Off-line Nepali Handwriting Recognition Using MLP & RBF Neural Networks

A Dissertation Presentation

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Presentation Outline

Handwriting Recognition

Handwriting

Handwriting is a person's individual style of writing.

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Handwriting Recognition

System's ability to understand intelligible handwritten input from various sources such as paper documents, photographs, touch-screens and other devices.

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System's ability to understand intelligible handwritten input from various sources such as paper documents, photographs, touch-screens and other devices.

Nepali Handwriting

- Handwriting corresponds to Nepali language.
- Belongs to Devanagari Script.

On-line & Off-line Handwriting Recognition

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On-line Handwriting Recognition

- Task of determining what character is being written in some writing device with some digital pen or plotter.
- Availability of trajectory data during writing.

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- Availability of trajectory data during writing.

Off-line Handwriting Recognition

- Task of determining what characters or words are present in a digital image of handwritten text.
- No temporal information available.

Applications of Handwriting Recognition

- Postal address reading.
- Bank cheque verification.
- Ancient document digitalization.
- Indexing of handwritten documents for searching and sorting.
- Assessment writing for school work.
- Forensic and medical analysis, and so on.

Problem Statement (off-line handwriting recognition)

- The high-level task is to classify the ordered sequence of images of off-line characters.

Challenges of Off-line Handwriting Recognition

- Varying writing styles and shapes
- Unconstrained writings
- Cursive handwritings
- Noise and unnecessary markings
- Segmentation of characters from documents

State of the Art of Handwriting Recognition

- Historic review of OCR research and development after the digital age and until 1990s is described in [1] by Suen et.el. It describes the Template Matching and Shape Analysis techniques on OCR.
- State of the art on on-line handwriting recognition till 1990s is described in [2].
- After 1990, ANN, HMM, fuzzy set reasoning and other statistical learning tools take the steering of OCR research.
- Handwriting recognition until 2010 is given in [3],[4],[5].
- Handwriting Recognition for Devanagari Script can be found in [6],[7],[8],[9],[10],[5].
- Nepali handwriting research is given in [11],[12].

Objectives of the Research

- To compare Accuracy and efficiency of Multilayer Perceptron and Radial Basis function Neural Network on Off-line Nepali Handwriting Recognition Problem.
- To investigate Geometric and Statistical feature extraction techniques for off-line Nepali handwriting recognition problem.
- To investigate preprocessing techniques (segmentation, skeletonization, normalization, etc.) for handwritten documents.
- To create benchmark databases for Nepali handwritten characters.

Proposed Handwriting Recognition System

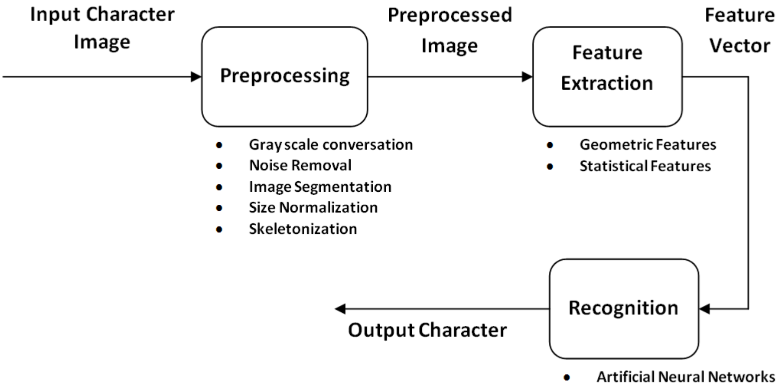


Figure: Off-line Handwriting Recognition System Architecture

Preprocessing

Image Preprocessing Algorithmic Steps

1. Read image.
2. Convert RGB images to gray scale image.
3. Remove noise using median filter.
4. Convert the gray scale images into binary image.
5. Invert the binary image.
6. Determine the universe of discourse of image.
7. Normalize the image to a predefined size of 36x36 pixels.
8. Convert the normalized image into single pixel thick skeleton image.

