Recognition of Marathi Handwritten Numerals Using Multi-layer Feed-Forward Neural Network

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Abstract— *Marathi is one of the ancient Indian languages majorly spoken in the state of Maharashtra. Marathi is one of the Devanagari script and the literals and numerals are almost similar to Hindi. Recognition of handwritten Marathi numerals is quite challenging task because people have the practice of writing these numerals in variant ways. In this work we have presented a method to recognize the handwritten Marathi numerals using multilayer feed-forward neural network. The scanned document image is pre-processed to eliminate the noise and care is taken to link the broken characters. Each numeral is segmented from the document and it is resized to 7 × 5 pixels using cubic interpolation. While resizing a technique is used to provide better representation for every pixel in segmented numeral. This resized numeral is converted into a vector with 35 values before inputting it to the neural network. We have used 100 sets containing 1000 numerals for this experimentation, of which 50 sets are used for training the network and 50 sets for the testing purpose. The overall recognition rate of the proposed method is 97%.*

Keywords— Neural Network; Classification; Character Recognition.

I. INTRODUCTION

Marathi is one of the 23 official languages of India. It is an Indo-Aryan Language spoken by about 73 million people across the world. Marathi has some oldest journalism of all modern Indic, Indo-European language. The dialects of Marathi are called warhadi Marathi and standard Marathi. There are other sub-dialects which are Dangi vadvali, Samavedi, Khandeshi, Ahirani, Dangi, Vadvali, and Malwani. Marathi is the official language of State Maharastra as well as Daman and Diu, Dadra and Nagar Haveli. Marathi language uses 60 phonemic letters, divided into three groups namely swear (Vowels 13 letters), Vyanjan (Consonants 38 letters) and Ank (numbers 10 digits) as well as Modifiers (Diacritics 12 letters).

Development of offline and Online OCR for Marathi handwritten characters and numbers recognition is challenging work for researchers because handwritten characters of each person are mimetic. People recognize the handwritten characters easily but machine has some difficulty to do this task. Few works are reported in literature for the recognition of Marathi and other Indian language characters and numbers. The character recognition task has been attempted by many researchers using techniques like template matching, statistical techniques and artificial neural network etc. Khanale and Chitnis [1] proposed the handwritten Devanagari characters recognition algorithm based on artificial neural network. They used a two layer feed forward neural network with 10 neurons and the log-sigmoid transfer function. This work reported 96% accuracy in recognition. Shelke and Apte [3] have proposed a multistage recognition technique for the recognition of handwritten Marathi compound character using multiple features. In their work firstly, they classified the compound characters using a two stage structural classification with different structural parameters. In the next stage, different features such as pixel density features, Euclidean distance and modified wavelet approximation features were obtained from characters which were structurally classified and normalized. These three features were fed to three different neural networks. The final recognition result was chosen based on majority voting. This work reported an accuracy of 97.95%. A work on structure based feature extraction of Marathi handwritten words is proposed by Mahender and kale [6]. They used rule based technique to recognize the words and claimed the accuracy of about 90%. The performance of the proposed method is poor when the size of vocabulary was increased.

Tian Fu Gao and Cheng-Lin-Liu [7] Proposed Chinese Character recognition by using linear discriminant analysis based on compound distances. They used LDA for the estimation of discriminant vector for good discriminability and shown that under restrictive assumptions, the CMF acts as a special case of LDA based method. They evaluated the proposed methods by conducting experiments on the databases from ETL9B and CASIA by adapting the modified quadratic discriminant function (MQDF) treated as baseline classifier. Cheng-Lin-Liu, Masashi Kogo and Hiromichi Fujisawa [8] had recognized Japanese Handwritten character string by using the lexicon driven segmentation and lexicon matching. This work first introduces some kind of effective techniques for text line image pre-processing and pre-segmentation. Here the lexicon matching is used for consecutive segments to dynamically combine them into candidate character patterns. A classifier technique for characters is embedded in lexicon matching to obtain the characters which have matched with a candidate pattern from an available dynamic category set. This method reported correct rate of 83.68% and error rate less than 1%. A template matching based approach was proposed by Hegadi R. S. [2] for the recognition of Kannada numerals. This method uses the correlation coefficient for matching the numeral. The proposed method achieves an accuracy of 91%. In another work by Hegadi R. S. [5] a multilayer feed-forward neural network is used for the classification of printed Kannada numerals. The experimentation is carried out using all the existing fonts of printed Kannada numerals and this algorithm could recognize all the numerals.

