the number of target samples of the i^{th} class classified by the recognition system into class j.

Table V shows recognition results for each class of Nepali handwritten vowel dataset.

Table VI shows recognition results for each class of Nepali handwritten consonant dataset.

TABLE IV
CONFUSION MATRIX OF NUMERAL DATASET TESTING.

Class	०	१	२	३	४	५	६	७	८	९
०	69	0	0	0	0	0	0	0	0	1
१	0	61	0	0	0	0	1	0	0	0
२	0	0	53	4	0	0	0	0	0	0
३	0	0	3	47	0	0	2	0	0	0
४	0	0	0	0	49	1	0	0	0	0
५	0	0	5	3	1	43	0	0	0	1
६	0	1	0	0	0	0	57	1	0	0
७	0	0	0	0	1	0	1	51	0	0
८	0	0	0	0	0	0	0	0	64	0
९	0	1	1	1	0	1	1	0	0	50

TABLE V
RECOGNITION RESULTS FOR EACH CLASS OF VOWELS.

Class	Recognition Algorithms	Recognition Accuracy (%)	Class	Recognition Algorithms	Recognition Accuracy (%)
अ	MLP	77.8	आ	MLP	93.5
	RBF	78.9		RBF	87.8
इ	MLP	84.2	ई	MLP	88.5
	RBF	91.1		RBF	90.5
उ	MLP	75.8	ऊ	MLP	85.2
	RBF	92.1		RBF	87.8
ए	MLP	78.4	ऐ	MLP	82.9
	RBF	97.6		RBF	85.7
ओ	MLP	71.4	औ	MLP	64.7
	RBF	76.5		RBF	80.0
अं	MLP	64.1	अः	MLP	86.5
	RBF	76.1		RBF	88.5

VIII. CONCLUSION

Off-line handwriting recognition with neural network is presented and evaluated on Nepali handwritten datasets. Recognition system evaluated on numeral dataset gives best accuracy of 94.44% over all other datasets. In other datasets, due to high variations on writing styles, shapes and cursive nature of characters, the recognition accuracy is decreased. For vowel dataset, recognition accuracy of 86.04% is obtained and for consonant dataset, recognition accuracy of 80.25% is obtained. In all cases, RBF based recognition system outperforms MLP based recognition system but it takes little more time for training.

Recognition accuracy is directly proportional to the set of good features. For extracting good features from character image, it should be well preprocessed. This research describes two very important category of feature extraction techniques: geometry based and pixel distribution based. Geometric features describe the physical shape of objects and statistical features describe the pixel distribution of the object.

To further improve the quality of recognition system, the combination of the proposed methods with additional preprocessing and feature extraction techniques are recommended. Especially, features extracting methods for shape informations which contain the semantic properties of the object have great impact on the efficiency of the recognition system. Proposed system can be enhanced for the recognition of multilingual characters, words, sentences and documents.

TABLE VI
RECOGNITION RESULTS FOR EACH CLASS OF CONSONANTS.

Class	Recognition Algorithms	Recognition Accuracy (%)	Class	Recognition Algorithms	Recognition Accuracy (%)
क	MLP	94.1	ख	MLP	78.3
	RBF	94.1		RBF	91.3
ग	MLP	80.8	घ	MLP	51.9
	RBF	92.3		RBF	77.8
ङ	MLP	60.0	च	MLP	84.6
	RBF	64.0		RBF	84.6
छ	MLP	66.7	ज	MLP	73.1
	RBF	77.8		RBF	80.8
झ	MLP	65.4	ञ	MLP	59.4
	RBF	73.1		RBF	68.8
ट	MLP	96.3	ठ	MLP	63.6
	RBF	92.6		RBF	72.7
ड	MLP	76.9	ढ	MLP	91.7
	RBF	88.5		RBF	91.7
ण	MLP	85.0	त	MLP	92.3
	RBF	90.0		RBF	96.2
थ	MLP	50.0	द	MLP	64.0
	RBF	72.7		RBF	76.0
ध	MLP	75.0	न	MLP	36.8
	RBF	79.2		RBF	38.8
प	MLP	87.5	फ	MLP	72.4
	RBF	100		RBF	86.2
ब	MLP	75.9	भ	MLP	63.6
	RBF	75.9		RBF	90.9
म	MLP	66.7	य	MLP	44.0
	RBF	73.3		RBF	56.0
र	MLP	89.3	ल	MLP	66.7
	RBF	82.1		RBF	77.8
व	MLP	73.9	श	MLP	80.0
	RBF	78.3		RBF	91.4
ष	MLP	76.0	स	MLP	55.2
	RBF	80.0		RBF	79.3
ह	MLP	88.2	क्ष	MLP	60.0
	RBF	82.4		RBF	72.0
त्र	MLP	73.1	ज्ञ	MLP	64.0
	RBF	76.9		RBF	80.0

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