1. RGB to Grayscale Conversion

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

RGB Image

Gray Image

2. Noise Removal

$$g(x, y) = median\{f(i, j) \mid (i, j) \in \ w\}$$

Gray Image

Denoised Image

3. Image Segmentation

$$g(x,y) = \begin{cases} 1 & \text{if } f(x,y) \geq t \\ 0 & \text{if } f(x,y) < t \end{cases}$$

Denoised Image

Binarized Image

4. Image Inversion

$$g(x, y) = 1 - f(x, y)$$

Binarized Image

Inverted Image

5. Universe of Discourse

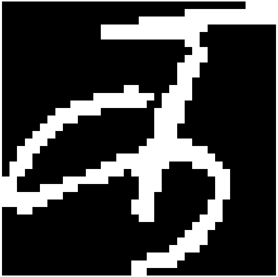
Inverted Image

Discoursed Image

6. Image Size Normalization

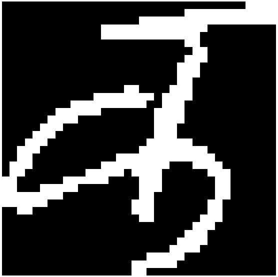
Discoursed Image

Size Normalized Image (36x36)

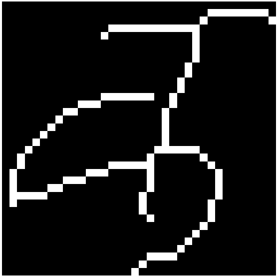


7. Image Skeletonization

Size Normalized Image (36x36)



Skeletonized Image



Geometric Feature Extraction

1. Directional Features

Image is zoned into 3*x*3 sub-images and directional vectors are extracted [13]. Features extracted from each zone are:

- The number of horizontal lines.
- The number of vertical lines.
- Number of Right diagonal lines.
- Number of Left diagonal lines.
- Normalized Length of all horizontal lines.
- Normalized Length of all vertical lines.
- Normalized Length of all right diagonal lines.
- Normalized Length of all left diagonal lines.
- Number of intersection points

Geometric Feature Extraction

2. Euler Number [14]

Difference between number of objects and number of holes in an character image.

Geometric Feature Extraction

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Difference between number of objects and number of holes in an character image.

3. Eccentricity

Ratio of the distance between the foci of the ellipse to the length of semi-major axis of the smallest ellipse that encloses the character image.

Statistical Feature Extraction

1. Moment Invariant Features [15],[16]

The 2-D moment of order $(p+q)$ for a digital image $f(x,y)$ of size MxN is given by,

$$m_{pq} = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} x^p y^q f(x,y) \quad p,q = 0,1,2,\ldots$$

A set of seven normalized central moments can be derived from the second and third moments [15] which are invariant to translation, scale change, mirroring, and rotation.

Statistical Feature Extraction

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2. Area of Character Skeleton

Number of pixels in character skeleton.

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2. Area of Character Skeleton

Number of pixels in character skeleton.

3. Centroid

Centre of mass for character image.

Artificial Neural Network (ANN)

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.

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ANN Learning Methods

1. Multilayer Perceptron (MLP)
2. Radial Basis Function (RBF)

1. Multilayer FeedForward Network

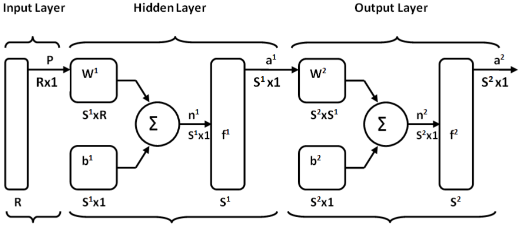


Figure: Multilayer Feedforward Network

The network output of layer $k+1$ is given by,

$$a^0 = p$$
$$a^{k+1} = f^{k+1}(W^{k+1}a^k + b^{k+1})$$

1. Multilayer FeedForward Network

Multilayer Feedforward Backpropagation Learning Algorithms

- Levenberg-Marquardt (LM) Learning [17]
  - Numerical optimization technique
  - Faster Convergence.
  - Requires more memory.
- Gradient Descent with Momentum and Adaptive Learning Rate (GDMA)
  - Heuristic based optimization technique
  - slower Convergence.
  - Highly sensitive to local minima.