In this paper we propose a multilayer feed-forward neural network based classification technique for recognition of Marathi handwritten numerals. Section 2 describes the proposed methodology, the neural network based classification is discussed in section 3, results of the

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Fig. 1. Sample handwritten Marathi numerals from ten different people

proposed method are discussed in section 4 and conclusions are drawn in section 5.

II. Proposed Method

Datasets are important component for any image processing and recognition problem. A small dataset has been created containing 100 sets of handwritten Marathi numerals forming 1000 digits. The data containing 10 sets of sample handwritten Marathi numerals are shown in Figure 1. The proposed method has three stages which are pre-processing, segmentation and classification. The image pre-processing and segmentation stages are discussed in detail in the following sub sections and the neural network based classification is discussed in Section III.

A. Image Pre-processing

Handwritten Marathi numeral image documents are scanned by using an optical scanner. This document will be the input for the proposed work. This document image is converted to a binary image by applying thresholding technique. This technique converts the bright pixels as white and dark pixels as black. The areas represented by the numerals will correspond to dark pixels whereas the background will contain the white pixels. The numbers will be representing black pixel and background pixels will be white. The scanned document image may contain the noise in the form of tiny dots. They are removed by applying the morphological opening operation. The morphological opening generally smoothes the contour of an object, breaks narrow isthmuses, and eliminates thin protrusions present in the image regions.

B. Numeral Segmentation

After pre-processing stage, this document image is scanned from top-left corner to the bottom-right corner to extract the numerals. First the document is segmented row-by-row, which yields each set of numerals, then each row of numerals is again segmented into columns to get every numeral separated. Each numeral image is subjected to edge

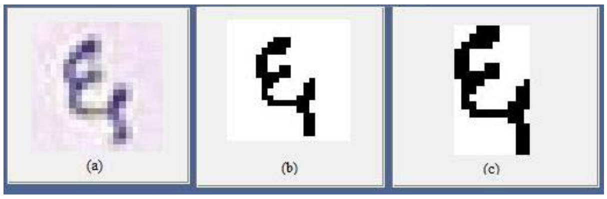

Fig. 2. Digit in processing stages (a) Digit in original form, (b) its binary form and (c) the dilated digit within the bounding box.

detection using Sobel operator. An approximation to the derivatives using Sobel approximation is applied for the Soble edge detection technique. If the gradient of the image is maxima at certain points then the Sobel method returns edges at those points. This operation may lead to formation of narrow isthmuses in the low gradient regions of the numerals. This image is subjected to dilation using a 3×3 structuring element. This dilation process will strengthen the thin or broken connectivity of numerals. Small holes within the character region may be generated due to edge detection process. These holes are filled using region filling algorithm. A bounding box is drawn to this numeral, which is a rectangle touching each side of the numeral. This process will remove unwanted pixels on all sides of the numeral. The numerals segmented using above said process will have different sizes. Every numeral image is resized to a standard size of 7×5 pixels. This resizing process starts with first resizing the image to a larger size of 70×50 pixels using cubic interpolation method. This image contains 3500 pixels in a matrix of 70 rows and 50 columns. Average value is computed for every block of 10×10 pixels from this image. This average value represents the pixel in the image with size 7×5. This image will have real values instead of binary values. This process ensures a better representation for every pixel in the original image and minimizes the loss of information when resizing is undertaken. Figure 2 shows stages in pre-processing and segmentation of a numeral from the input document image. Figure 2(a) shows a digit from the original document image. The extracted numeral from its binary image is shown in Figure 2(b). The dilated image after applying bounding box is shown in Figure 2(c). A neural network based classification is used to classify the numerals, which is discussed in the next section.

