

## **Real Coded Genetic Algorithm Based Neural Network Model for Odia Numerals Recognition**

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**Abstract:** Character recognition has great importance in present scenario. It has many application areas in the field of business, postal system, banking, library, form processing, document processing etc. A highly efficient character recognition system is required for such type of applications. Various authors have used different classifiers, mainly based on neural networks for this purpose. As BackPropagation (BP) algorithm is a derivative based algorithm, the chances of the results to falling to local minima is there. To alleviate problem in this paper we have proposed a hybrid system for recognition of Odia numerals by using multi layer neural Network (MLNN) and real coded genetics algorithm (RCGA). As RCGA is a derivative free algorithm it will overcome the problem of trapping the results into local minima. And as we are using the real coded GA (Genetics Algorithm) it will be advantageous over the binary coded GA, as we do not have to do the conversion from binary to real each time which saves the training time. Real coded chromosomes are used by GA to determine the weights of Neural Network (NN). Before recognition, preprocessing, feature extraction and feature reduction steps are carried out. For feature extraction Gradient based approach is used. The gradient of the images are calculated by applying Robert's filter and the feature vector is generated. After the generation of feature vector PCA (Principal Component Analysis) is applied to reduce the size of features. The proposed system is applied on the standard dataset taken from ISI Calcutta containing 1200 samples of Odia handwritten numerals. From experimental result it is observed that the proposed system has achieved 98.33% accuracy on test dataset.

**Keywords:** Character recognition, Preprocessing, Feature extraction, Feature reduction, Classification, Real Coded Genetics Algorithm (RCGA), MLNN (Multi Layer Neural Network) and BackPropagation (BP) algorithm.

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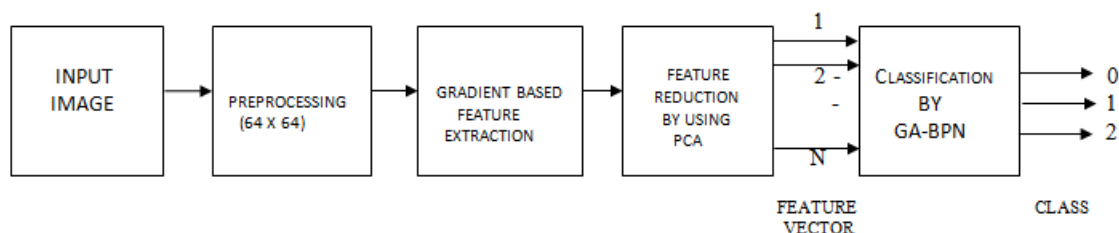
### **1. INTRODUCTION**

Hybrid system is the integration of one or more techniques to solve a problem. The objective of hybrid system is to provide a better solution by integrating various techniques so as to overcome the weakness of one technique with the strength of other technique. In literature several research works have been conducted by using hybrid techniques for recognition of characters. In [3] genetic programming is applied to the USPS data set for recognition of hand written digits. Aged members, directed crossover, inter-output crossover, node mutation etc are introduced on selection and evolution methods. A hybrid Genetic Algorithm (GA) and Harmony Search algorithm (HS) is highlighted in [4] for online Arabic text Recognition. The strategy of the system is divided into two phases: text segmentation using dominant point detection, and recognition-based segmentation using GA and HS. The system is applied on 4500 Arabic words and benchmark ADAB dataset 2 consist of 7851 Arabic words with recognition rate 93.4% and 94–96% respectively. A feed forward neural network by two Evolutionary algorithms is proposed by S. Shrivastava et.al [5] with three different soft computing techniques for recognition of hand written English alphabets in. The problem of non convergence the weight in conventional backpropagation has also eliminated by using the soft computing techniques. It has been observed that, there are more than one converge weight matrix in character recognition for every training set. In [6] a novel GA-based feature selection algorithm based on separability index is proposed for recognition of handwritten digits. The proposed index is based on an extension of the Fisher Linear Discriminant method and uses covariance matrices for estimating class probability distributions in  $N$ -dimensional feature space. Three standard databases of hand written digits and a standard database of handwritten letters are used for experimentation. For