For MLP algorithm, the performance index to be minimized is defined as,

$$E = \frac{1}{2}\sum_{p=1}^{Q}\sum_{k=1}^{K}(t_{kp} - a_{kp})^2$$

1. Multilayer FeedForward Network

(a). Levenberg-Marquardt (LM) Learning Algorithm

The increment of weights Δw at iteration t can be obtained as,

$$\Delta w = -(J^T J + \mu I)^{-1} J^T E$$

Now, network weights are updated as,

$$w_{t+1} = w_t + \Delta w$$

1. Multilayer FeedForward Network

(b). Gradient Descent with Momentum & Adaptive Learning Rate

The increment of weights Δw at iteration $t+1$ can be obtained as,

$$\Delta w(t+1) = \mu \Delta w(t) + (1-\mu)\eta \nabla E$$

Now, network weights are updated as,

$$w(t+1) = w(t) + \Delta w(t+1)$$

2. Radial Basis Function Network

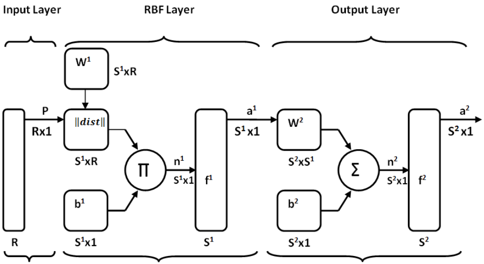


Figure: Radial Basis Function Network

The network output for RBF network can be obtained as,

$$t_k = \sum_{j=1}^{M} w_{kj}\phi_j(x) + b_k$$

2. Radial Basis Function Network

Gaussian Radial Basis Function

A normalized Gaussian radial basis function is given by,

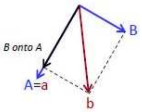
$$\phi_j(x) = \exp(-\frac{\|x - \mu_j\|^2}{2\sigma_j^2})$$

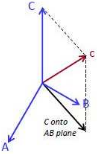
where μ_j and σ_j denote the centre and spread width of the j^{th} neuron,respectively.

2. Radial Basis Function Network

Orthogonal Least Square (OLS) Learning Algorithm [18]

- Supervised algorithm for radial basis neural network training
- Forward stepwise regression procedure
- Sequentially selects the centre that results in the largest reduction of sum-square-error at the output using Grahm-Schmidt orthogonalization procedure



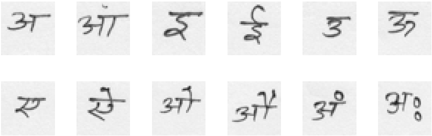


Nepali Handwritten Consonant Dataset

- **36** classes
- **205** samples each class (total **7380** images)
- Samples are taken from **45** different writers

Nepali Handwritten Vowel Dataset

- **12** classes
- **221** samples each class (total **2652** images)
- Samples are taken from **44** different writers



Nepali Handwritten Numeral Dataset

- **10** classes
- **228** samples each class (total **2280** images)
- Samples are taken from **45** different writers

Neural Network Configuration

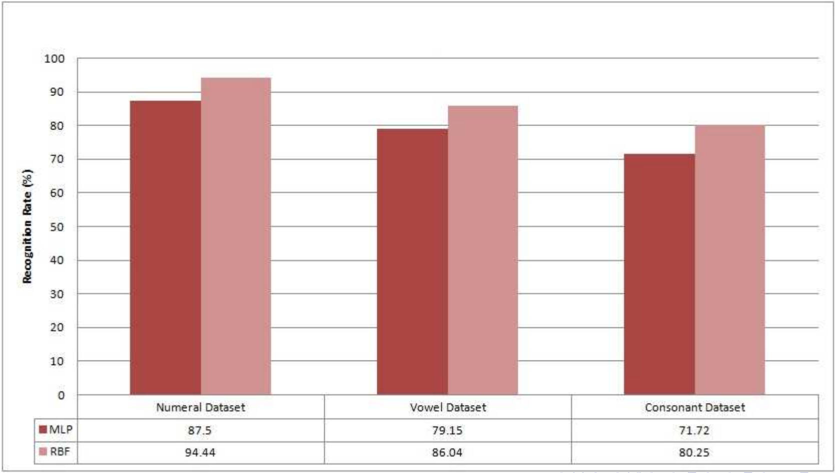
Dataset Name	Dataset Size	Recognition Algorithm	Train/Test Samples	Hidden Layer Neurons	No. of Epochs
Numeral Dataset	10 * 288 = 2880	MLP (LM)	2016/432	30	9
		RBF	2304/576	580	580
Vowel Dataset	12 * 221 = 2652	MLP (LM)	1857/397	30	12
		RBF	2122/530	840	840
Consonant Dataset	36 * 205 = 7380	MLP (GDMA)	5411/891	100	1000
		RBF	5166/891	1025	1025

