Off-line Nepali Handwritten Character Recognition Using MLP & RBF Neural Networks

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Presentation Outline

Handwriting Recognition

Handwriting

Handwriting is a person's individual style of writing.

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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.

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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.

Nepali Handwriting

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

On-line & Off-line Handwriting Recognition

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.

On-line & Off-line Handwriting Recognition

On-line Handwriting Recognition

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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 the Handwriting Recognition

- Postal address reading.
- Bank cheque verification.
- Number plate recognition.
- Ancient document digitalization and indexing.
- Assessment writing for school work.
- Forensic and medical analysis, and so on.

Challenges of Off-line Handwriting Recognition

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

Problem Statements (off-line handwriting recognition)

- The high-level task is to classify the ordered sequence of images of off-line characters to their corresponding classes.
- Comparative study of MLP and RBF neural network recognition tools on Nepal handwriting recognition problem.
- Creation of benchmark datasets of Nepali handwritten characters.

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].

Proposed Handwriting Recognition System

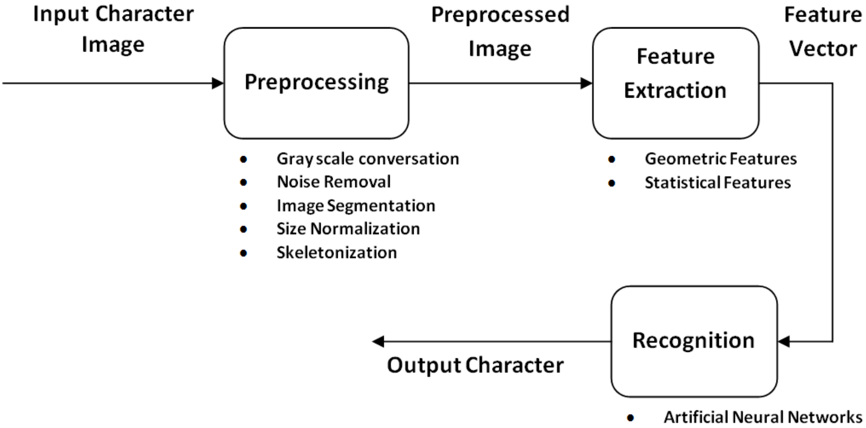

Figure: Off-line Handwriting Recognition System Architecture

Preprocessing Steps

1. Gray Scale Conversion.
2.
3.
4.
5.
6.
7.

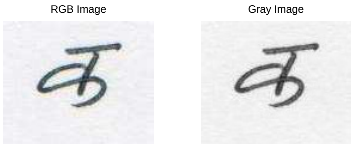

Figure: RGB to Grayscale Conversion.

Preprocessing Steps

1. Gray Scale Conversion.
2. Noise Removal.
3.
4.
5.
6.
7.

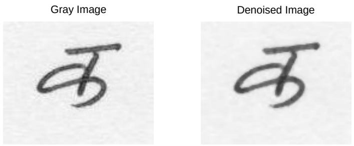

Figure: Noise Removal.

Preprocessing Steps

1. Gray Scale Conversion.
2. Noise Removal.
3. Image Binarization.
4.
5.
6.
7.

Figure: Image Binarization.

Preprocessing Steps

1. Gray Scale Conversion.
2. Noise Removal.
3. Image Binarization.
4. Image Inversion.
5.
6.
7.

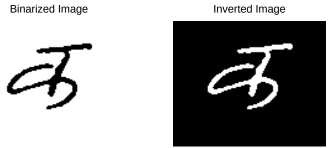

Figure: Image Inversion.

Preprocessing Steps

1. Gray Scale Conversion.
2. Noise Removal.
3. Image Binarization.
4. Image Inversion.
5. Universe of Discourse Determination.
6.
7.

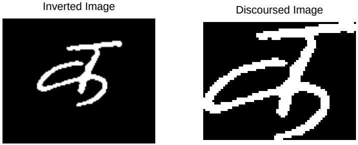

Figure: Universe of Discourse.

Preprocessing Steps

1. Gray Scale Conversion.
2. Noise Removal.
3. Image Binarization.
4. Image Inversion.
5. Universe of Discourse Determination.
6. Size Normalization.
7.