recognition three classification methods were used. M. Kherallah et.al [7] developed a handwriting recognition system based on visual coding and genetic algorithm "GA". The system is applied on Arabic script. The importance was on the encoding system and the fitness function of GA. For calculation of the evaluation function visual indices similarity approach is used. The times cooling of the system is optimized to give the final output and obtained promising results. A probabilistic neural network (PNN) is presented [8] for the recognition of the handwritten Indian numerals one to nine (1–9). The feature extraction process is based on the center of gravity and a set of vectors to the boundary points of the digit object. A set of experiments were conducted and to test the performance of the system under different angles between the vectors from the centroid to the boundary of the digit object. It was observed with 30° angle the recognition rate is found to be 99.72%. In [9] the authors employed genetic algorithm for recalling of memorized patterns in random form and sub-optimal form corresponding to the noisy input patterns. They proposed an optimal weight matrix for correct recalling of characters from noisy English characters. For this they used two aspects of GA: random nature of the GA and suboptimal nature of the GA. The simulated results demonstrate the better performance of network for recalling of the stored letters of English alphabets. It is observed that NN with Genetic algorithm on the suboptimal weight matrix outperformed as compared to other approach. C. De Stefano et.al [10] used genetic programming as a tool for automatically inferring the set of classification rules to be used during a pre classification stage by a hierarchical handwritten character recognition system. The NIST database comprising of 10,000 digits were used for experimentation and achieved accuracy more than 87%. In [11]The authors proposed a new method by combining Genetic Algorithm and Simulated Annealing for feature subset selection on Persian fonts and achieved good recognition rate. The convergence rate of Guided Evolutionary Simulated Annealing is observed to be better than Genetic Algorithm. A hybrid approach is proposed in [12] with neural networks (NNs) and genetic algorithms (GAs) to reduce the computational complexity of feature recognition problem. Optimum network architecture is proposed by using GA input selection approach. In [13] the authors proposed a methodology for creating local regions of varying heights and widths dynamically. Genetic algorithm (GA) is then applied on these local regions to form optimal feature set. The proposed system is evaluated on a dataset of handwritten Bangla digits with SVM classifier. Other popular optimization techniques like simulated annealing (SA) and hill climbing (HC) have also been evaluated with 97%, 96.7% and 96.7% for GA, SA and HC, respectively. A genetic framework is proposed by Javad Sadri et.al [14] using contextual knowledge for segmentation and recognition of unconstrained handwritten numeral strings. The author tried to search and evolve the population of segmentation hypotheses to obtain highest segmentation/recognition confidence. The system was applied on NIST NSTRING SD19 and CENPARMI databases obtained recognition rates of 95.28% using neural network and 96.42% using SVM on handwritten numeral strings. For recognition of Bangla compound characters a Genetics Algorithm (GA) and Support Vector Machine (SVM) based multistage recognition strategy has been developed in [15]. The system is applied on handwritten *Bangla* Compound characters having 8254 numbers of samples of 171 character classes and achieved accuracy of 78.93%. In another reference [16] the authors put forward an adaptive genetic algorithm method for multi-step offline handwritten Chinese characters segmentation. The method is carried out for segmentation of Chinese characters, punctuation and digital numbers correctly. The experiment is carried on HIW-MW database achieved segmentation rate of 74.55%. A method for feature selection in unsupervised learning is proposed in [17]. A multiobjective genetic algorithm is used to improve the recognition speed and accuracy. To discriminate features measures like minimization of the number of features and a validity index are used to guide the search. The proposed strategy is applied to Arabic handwritten characters recognition.

