# A Neural Network Approach to Printed Devanagari Character Recognition

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## ABSTRACT
In this paper we deals with the recognition of printed Devanagari Characters with neural network approach. The paper shows measurement of the effectiveness classifier in terms of precision in recognition. It is also a benchmark for testing and verifying new pattern recognition theories and algorithms. 10 samples of each devanagari vowel and consonant from 10 different printed kruti dev font have been sampled and database was prepared. After segmentation, an individual image is normalized to 100X100 pixel size. Seven moment invariants (MIs) are evaluated for each character along with GLCM properties like Contrast, Homogeneity, Entropy, Correlation , color domain and histogram. The Neural network function has been adopted for classification. The main objective of the paper is to test the possibility of using the MI for recognition of printed character independent of its Size, slant and other variations.

## General Terms
Pattern Recognition

## Keywords
Histogram, Moment Invariant, GLCM, color domain, ANN;

## 1. INTRODUCTION
Printed character recognition (PCR) is one of the most difficult tasks in the pattern recognition system. There are a lot of difficult things that need many image processing techniques to solve, for examples: 1) How to separate printed Characters into an individual character, 2) How to recognize unlimited character fonts and printed different styles, and 3) How to Distinguish character that have the same shape but different meaning such as the character **o** and number **0**. Many researchers try to apply many techniques for breaking through the complex problems of optical character recognition. The objective of this paper is to try to help researchers to recognize optical Devanagari characters by using the ANN. The Devanagari alphabet has **34** consonant characters, **12** vowels, and **10** numerical symbols. Normally, Devanagari characters consist of small circles or loops, which are connected to circular zigzag lines and straight lines called as shiro rekha. [2]

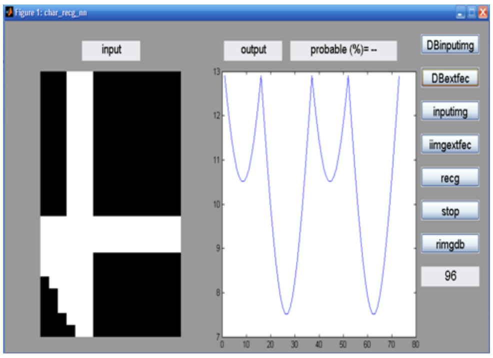
## 2. HISTORY
In India, more than 300 million people use Devanagari script for documentation. There has been a significant improvement in the research related to the recognition of printed as well as handwritten Devanagari text in the past few years. State of the art from 1970s of machine printed and handwritten Devanagari optical character recognition (DOCR) is discussed in this paper. All feature-extraction techniques as well as training, classification and matching techniques useful for the recognition are discussed in various sections of the paper. An attempt is made to address the most important results reported so far and it is also tried to highlight the beneficial directions of the research till date.

Printed Character Recognition is difficult task, since the variation in font's type representation. India is multilingual and multi script country and uses 18 scripts. Officially Indian states are using three scripts viz., English as first language, Hindi as second language and local language of the states as third language. Hence there is a need for an OCR system for multilingual and multi script for an Indian contest OCR system. Thus a development of multilingual OCR system is one of the thrust areas and it has potential contribution for scientific and economy advancement of the country

## 3. FEATURE EXTRACTION:
The extraction methods give us the optical character segmentation and showing the character images. Following are various methods of extractions.

### 3.1HISTOGRAM [12]
The Image Histogram control allows you to see how intensity values are distributed in our image. Histograms show the distribution of data values across a data range. They do this by dividing the data range into a certain number of intervals (called "binning" the data), tabulating the number of values that fall into each interval (or "bin"), and plotting the values in the bins using bars or wedges of varying height. The functions that create histograms are hist and rose You can specify the number of bins to use as a scalar second argument. If omitted, the default is 10 (hist) or 20 (rose). Data values passed to hist can be in any units and can be *n*-by-*m*, but rose expects values to be in radians in a 1-by-*n* or *n*-by-1 vector. The height (or length when using rose) of the bins represents the number of values that fall in each bin. You can also vary the size of bins

by specifying a vector for apportioning bin widths as the second argument.




