# OFFLINE HANDWRITTEN GUJRATI NUMERAL RECOGNITION USING MLP CLASSIFIER

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***Abstract : The goal of Optical Character Recognition (OCR) is to classify optical patterns (often contained in a digital image) corresponding to alphanumeric or other characters. The process of OCR involves several steps including image acquisition, segmentation, feature extraction, and classification. Text capture is a process to convert analogue text based resources into digitally recognizable text resources. An essential first stage in any text capture process is to convert the available text image into digital image of the text. This will provide the base for character recognition. Some basic statistical features are extracted from the digital image of numeral and the same is classified with the help of neural network. This research paper presents the innovative method for handwritten Gujarati Numeral recognition using neural network and the accuracy of recognition of numeral is obtained 95.12% on Training, 90% on Testing and 93.83% on Cross Validation.***

***Index Terms: OCR, MLP, MSV, SVM,***

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## I. INTRODUCTION:

Optical Character Recognition (OCR) is a type of document image analysis where a scanned digital image that contains either machine printed or handwritten script is input into an OCR software engine and translating it into an editable machine readable digital text format (like ASCII text). OCR works by first pre-processing the digital page image into its smallest component parts with layout analysis to find text blocks, sentence/line blocks, word blocks and character blocks. Other features such as lines, graphics, photographs etc are recognized and discarded. The character blocks are then further broken down into components parts, pattern recognized and compared to the OCR engines large dictionary of characters from various fonts and languages. Once a likely match is made then this is recorded and a set of characters in the word block are recognized until all likely characters have been found for the word block. The word is then compared to the OCR engine's large dictionary of complete words that exist for that language. These factors of characters and words recognized are the key to OCR accuracy – by combining them the OCR engine can deliver much higher levels of accuracy. Modern OCR engines extend this accuracy through more sophisticated pre-processing of source digital images and better algorithms for fuzzy matching, sounds-like matching and grammatical measurements to more accurately establish word accuracy.

### 1. On Line Character Recognition :

The research of online character recognition started in the 1960s and has been receiving intensive interest from the 1980s. The comprehensive survey of Tappert et al. reviewed the status of research and applications before 1990 and early works of online Japanese character recognition have been reviewed.[1,2].

### 2. Off-Line Character Recognition :

Off-line handwriting recognition involves the automatic conversion of text in an image into letter codes which are usable within computer and text-processing applications. The data obtained by this form is regarded as a static representation of handwriting. The technology is successfully used by businesses which process lots of handwritten documents, like insurance companies. The quality of recognition can be substantially increased by structuring the document. The off-line handwriting recognition is comparatively difficult, as different people have different handwriting styles. Nevertheless, limiting the range of input can allow recognition to improve. For example, the ZIP code digits are generally read by computer to sort the incoming mail. Off-line recognition requires converting the numeral into an image file. However, the convertion process may lose the temporal information of that numeral. Other complexities that an off-line recognition system has to deal with lower resolution of the document and the poor binarization, which may reduce the features of the numeral. The researchers Ramaraj N. and Sutha J [3] propose an approach to recognize Off-line Tamil Handwritten Character Recognition Using Neural Networks. For this work, researcher used Fourier Descriptors and Multi Layer Perceptron (MLP) network with one hidden layer. The scanned image is first passed through preprocessing modules like smoothing, thresholding, skeletonization and extraction of features. Selection of a feature extraction method is probably the single most important factor in achieving high recognition performance in character recognition systems. Different feature extraction methods are designed for different representations of the characters, such as solid binary characters, character contours, skeletons (thinned characters) or gray-level subimages of each individual character[4]. The feature extracted from the handwritten character or numeral is carried out for structure analysis.

## II. DATABASE PREPARATION:

Standard database for Gujrati numeral is not available, so initial task for this research is to design sufficient database of Gujarati Numeral. This handwritten database is developed with the help of students, person and housewives of different educational background and different mother tongues. In offline handwritten numeral recognition, the handwritten document has to be scan and store as image for processing.