Recognition Results

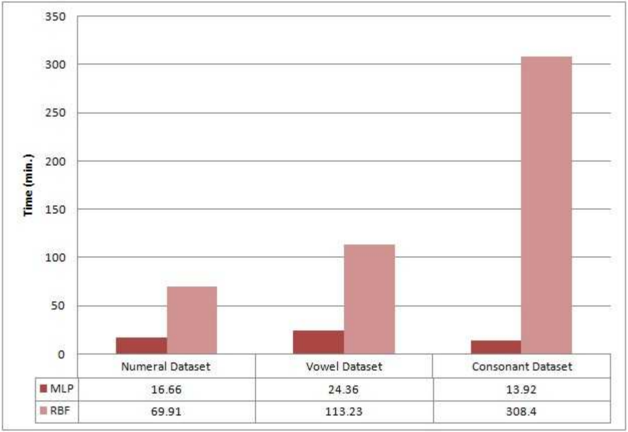
Dataset Name	Recognition Algorithm	Training Time (min.)	Recognition Accuracy (%)	Miss-classification Rate (%)
Numeral Dataset	MLP	16.66	87.50	12.50
	RBF	69.91	**94.44**	5.55
Vowel Dataset	MLP	24.36	79.15	20.85
	RBF	113.23	**86.04**	13.96
Consonant Dataset	MLP	13.92	71.72	28.28
	RBF	308.4	**80.25**	19.75

Experimentation Results

Recognition Accuracy Graph



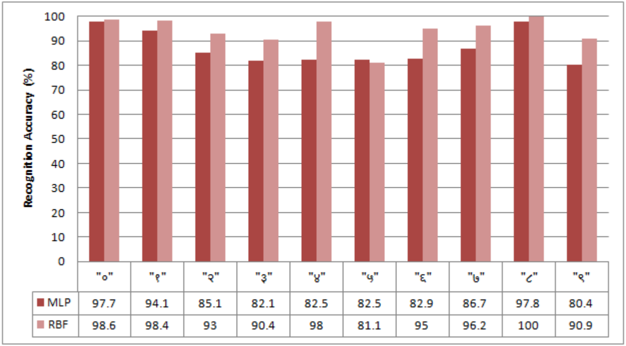
Network Training Time Graph



Individual Recognition Result for Numeral Dataset

Class	Recognition Algorithms	Recognition Accuracy (%)	Class	Recognition Algorithms	Recognition Accuracy (%)
	MLP	97.7		MLP	94.1
	RBF	98.6		RBF	98.4
	MLP	85.1		MLP	82.1
	RBF	93.0		RBF	90.4
	MLP	82.5		MLP	82.5
	RBF	98.0		RBF	81.1
	MLP	82.9		MLP	86.7
	RBF	95.0		RBF	96.2
	MLP	97.8		MLP	80.4
	RBF	100		RBF	90.9

Individual Recognition Result for Numeral Dataset Graph



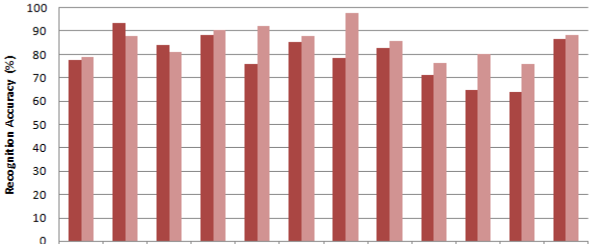
Confusion Matrix for Numeral Dataset Testing

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

Individual Recognition Results for Vowel Dataset

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

Individual Recognition Result for Vowel Dataset Graph



	"अ"	"आ"	"इ"	"ई"	"उ"	"ऊ"	"ए"	"ऐ"	"ओ"	"औ"	"अँ"	"अः"
MLP	77.8	93.5	84.2	88.5	75.8	85.2	78.4	82.9	71.4	64.7	64.1	86.5
RBF	78.9	87.8	81.1	90.5	92.1	87.8	97.6	85.7	76.5	80	76.1	88.5