When Y is a matrix, hist creates a set of bins for each column, displaying each set in a separate color. The statements

Y = randn(10000,3);

hist(Y)

## 3.2. MOMENT INVARIANTS ($MI_S$) [11]

The moment invariants (MIs), are used to evaluate seven distributed parameters of a numeral image. In any character recognition system, the characters are processed to extract features that uniquely represent properties of the character. The MIs are well-known to be invariant under translation, rotation, scaling and reflection. They are measures of the pixel distribution around the center of gravity of the character and allow to capture the global character shape information. In the present work, the moment invariants are evaluated using central moments of the image function f(x, y) up to third order. Regular moments are defined as

$$M_{pq} = \iint X^p Y^q \, f(X,Y)dxdy \qquad [1]$$

where for p, q = 0,1,2,….and Mpq is the $(p+q)^{th}$ order moment of the continuous image function f(x,y). If the image is represented by a discrete function, integrals are replaced by summations. Equation (1) can be written as follows

$$M_{pq} = \sum_X \sum_Y X^p Y^q \, f(X,Y)$$

The central moments of f(x,y) are defined by the expression$\mu_{pq} = \sum_X \sum_Y (X-\bar{X})^p (Y-\bar{Y})^q f(X,Y)$

Where

$\bar{X} = m_{10}/m_{00}$ and $\bar{Y} = m_{10}/m_{00}$

which are the centroid of the image The central moments of order up to 3 are as follow

$\mu_{10} = 0$

$\mu_{01} = 0$

$\mu_{11} = m_{11} - \bar{Y}\, m_{10}$

$\mu_{20} = m_{20} - \bar{X}\, m_{10}$

$\mu_{02} = m_{02} - \bar{Y}\, m_{01}$

$\mu_{30} = m_{30} - 3\bar{X}\, m_{20} + 2\bar{X}^2 m_{10}$

$\mu_{03} = m_{03} - 3\bar{Y}\, m_{02} + 2\bar{Y}^2 m_{01}$

$\mu_{21} = m_{21} - 2\bar{X}\, m_{11} - \bar{Y} m_{20} + 2\bar{X}^2 m_{01}$

$\mu_{12} = m_{12} - 2\bar{Y}\, m_{11} - \bar{X} m_{02} + 2\bar{Y}^2 m_{10}$

The normalized central moment to shape and size of order (p+q) is defined

$$\eta_{pq} = \mu_{pq}/\mu_{00}{}^{\gamma} \qquad [3]$$

Where

$$\gamma = \frac{(p+q)}{2} + 1 \qquad \text{for } (p+q) = 2,3,\ldots$$

Based on normalized central moments, a set of seven moment Invariants can be derived as follows

$$\phi_1 = \eta_{20} + \eta_{02}$$

$$\phi_2 = (\eta_{20} - \eta_{02})^2 + 4\eta_{11}{}^2$$

$$\phi_3 = (\eta_{30} - 3\eta_{12})^2 + (3\eta_{21} - \eta_{03})^2$$

$$\phi_4 = (\eta_{30} + 3\eta_{12})^2 + (\eta_{21} + \eta_{03})^2$$

$\phi_5 = (\eta_{30} - 3\eta_{12})(\eta_{30} + \eta_{12})\left[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2\right] + (3\eta_{21} - \eta_{03})(\eta_{21} + \eta_{03})[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2]$ $\phi_6 = (\eta_{20} - \eta_{02})[(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] + 4\eta_{11}(\eta_{30} + \eta_{12})(\eta_{21} + \eta_{03})$
$\emptyset_7 = (3\eta_{21} - \eta_{03})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2] + (3\eta_{12} - \eta_{30})(\eta_{21} + \eta_{03})[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2]$ [4]