The datasheet paper is scanned and after the preprocessing [5,6,7] the scanned images are stored in database. Every numeral is converted into image form. Following Algorithm is used to developed database.

1. Read Datasheet file (Scan file)
2. Convert to gray
3. Convert gray to binary
4. Take compliment of this data file
5. Crop each Line and then each numeral image
6. Resize each Numeral image to 40 x 40 size
7. Store set of images of each numeral.

The sample database is shown in Figure 1.

*Figure 1: Sample Database of Gujarati Numeral.*

**III. FEATURE EXTRACTION:**

The accuracy of recognition is based on the feature extracted and its selection. To get benefit from dimensionality reduction techniques for the purpose of maximizing accuracy of learning algorithm, there is need to have awareness of various advantages of these techniques. L. Ladha et al in have been offered following advantages of feature selection [8,9]:

- It reduces the dimensionality of the feature space, to limit storage requirements and increase algorithm speed.
- It removes the redundant, irrelevant or noisy data.
- The immediate effects for data analysis tasks are speeding up the running time of the learning algorithms.
- Improving the data quality.
- Increasing the accuracy of the resulting model.
- Feature set reduction, to save resources in the next round of data collection or during utilization.
- Performance improvement, to gain in predictive accuracy.
- Data understanding to gain knowledge about the process that generated the data or simply visualizes the data.

For this recognition system, we use minimum shape and statistical features. The selected features are as follows:

**1. Convex Area**

A set of points is defined to be convex if it contains the line segments connecting each pair of its points. In mathematics, the convex area or convex envelope of a set X of points in the Euclidean plane or Euclidean space is the smallest convex set that contains X. For instance, when X is a bounded subset of the plane, the convex hull may be visualized as the shape enclosed by a rubber band stretched around X. Formally, the convex area may by defined as the intersection of all convex sets containing X or as the set of all convex combinations of points in X. With the latter definition, convex hulls may be extended from Euclidean spaces to arbitrary real vector spaces. **Filled Area**

An area graph displays elements in Y as one or more curves and fills the area beneath each curve. When Y is matrix, the curves are stacked showing the relative contribution of each row element to the total height of the curves at each X interval. Some area object properties that you set on an individual area object set the values for all area objects in the graph. See Area Properties for information on specific properties.

**2. Euler Number**

In mathematics, the Euler numbers are a sequence En of integers A122045 in defined by the Taylor series expansion

$$t = 2 e t + e-- t = \Sigma n = 0 \infty En$$

The Euler number appears as a special value of the Euler polynomials.

The odd-indexed Euler numbers are all zero. The even-indexed ones have alternating. The Euler numbers appear in the Taylor series expansions of the secant and hyperbolic secant functions. The latter is the function in the definition. They also occur in combinatory, specifically when counting the number of alternating permutations of a set with an even number of elements.

**3. Eccentricity**

Any conic section can be defined as the locus of points whose distances to a point and a line are in a constant ratio that ratio is called eccentricity, denoted as e. All types of conic sections, arranged with increasing eccentricity. Note that curvature decreases with eccentricity, and that none of these curves intersect. The eccentricity, denoted e or ε {\displaystyle \varepsilon}, is a parameter associated with every conic section. It can be thought of as a measure of how much the conic section deviates from being circular. In particular,

- The eccentricity of a circle is zero.
- The eccentricity of an ellipse which is not a circle is greater than zero but less than 1.
- The eccentricity of a parabola is 1.
- The eccentricity of a hyperbola is greater than 1.

**IV. CLASSIFICATION:**

The main task of classification is to use the feature vectors provided by the feature extraction algorithm to assign the object to a category. In our work, we used Support Vector Machine and Multilayer perceptron for the classification of Devanagari characters. Support Vector Machine has been used successfully for pattern recognition and regression tasks [11] formulized under the concept of structural risk

minimization rule [10]. SVMs are known to generalize well even in high dimensional spaces under small training sample conditions [12]. SVMs have been successfully applied to a number of applications ranging from face detection, verification, and recognition.