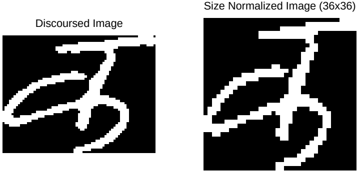

Figure: Size Normalization.

Preprocessing Steps

1. Gray Scale Conversion.
2. Noise Removal.
3. Image Binarization.
4. Image Inversion.
5. Universe of Discourse Determination.
6. Size Normalization.
7. Image Skeletonization.

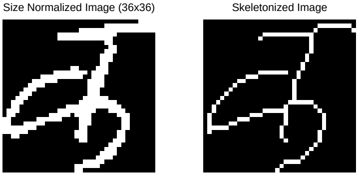

Figure: Image Skeletonization.

Types of Features Extracted

1. Directional Features

Image is zoned into 3x3 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

Types of Features Extracted

2. Euler Number

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

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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 major axis of the smallest ellipse that encloses the character image.

Types of Features Extracted

4. Moment Invariant Features [14],[15]

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 [14] which are invariant to translation, scale change, mirroring, and rotation.

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5. Area of Character Skeleton

Number of pixels in character skeleton.

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5. Area of Character Skeleton

Number of pixels in character skeleton.

6. 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 Recognition Algorithms

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

1. Multilayer Perceptron

- Feedforward neural network.
- Uses a supervised learning strategy called back-propagation for training.

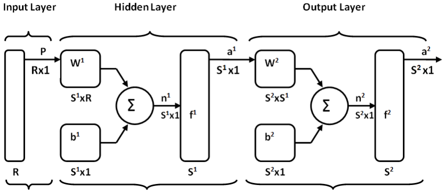


Figure: Multilayer Perceptron.

2. Radial Basis Function Network

- Uses radial basis function as activation function.
- Linear combination of radial basis functions.
- Uses stepwise regression procedure for selecting basis function.

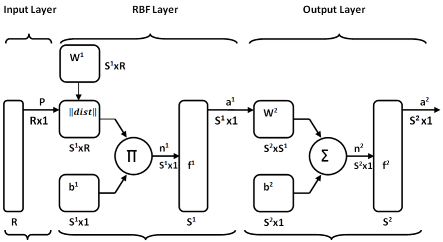


Figure: Radial Basis Function Network.

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
- **288** samples each class (total **2880** images)
- Samples are taken from **45** different writers

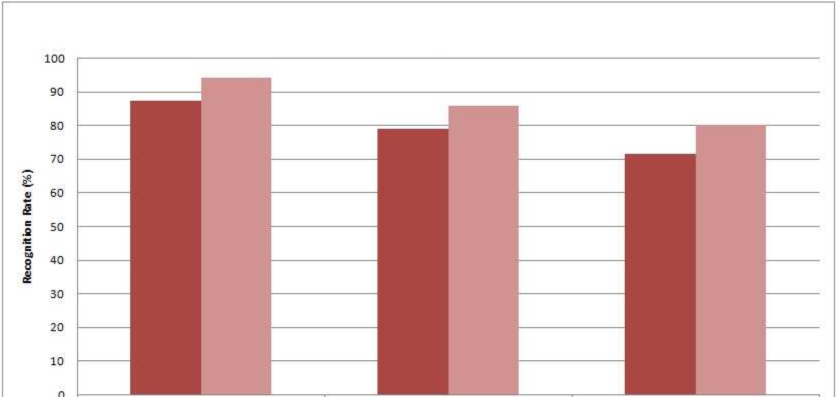
Neural Network Configuration

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

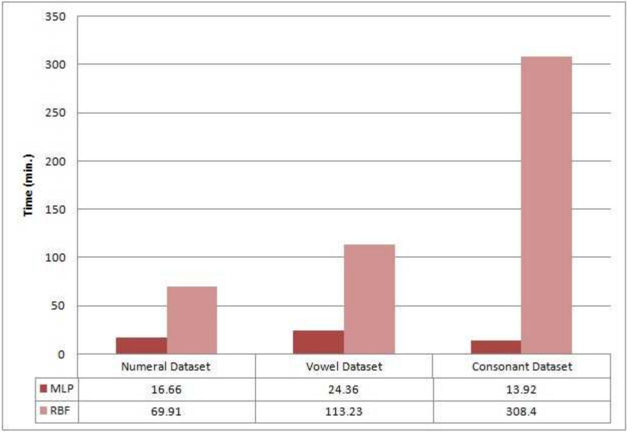
Dataset Name	Recognition Algorithm	Training Time (min.)	Recognition Accuracy (%)	Miss-classification Rate (%)
Numeral Dataset	MLP	16.66	87.50	12.50
	RBF	69.91	**94.44**	5.55
Vowel Dataset	MLP	24.36	79.15	20.85
	RBF	113.23	**86.04**	13.96
Consonant Dataset	MLP	13.92	71.72	28.28
	RBF	308.4	**80.25**	19.75