Confusion Matrix for Vowel Dataset Testing

Class	अ	आ	इ	ई	उ	ऊ	ए	ऐ	ओ	औ	अं	अः
अ	45	6	0	0	0	4	0	0	1	0	1	0
आ	3	36	0	0	0	0	0	0	0	1	0	1
इ	0	0	51	0	1	0	0	0	1	1	2	0
ई	0	0	2	38	0	0	0	1	0	0	1	0
उ	1	0	2	0	35	0	0	0	0	0	0	0
ऊ	2	0	0	0	1	36	0	0	0	0	0	2
ए	1	0	0	0	0	0	40	0	0	0	0	0
ऐ	1	0	0	0	0	0	2	36	2	0	1	0
ओ	0	0	0	0	0	0	0	1	26	5	2	0
औ	0	0	0	0	0	0	0	0	6	32	2	0
अं	1	0	0	2	0	0	0	1	5	2	35	0
अः	1	3	0	0	0	0	0	0	0	2	0	46

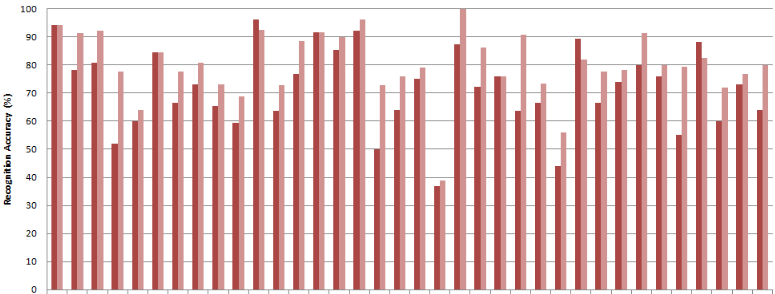
Individual Recognition Results for Consonant Dataset

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
ध	MLP	50.0	द	MLP	64.0
	RBF	72.7		RBF	76.0

Individual Recognition Results for Consonant Dataset

Class	Recognition Algorithms	Recognition Accuracy (%)	Class	Recognition Algorithms	Recognition Accuracy (%)
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

Individual Recognition Result for Consonant Dataset Graph



	"क"	"ख"	"ग"	"घ"	"ङ"	"च"	"छ"	"ज"	"झ"	"ञ"	"ट"	"ठ"	"ड"	"ढ"	"ण"	"त"	"थ"	"द"
MLP	94	78	81	52	60	85	67	73	65	59	96	64	77	92	86	92	50	64
RBF	94	91	92	78	64	85	78	81	73	69	93	73	89	92	90	96	73	76

	"ध"	"न"	"प"	"फ"	"ब"	"भ"	"म"	"य"	"र"	"ल"	"व"	"श"	"ष"	"स"	"ह"	"क्ष"	"त्र"	"ज्ञ"
MLP	75	37	88	72	76	64	67	44	89	67	74	80	76	55	88	60	73	64
RBF	79	39	10	86	76	91	73	56	82	78	78	91	80	79	82	72	77	80