III. Neural Network based Classification

Each numeral extracted from the process described in above section will be converted into one dimensional column vector. The values of this vector will be in the range from 0 to 1 due to the process used in the resizing of numerals. There will be 35 values in this vector which will be input features for the neural network based classification. A multilayer feed-forward neural network is used with one hidden layer for the classification purpose. Typical multilayer feed-forward neural network architecture is shown in Figure 3. A multilayer feed-forward neural network can have several layers. MLPs are the most commonly found feed-forward networks. The MLP shown in Figure 3 has three types of layers, namely, input layer, output layer and hidden layer. The neurons in input layer will buffer the signals x_i ($i = 1, 2, \ldots, n$) for distribution of these signals to neurons in the hidden layer. The input signals, x_i, are summed-up for every neuron j present in the hidden after weighting them by using strengths of the corresponding

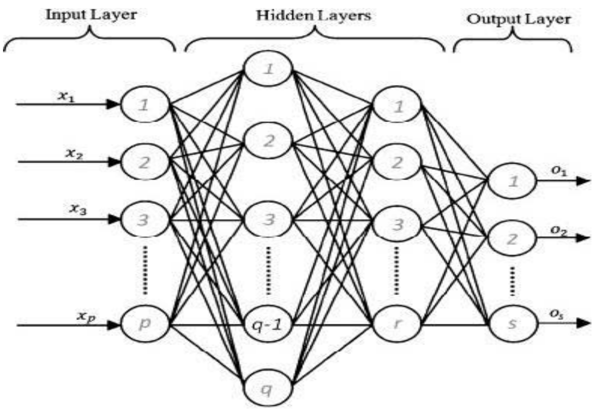

Fig. 3. Architecture of a multilayer feed-forward neural network

connections, w_{ji}, from the input layer and derives its output, y_j, as a summing function f as shown in Figure 4.

$$y_j = f\left(\sum_{i=1}^{n} w_{ji} x_i\right) \quad (1)$$

where f may be a simple function for threshold or a sigmoidal, hyperbolic tangent or it may be a radial basis function.

The output of neurons corresponding to the output layer is computed in the similar way. The back propagation algorithm, which is a gradient descent algorithm, is generally used MLP training algorithm. It results in change Δw_{ji}, also known as weight of a connection between neurons i and j as follows:

$$\Delta w_{ji} = \eta \delta_j x_i \quad (2)$$

where η is learning rate parameter and the factor δ_j depends on neuron j, whether it is a hidden neuron or an input neuron. For the output neurons

$$\delta_j = (\partial f / \partial \text{net}_j)(y_j^{(t)} - y_j) \quad (3)$$

and for hidden neurons

$$\delta_j = (\partial f / \partial \text{net}_j)(\textstyle\sum_q w_{jq} \delta_q) \quad (4)$$

where, net_j in the Eq. (3) is total weighted sum of the input signals to the neurons j and $y_j^{(t)}$ is the for neuron j's target output.

Since hidden neurons do not have target outputs, as in Eq. (4), the weighted sum replaces the difference among the target and actual output of the hidden neurons, j, by the weighted sum of the δ_q. These terms were already obtained for neurons q, which is connected to the output of j. In the process the δ will be computed for every neuron at every

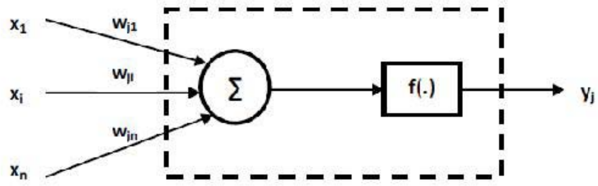

Fig. 4. Details of process in perceptron

layer and updated weights are determined iteratively for every connection. The process of updating the weights can occur after the presentation of every training pattern, known as pattern-based training, or it may occur after presentation of the complete set of training patterns, known as batch training. Once all the training patterns have been presented to the MLP, the training of epoch completes. The network training process may be speeded up by adding a commonly adopted method known as "momentum" term to Eq. (5) which effectively lets the change in the new weight due to change in the previous weight:

$$\Delta w_{ij}(I+1) = \eta \delta_j x_i + \mu \Delta w_{ij}(I) \quad (5)$$

where $\Delta w_{ij}(I + 1)$ and $\Delta w_{ij}(I)$ are change in weight in epochs $(I + 1)$ and (I), respectively, and μ is "momentum" coefficient.

For our problem a multilayer perceptron (MLP) structure with two hidden layers having 35 neurons and 20 sigmoid for linear activation are built to classify the numerals. Matlab simulation function is used to simulate testing dataset. The result of this simulation function is a vector containing ten normalized values. Among these values the position of highest value will be chosen, which will be the matching numeral. The character plot of array of input data for neural network and recognized output are shown in Figure 5.