From literature review it is observed that a few work has been done on hybridization for recognition of Odia numerals. In this paper two approaches GA and BPN are used for hybridization. Genetics algorithm and neural network are soft computing techniques inspired by the biological computational processes. Neural networks (NNS) are the models based on the human nerve system. They have the ability to adapt to circumstances. They learn from past experience. NN network can recognize patterns similar to those that they have learned earlier. But they do not have the ability to recognize totally new patterns. On the other hand genetic algorithms are inspired by the biological evolution process. They are based on the mechanics of natural genetics and natural selection. They have high adaptive search capability and are used for optimization. NN have the risk of encountering local minima problem, on the other hand GA provides good acceptable solutions although they do not

guaranteed to give global optimum solution. In this paper GA and NN are hybridized for the weight optimization of NN. The optimized weights are used for the recognition of numerals by the NN. Before the recognition phase preprocessing, feature extraction and feature reduction steps are carried out on the data set. The steps of character recognition of the proposed mode are shown in Fig 1. The data set consists of three classes with each class existing 400 times in the dataset. The data set is collected from ISI Calcutta.



**Fig.1.** Steps of the proposed model for the recognition of numerals.

The paper is organized as follows: Section I presents introduction and related work on hybrid models for character recognition. Section II discusses the dataset, preprocessing, feature extraction and feature reduction step. Section III describes the recognition phase. Section IV shows the simulation study and experimental results. Conclusion and future scope of the research are discussed in section V and VI.

**2. DATASET, PREPROCESSING AND FEATURE EXTRACTION**

*A) Dataset*

The dataset used in this paper is taken from Indian Statistical Institute (ISI) Kolkata. The database contains 1200 samples of Odia handwritten numerals from (0-2). All the samples of the database belong to three classes (0-2). Each numeral (0-2) appears 400 times in the database. 90% of the dataset is used for training and the rest is used for testing. Some samples of Odia numerals are shown in Fig.2.



**Fig.2.** Samples of Odia handwritten numerals

*B) Pre processing of data*

Pre-processing is a series of operation which includes background noise reduction, filtering, original image restoration etc performed on the input image. This step is carried out for improving the quality of the image before the application of other character recognition steps. In this paper first the data is normalized to a standard pixel size of 64X64. Then the gray scale image of the data is generated by using Mean filtering method. The gray scale images of the numerals are shown in Fig.3.



**Fig.3.** Odia Numerals in Gray Scale Image

*C) Feature extraction*

Feature extraction is carried out to find the important features to be used in the recognition phase. In this paper gradient based approach is used for feature extraction. For obtaining gradient feature Robert filter [1],[18] is applied. The gradient is calculated from the strength and directions of the pixels. Then the feature vectors are generated. Then PCA is applied on the feature vectors to reduce the features from 2519 to 75 numbers by using PCA.

*Calculation of direction and strength of gradient*

The Gradient feature represents a directional change in the intensity or color of the numeral. From the original numeral gradient numeral is obtained by convolving with a filter. The gradient of each pixel is a 2D vector with derivatives in the horizontal and vertical directions. The direction of largest possible intensity increase is pointed by the gradient vector at each image point and the rate of change

in that direction corresponds to the gradient vector's length. In this paper for calculation of gradient Roberts Filter given by is applied to each pixel on the normalized numeral. The direction and strength of gradient so obtained are shown in (Figs. 4(a) and 4(b)) respectively. The direction  $\theta(u, v)$  and strength  $f(u, v)$  is computed as follows

$$\left. \begin{aligned} g_u &= g(u+1, v+1) - g(u, v) \\ g_v &= g(u+1, v) - g(u, v+1) \\ \text{Direction: } \theta(u, v) &= \tan^{-1}\left(\frac{g_u}{g_v}\right) \\ \text{Strength: } f(u, v) &= \sqrt{(g_u)^2 + (g_v)^2} \end{aligned} \right\} \quad (1)$$