confusion Matrix for Consonant Dataset Testing

Class	क	ख	ग	घ	ङ	च	छ	ज	झ	ञ	ट	ठ	ड	ढ	ण	त	थ	द	ध	न	प	फ	ब	भ	म	य	र	ल	व	श	ष	स	ह	क्ष	त्र	ज्ञ
क	16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
ख	0	21	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0
ग	0	0	24	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0
घ	0	0	0	21	0	0	1	0	0	0	0	0	0	0	0	0	1	0	1	0	2	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
ङ	1	0	0	0	16	0	0	1	0	0	0	0	2	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	2	0	0	0	0	0	0
च	0	0	0	1	0	22	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0
छ	0	0	0	0	0	0	14	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0
ज	0	0	0	0	0	0	0	21	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1
झ	1	1	0	0	0	0	0	0	19	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	0	1	0	1	0	1
ञ	0	0	1	0	0	0	0	1	0	22	0	0	0	0	0	0	0	0	0	0	0	0	2	1	2	0	0	0	0	0	0	0	0	0	3	0
ट	0	0	0	0	0	0	1	0	0	0	25	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
ठ	0	0	0	0	0	0	0	0	0	0	0	16	1	1	0	0	0	2	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
ड	0	0	0	0	1	0	0	0	0	0	0	0	23	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0
ढ	0	1	0	0	0	0	0	0	0	0	0	0	1	22	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
ण	0	0	1	0	0	0	0	0	0	0	0	0	0	0	18	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
त	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	25	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
थ	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	16	0	2	0	1	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0
द	1	0	0	0	0	0	2	0	0	0	0	1	0	1	0	0	0	19	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
ध	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	1	0	19	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0
न	0	0	1	0	0	0	0	1	0	2	0	0	0	0	0	2	0	0	0	7	0	0	0	0	2	0	1	1	1	0	0	0	0	0	0	1
प	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	24	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
फ	0	0	0	0	0	0	0	0	2	0	0	0	0	0	1	0	0	0	0	0	1	25	0	0	0	0	0	0	0	0	0	0	0	0	0	0
ब	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	2	0	0	0	0	22	0	1	0	0	0	1	0	0	0	0	0	0	0
भ	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	0	0	20	0	0	0	0	0	0	0	0	0	0	0	0
म	0	0	0	0	0	0	0	2	0	1	0	0	0	1	0	0	0	0	0	0	2	0	0	0	22	0	0	0	0	0	0	0	0	0	2	0
य	0	0	1	0	0	1	0	1	0	0	0	0	0	0	2	1	0	0	0	0	3	0	0	1	0	14	0	1	0	0	0	0	0	0	0	0
र	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	23	0	0	0	0	0	0	0	1	0
ल	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	14	0	0	0	0	0	0	0	1
व	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	1	0	0	0	0	0	18	0	0	0	1	1	0	0
श	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	1	32	0	0	0	0	0	0
ष	0	0	0	0	0	0	2	0	0	0	0	0	0	0	1	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	20	0	0	0	0	0
स	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	2	0	0	0	0	2	0	23	0	1	0	0
ह	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	0	14	0	0	0
क्ष	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	1	0	0	1	1	0	0	0	0	0	0	0	1	0	18	0	0
त्र	1	0	2	0	0	1	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	20	0
ज्ञ	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	2	0	0	0	0	0	0	1	20

Conclusion

- Handwriting recognition is a difficult problem due to high variations in human handwritings, overlapped and joined characters, shape, size and styles of written characters, etc.
- Neural Network based off-line handwriting recognition system is experimented on self created Nepali handwritten datasets.
- Preprocessing is an important part of recognition engine for extracting area of interest from character image.
- Feature extraction engine is the most important part of the recognition system for higher accuracy.
- RBF based recognition system outperforms MLP based recognition system, but it takes little more time while training.

Future Enhancement

- Proposed system can be tested with known handwritten datasets like Germana database, IAM database, MNIST database, etc.
- Experimentation can be enhanced by taking other spatial domain features along with frequency domain features.
- Purposed system can be extended for the recognition of words, sentences and documents.
- Purposed system can be extended for multilingual character recognition.

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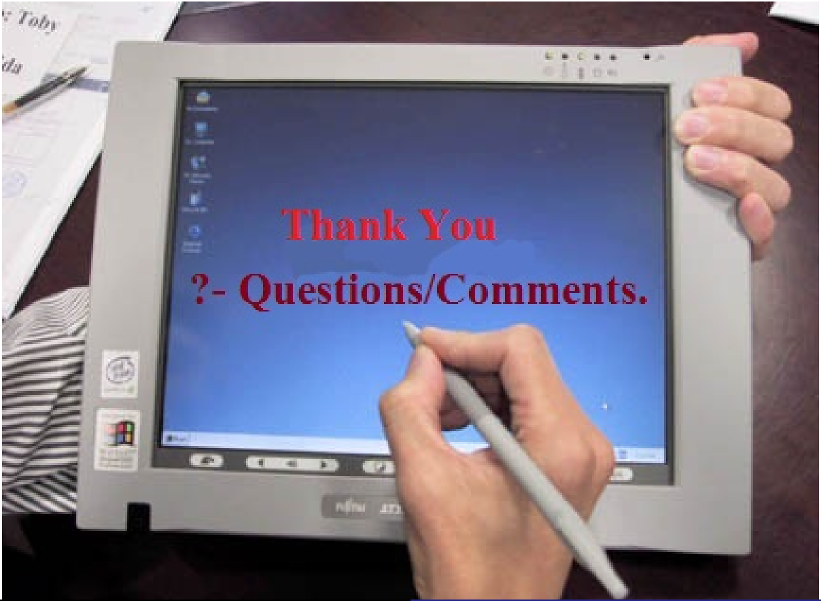
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