IV. RESULTS

The experiment has carried out on 100 different sets of handwritten Marathi numerals containing 1000 digits. Out of these 50 sets with 500 digits are used for training the network and remaining 50 sets with same number of digits are used for testing. An Intel core i3 processor based system is used for experimentation and Matlab 7.0 version is used for implementation. The performance of the network is shown in Figure 6. Table 1 shows the recognition rate for each numeral using the proposed algorithm. Our algorithm could recognize numeral 0 in all cases but the numerals 1, 4, 7 and 8 were recognized with an accuracy of 98%. The rate of accuracy in recognizing numerals 2, 5, 6 and 9 is 96%, while the numeral 3 has been recognized with a lowest recognition rate of 94%. The overall rate of recognition of the proposed method is 97%.

TABLE I. ACCURACY IN DETECTING NUMERALS USING NEURAL NETWORK BASED CLASSIFICATION METHOD

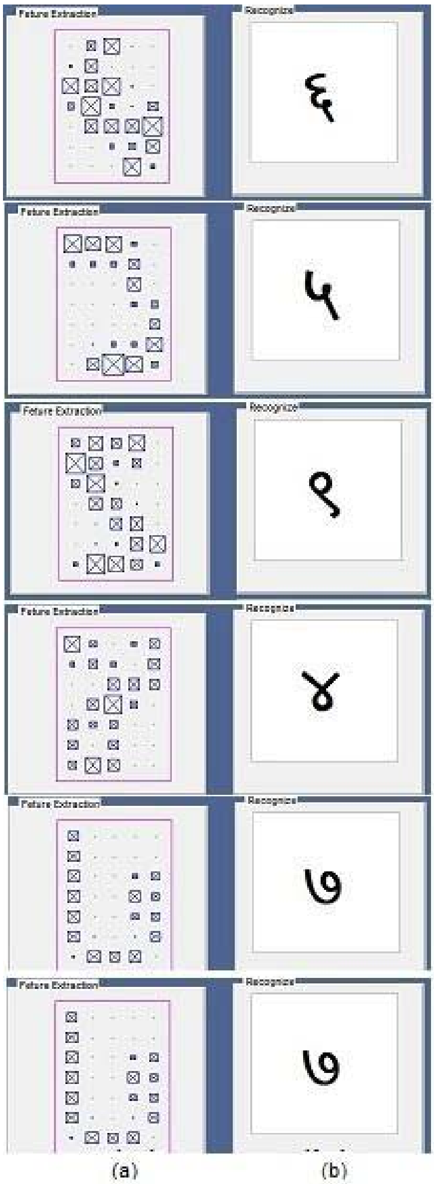

Fig. 5. Recognition results of the proposed method. (a) The character plot of input data for network and (b) recognized numeral

Numeral	1	2	3	4	5	6	7	8	9	0
Correct Detection	49	48	47	49	48	48	49	49	48	50
Rate of accuracy	98	96	94	98	96	96	98	98	96	100

V. CONCLUSIONS

In our work we have presented a neural network based classification technique to recognize the handwritten Marathi numerals. The pre-processing will eliminate the noise present in the input image in the form of tiny dots. We have also undertaken care for the breakages at the low gradient parts of the numerals due to edge detection by applying morphological dilation operation. The resizing process used in this work will provide better representation to every pixel in the original numeral image. Even though the proposed algorithm has lesser rate of recognition for one numeral 3, the overall performance of the proposed algorithm is 97%, which is reasonably good. In our future work we would like to test this algorithm with large database and by including additional features in training the network.

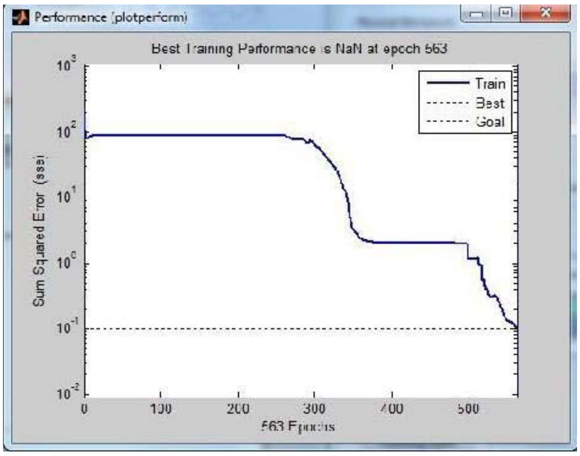

Fig. 6. Neural network performance for Marathi handwritten numerals.

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