Fig.4(a). Image showing direction of gradient

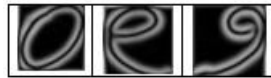


Fig.4(b). Image showing strength of gradient

### 3. CLASSIFICATION

For classification two approaches GA and NN are hybridized to find a suitable weight for NN so as to best discriminate the classes [2]. 312 numbers of weights are taken for the NN with architecture (75 – 4 – 3). The gene length is chosen as 5 with 312 number of gene in the chromosomes. Initially a population  $P_0$  is generated randomly with size  $N$ . In this paper the algorithms GA-NN-WT ( ) and FITCAL ( ) is used for weight optimization and evaluation of fitness function respectively. The weights of the NN network are extracted from the chromosomes by using the algorithm GA-NN-WT ( ). Then the NN is trained for each set of weights with all input samples. The generated error is used to calculate the fitness function of each chromosome by using the algorithm FITCAL ( ). Next the worst fit chromosomes are replaced with best fit chromosomes. A two point cross over is carried out to produce the offspring. The fitness functions of the off springs are calculated. The offspring so formed is used for the next generation. The process is repeated from generation to generation till convergence. The algorithms for weight optimization and calculation of fitness function is as follows

*Algorithms for weight optimization by GA (GA-NN-WT)*

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$i \leftarrow 0;$

Generate initial population  $P_i$  consisting of n number of real coded chromosomes  $C_j^i$ . Each chromosome represents a weight set for the NN.

While the current population  $P_i$  has not converged

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Obtain the fitness  $F_j^i$  value of each chromosome  $C_j^i$  by using the algorithm FITCAL ( );

Create the mating pool by replacing the chromosomes with minimum fitness with the high fitness chromosome.

Use two point crossover mechanisms to reproduce offspring from the parent chromosomes.

$i \leftarrow i + 1;$

Make the new population obtained as  $P_i$

}

Extract weights from  $P_i$  to be used finally by BPN

}

*Algorithm FITCAL ( )*

Let  $I_i = (I_{1i}, I_{1i}, I_{1i}, \dots, I_{li})$  and  $T_i = (T_{1i}, T_{1i}, T_{1i}, \dots, T_{li})$  represents the input and output pairs for a  $(l - m - n)$  BPN architecture. Where  $i = 1, 2, \dots, N$ .

For each chromosome  $C_i, i = 1, 2, \dots, P$  of current population  $P_i$  with population size  $P$

{

Extract weights  $W_i$  from  $C_i$  by using the following equation

Let  $x_1, x_2, \dots, x_d, \dots, x_l$  represent a chromosome and  $x_{kd+1}, x_{kd+2}, \dots, x_{(k+1)d}$  represent the  $k^{\text{th}}$  gene ( $k \geq 0$ ) in the chromosome. The weight  $w_k$  is calculated as follows

$$W_k = \begin{cases} + \frac{x_{kd+2}10^{d-2} + x_{kd+3}10^{d-3} + \dots x_{(k+1)d}}{10^{d-2}}, & \text{if } 5 \leq x_{kd+1} \leq 9 \\ - \frac{x_{kd+2}10^{d-2} + x_{kd+3}10^{d-3} + \dots x_{(k+1)d}}{10^{d-2}} & \text{if } 0 \leq x_{kd+1} < 5 \end{cases}$$

Train BPN for  $N$  input samples keeping  $W_i$  as a fixed set of weight

For each input instances calculate the error by using the formula

$$E_i = \sum_j (T_{ji} - o_{ji})^2 \text{ Where } O_i \text{ represents the calculated output by FFNN}$$

Find the root mean square error  $E$  of the errors  $E_i$  where  $i = 1, 2, \dots, N$  by using the following equation

$$E = \sqrt{\frac{\sum_i E_i}{N}}$$

Calculate the fitness value  $F_i$  of each chromosome by using the equation

$$F_i = \frac{1}{E}$$

}

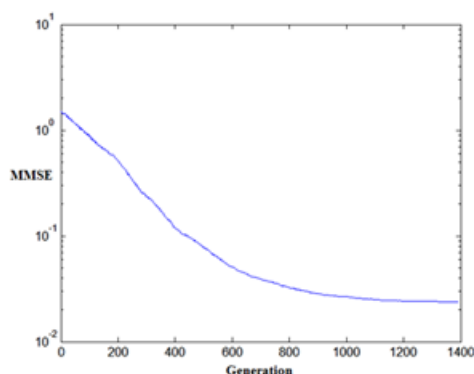
Output  $F_i$  for each  $C_i, i = 1, 2, \dots, p;$