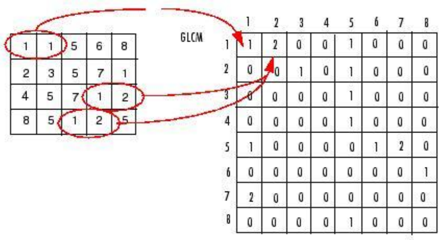
It has been shown that normalized moments are invariant under translation, rotation, scale change and reflection. In this work each number is scanned as 100 x 100 pixel image. The image obtained represents the number with black color on a white background. The image matrix f(x,y) is processed to obtain the character with white color on black background by image complement. The expressions given by Equations are used to evaluate 7 central moment invariants i.e. ($\Phi_1$ to $\Phi_7$) which are used as features. Further, mean and standard deviation are determined for each feature using 392 samples. Thus we had 14 features (7 means and 7 standard deviations), which are applied as features for recognition using Gaussian Distribution Function. To increase the success rate, the new features need to be extracted based on divisions of the images and other methods. [13]

## 3.3GREY LEVEL CO-OCCURRENCE MATRIX (GLCM)[14]

The following figure shows how graycomatrix calculates the first three values in a GLCM. In the output GLCM, element (1,1) contains the value 1 because there is only one instance in the input image where two horizontally adjacent pixels have the values 1 and 1, respectively. glcm (1,2) contains the value 2 because there are two instances where two horizontally adjacent pixels have the values 1 and 2. Element (1,3) in the GLCM has the value 0 because there are no instances of two horizontally adjacent pixels with the values 1 and 3. graycomatrix continues processing the input image, scanning the image for other pixel pairs (*i*,*j*) and recording the sums in the corresponding elements of the GLCM.

glcms = graycomatrix(GrayLimits, NumLevels, Offsets, Symmetric)

**Table-1**




**Texture Features from GLCM**

GLCM's used for texture description be replaced by their sum and difference histograms which can be estimated directly from the image. Some of the GLCM-based texture features can easily be obtained from such sum and difference histograms.

Contrast = $\sum_{N=0}^{G-1} n^2 \{\sum_{i=1}^{G} \sum_{j=1}^{G} P(i,j)\}, |i-j| = n$ [5]

This measure of contrast or local intensity variation will favour contributions from P(i, j) away from the diagonal, i.e. I ≠ j.

Homogeneity= $\sum_{j=0}^{2G-2} \frac{1}{1+j^2} H_d(j|\Delta x, \Delta y)$ [6]

Entropy = $-\sum_{i=0}^{G-1} \sum_{j=0}^{G-1} P(i,j) \times \log(P(i,j))$ [7]

Inhomogeneous scenes have low first order entropy, while a homogeneous scene has high entropy.

Correlation=
$\frac{1}{2}(\sum_{i=0}^{2G-2}(i-2\mu)^2 H_s(i|\Delta x, \Delta y) - \sum_{i=0}^{2G-2} i^2 H_d(j|\Delta x, \Delta y))$[8]

Correlation is a measure of gray level linear dependence between the pixels at the specified positions relative to each other.

## 3.4 COLOR DOMAIN

This descriptor highlights the salient colour in images or regions in pixel domain via colour clustering process. Hence, the descriptor is defined to include the representative colours, their percentages in the region, spatial coherency of dominant colours, and colour variances for each dominant colour. Its full definition is given below

$F = \{\{C_i P_i, V_i\}, S\}$ (i=1,2,3,….N) [9]

where $c_i$ is the $i^{th}$ dominant colour; pi represents its percentage value; vi is its colour variance; and s represents the spatial coherency

It is reported that this descriptor achieves competitive performances in comparison with those high-dimensional histogram methods

## 4. CLASSIFIERS

In this paper, we are finding the classification accuracy of ANN classifier

## 4.1 ANN (Artificial Neural Network)

Neural network is also known **as Artificial Neural Network (ANN)**, is an artificial intelligent system which is based on biological neural network. Neural networks able to be trained to perform a particular function by adjusting the values of the connections (weight) between these elements. [8]

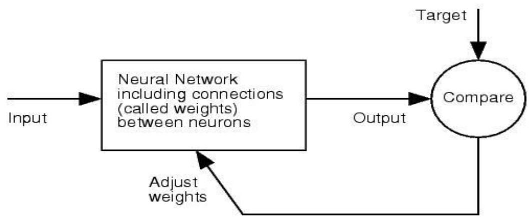



**Figure 1: Neural Network Block Diagram**

Neural network is adjusted and trained in order the particular input leads to a specific target output. Example at Figure 1, the network is adjusted, based on a comparison of the output and the target until the network output is matched the target.Nowadays, neural network can be trained to solve many difficult problems faced by human being and computer

Characteristics of Artificial Neural Network[14]

A neural network can perform tasks which a linear program will not be able.