**V. RESULT AND DISCUSSION:**

The value of Processing Element is 10 for output. This value is used for MLP classifiers. The recognition accuracy of numerals with these classifiers for training, cross validation and testing are shown in Table 1. The Figure 2. shows the MSE ( Mean Square Error) and results of each numeral for Training, Testing and CV.

Table1. The Recognition accuracy of numerals with these classifiers for training, cross validation and testing

| ***Numeral*** | MSE | Training | Testing | CV |
|---|---|---|---|---|
| ***out(se)*** | 0.004619 | 100 | 100 | 100 |
| ***out(fi)*** | 0.021093 | 100 | 86.66667 | 80 |
| ***out(on)*** | 0.003834 | 100 | 100 | 100 |
| ***out(ni)*** | 0.004888 | 100 | 100 | 100 |
| ***out(si)*** | 0.019495 | 100 | 100 | 100 |
| ***out(th)*** | 0.039731 | 70 | 50 | 75 |
| ***out(ei)*** | 0.003554 | 100 | 100 | 100 |
| ***out(z)*** | 0.00426 | 97.05882 | 80 | 83.33333 |
| ***out(tw)*** | 0.009544 | 100 | 100 | 100 |
| ***out(fo)*** | 0.027046 | 84.21053 | 83.33333 | 100 |
| ***Average %*** | | 95.12693 | 90 | 93.83333 |

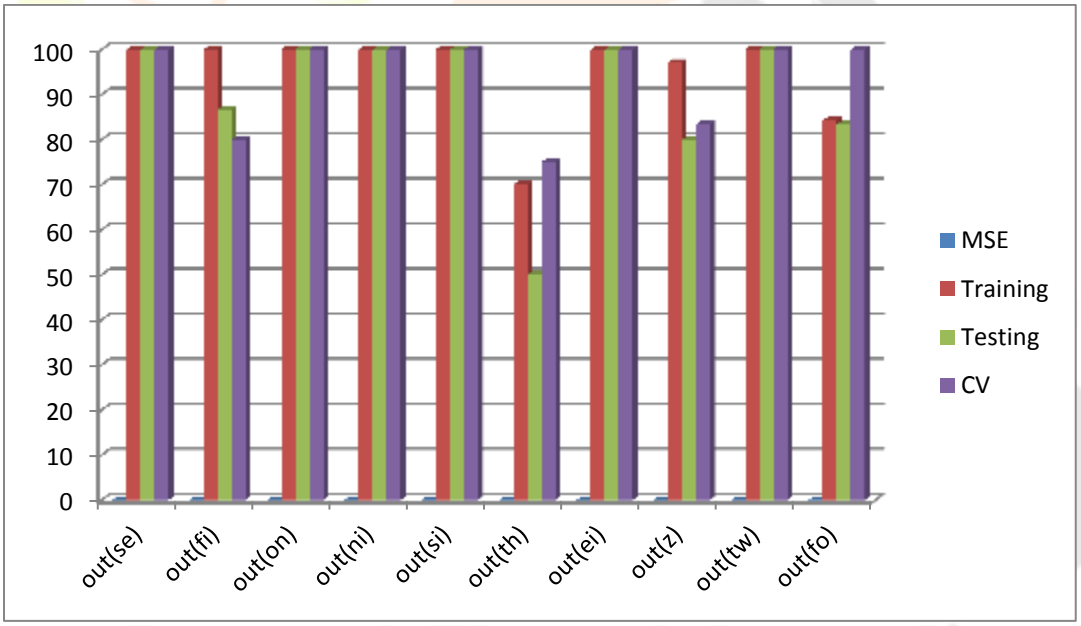


Figure 2. MSE ( Mean Square Error) and results of each numeral for Training, Testing and CV

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