}

#### **4. SIMULATIONS AND RESULTS**

The simulation work is carried out on MATLAB 2012b Platform. First the phases of character recognition steps like preprocessing, feature reduction and feature extraction are carried out before recognition step. The images are normalized to standard size 64X64 pixels. Then mean filtering method is applied for obtaining gray scale images. Then gradient approach is used for obtaining the feature vectors. The feature set is reduced from 2519 to 75 numbers by using PCA. For recognition 1080 samples of the dataset are used for training and rests are used for testing. All samples in the dataset belong to three classes (0-2). 90% of the dataset is applied for training and 10% for testing the system. The training sample consists of 360 samples of each class and testing sample consists of 40 samples of each class. For recognition NN architecture is used and the weight of the NN architecture is optimized by using GA. For BPN a 75-4-3 architecture is used. The parameters used for GA are: population size 80, number of genes 319, rank selection, two point crossover operation, crossover probability 0.8 and mutation probability 0.001. Initially 80 numbers of chromosomes are taken as initial population. Weights are extracted from the chromosomes by using the algorithm GA-NN-WT ( ). Each population passes through the process of selection, reproduction and crossover. Then NN is trained with 75 numbers of inputs. By using sigmoid activation function the outputs are generated. The network is trained for each chromosome with same weight for all input samples. The mean square error is generated in each iteration by using and the fitness of each chromosome is evaluated by using FITCAL ( ) algorithm. Then a two point cross over operations is carried out to form the next generation. The process of generation is repeated for 1000 generations to reach the convergence level. Finally the weights are extracted from the population. Fig.5 shows the convergence graph for the

training dataset. Table 1 and 2 shows the confusion matrix and accuracies of the GA-NN model for the three classes on test dataset respectively.



**Fig.5** Convergence graph for the training dataset

**Table 1.** Confusion matrix of the system on test dataset

Class	0	1	2
0	39	1	0
1	0	40	0
2	0	1	39

**Table 2.** Classification accuracy of the GA-NN system on test dataset

Class	No of Samples	No. of Correct Prediction	Accuracy
0	40	39	97.7%
1	40	40	100.0%
2	40	39	97.7%
Overall Accuracy			98.33%

## 5. FUTURE SCOPE

In this paper the weights of the BPN are optimized by using GA. Other evolutionary techniques like PSO, BFO, and ACO can be used for optimization. The system can be extended for digits (0-9) and can be applied on other standard databases. The proposed system can be applied for optical and handwritten character recognition. Further a number of approaches can be applied on preprocessing, feature extraction and feature reduction step to improve the recognition phase. Post processing can be applied to improve the performance of the system. Homogeneous and heterogeneous ensemble of classifiers can be modeled to improve the classification accuracy of the system.

## 6. CONCLUSION

In this paper a hybrid system is proposed for recognition of Odia handwritten numerals. Two approaches GA and NN are used for recognition. The weights of NN network are optimized by using GA so as to best discriminate the classes from one another. Various steps of character recognition like preprocessing, feature extraction and feature reduction steps are executed before the recognition phase. Features are extracted by using gradient based approach and PCA is applied to reduce the feature from 2519 to 75 numbers. After feature reduction 1080 samples of the database are used for training and 120 samples for testing in the recognition phase. From the experiment it is observed that the system has achieved 98.33% accuracy on test dataset. Thus GA based NN hybrid architecture can be employed successfully for the determination of weights of NN. This indicates the effectiveness of GA-NN hybrid system for the recognition of Odia numeric digits.

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