- When an element of the neural network fails, it can continue without any problem by their parallel nature.
- Whatever a neural network learns earlier will not be required to be reprogrammed.
- It can be implemented in any application.
- It can be implemented without any problem.

- The neural network needs training to operate.
- The architecture of a neural network is different from the architecture of microprocessors therefore needs to be emulated.

Input Layer — A vector of predictor variable values (x1...xp) is presented to the input layer. The input layer (or processing before the input layer) standardizes these values so that the range of each variable is -1 to 1. The input layer distributes the values to each of the neurons in the hidden layer. In addition to the predictor variables, there is a constant input of 1.0, called the bias that is fed to each of the hidden layers; the bias is multiplied by a weight and added to the sum going into the neuron. Hidden Layer — Arriving at a neuron in the hidden layer, the value from each input neuron is multiplied by a weight (wji), and the resulting weighted values are added together producing a combined value uj. The weighted sum (uj) is fed into a transfer function, σ, which outputs a value hj. The outputs from the hidden layer are distributed to the output layer. Output Layer — Arriving at a neuron in the output layer, the value from each hidden layer neuron is multiplied by a weight (wkj), and the resulting weighted values are added together producing a combined value vj. The weighted sum (vj) is fed into a transfer function, σ, which outputs a value yk. The y values are the outputs of the network.

## 5. RESULT AND CONCLUSION

For our review objective by applying the extraction methods with classifiers technique for recognizing optical Devanagari characters, based on the basic features of characters presentation namely, 1) loop, 2) line, and 3) Location of loop and line connection. We tested our Devanagari document reading system on various printed documents and gathered various results. A performance of approximately for database -1 is 87.88 % and for database – 2 is 70.27% database – 3 is 100% & database – 4 is 100% character level is obtained. A sample few characters and the text after recognition is shown in below table -2. The image after conjunct segmentation and the OCR output after post-processing are shown in below figures. In this paper, we have presented a complete method for segmentation of text printed in Devanagari. We have used a set of filters that are robust and two distance based classifiers to classify the segmented images into known classes.

We have used a two level partitioning scheme and search algorithm for the correction of optically read Devanagari characters of text recognition system for Devanagari script. We have extended the concept of uniform penalty for a mismatch to include different penalties for various kinds of mismatches

**Database – 1 (End-bar Character)**

| Input(Characters) | Recognition Rate |
|---|---|
| व | 100 |
| अ | 100 |
| ल | 87.11 |
| म | 84.82 |
| च | 81.31 |
| ज | 81.10 |
| न | 80.83 |
| Avg Recognition Rate | 87.88 |

**Database – 2 (No-bar Characters)**

| Input(Characters) | Recognition Rate |
|---|---|
| ह | 100 |
| उ | 96.20 |
| र | 79.50 |
| द | 66.88 |
| इ | 8.79 |
| Avg Recognition Rate | 70.27 |

**Database-3 (Middle-bar Character)**

| Input(Characters) | Recognition Rate |
|---|---|
| क | 100 |
| Avg Recognition Rate | 100 |

**Database-4 (Modifier)**

| Input(Characters) | Recognition Rate |
|---|---|
| ॅ | 100 |
| ा | 100 |
| Avg Recognition Rate | 100 |

**Total Success rate is 89.53.**
**The characters used for training 10 fonts of each.**

For the Character recognition, neural networks and their combinations are used as the powerful tools. For the high reliability in character recognition, segmentation and classification have to be treated in an integrated manner to obtain more accuracy in complex cases. This paper has focused on an appreciation of principles and methods. The compare of effectiveness of various algorithms has not been attempted in the present work.

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