Recognition Accuracy Graph



	Numeral Dataset	Vowel Dataset	Consonant Dataset
MLP	87.5	79.15	71.72
RBF	94.44	86.04	80.25

Network Training Time Graph

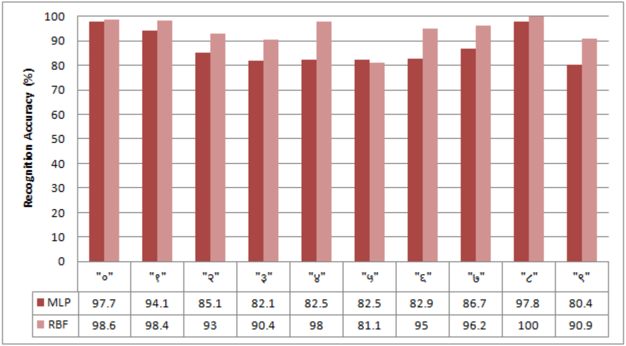


Individual Recognition Result for Numeral Dataset

Class	Recognition Algorithms	Recognition Accuracy (%)	Class	Recognition Algorithms	Recognition Accuracy (%)
०	MLP	97.7	९	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	१	MLP	86.7
	RBF	95.0		RBF	96.2
७	MLP	97.8	८	MLP	80.4
	RBF	100		RBF	90.9

Numeral Dataset Experimentation Results

Individual Recognition Result for Numeral Dataset - Graph



	"०"	"१"	"२"	"३"	"४"	"५"	"६"	"७"	"८"	"९"
MLP	97.7	94.1	85.1	82.1	82.5	82.5	82.9	86.7	97.8	80.4
RBF	98.6	98.4	93	90.4	98	81.1	95	96.2	100	90.9

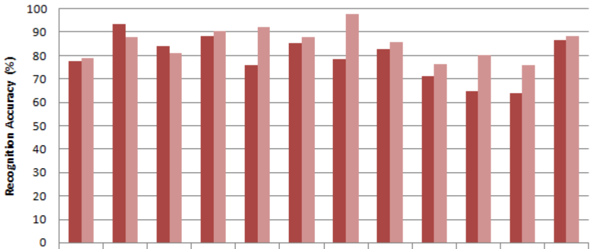
Confusion Matrix for Numeral Dataset Testing

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

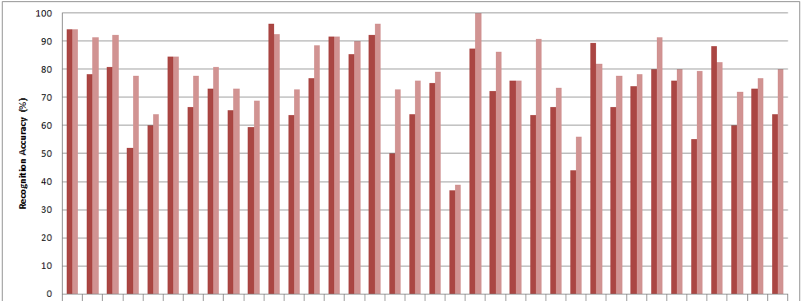
Individual Recognition Results for Consonant Dataset

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
थ	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

- RBF based recognition system have better recognition accuracy than MLP based recognition system, evaluated on three handwritten datasets.
- RBF based recognition system takes little more time for training the network than MLP based recognition system.
- Handwriting recognition is a difficult problem due to high variations in human handwritings, overlapped and joined characters, shape, size and styles of written characters.

Future Work

- Proposed system will be tested with known handwritten datasets like Germana database, IAM database, MNIST database, etc.
- Purposed system will be extended for the recognition of words, sentences and documents.
- Purposed system will be extended for multilingual character recognition.

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Thank You
?- Questions/Comments.