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Odia Handwritten Vowel Recognition System using Slantlet Transform and Differential Evolution based Functional Link Artificial Neural Network Classifier

Puspalata Pujari and Babita Majhi
Department of Computer Science and Information Technology, Guru Ghasidas Vishwavidyalaya,
Central University, Bilaspur (CG), India

Abstract: One of the challenging problems in optical character recognition (OCR) is the identification of handwritten characters. It has several complexities like missing part, size variation, added noise, media devices used, slant variation etc. The goal of this paper is to develop an effective system for recognition of Odia handwritten vowels using functional link artificial neural network (FLANN) classifier and differential evolution (DE) optimization technique. In this paper the emphasis is on preprocessing, feature extraction, feature reduction and classification with optimization technique. Various preprocessing operations like size normalization mean filtering and canny edge detection methods are carried out on the vowel images to enhance the quality. Slantlet transform (SLT) is applied for feature extraction and the extracted features are further reduced by principal component analysis (PCA) method. FLANN classifier is applied on the reduced feature vector and the weights of the FLANN are optimized with DE evolutionary technique. The system has achieved a good classification accuracy of 91.32% on the dataset.

***Keywords*:** Evolutionary techniques, Character recognition, Feature extraction, Classification, Slantlet transform (SLT), Functional Link Neural Network (FLANN), Differential Evolution (DE), Differential Evolution based Functional Link Artificial Neural Network (DE-FLANN).

I. INTRODUCTION

Hybrid models are widely used integrated techniques which provide efficient solutions to a wide range of complex problems belonging to different domain. Hybrid systems are specially used to overcome the weakness of one technique with the strength of other technique. Neural networks can model non linear relationships from given input patterns. But, due to the gradient search techniques artificial neural network (ANN) suffers from the problem of local minima. On the other hand DE provides potential candidate solutions for the neural network parameters. This paper presents a hybrid model of integrating FLANN and DE algorithm. In this model FLANN is used as a classifier and DE evolutionary algorithm is used to optimize the weight of FLANN.

Nibaran Das et.al [1] have proposed a soft computing paradigm embedded within the frame work of a two pass approach for recognition of basic, compound and allographs of Bangla character. An algorithmic approach has been developed for formation of pattern groups. To improve recognition accuracy, GA (Genetics Algorithm) based local region selection method has been used. The authors have achieved significant improvement over one pass approach. A handwriting recognition system has been developed in [2] based on genetics algorithm and visual coding. The system has been applied on Arabic script and obtained promising results. The authors have implemented a character recognition system for Devnagari script using SVM (Support Vector Machine) and particle swarm optimization in [3]. A comparative analysis has been carried out between the two techniques. An accuracy of 90 % has been achieved with particle swarm optimization (PSO). Laheeb M. AI-zoubaidy [4] has proposed a multiobjective genetic algorithm to minimize the number of features and a validity index method to measure the quality of cluster. The strategy has been applied on Arabic handwritten characters. Genetics algorithm has been used to improve recognition speed and accuracy. A multistage recognition system based on GA and SVM has been developed by Nibarana Das et.al in [5] for recognition of handwritten Bangla compound characters. The pattern classes are identified in the first pass and optimal local discriminating regions are identified in the second pass. The system has achieved an accuracy of 78.93%. In [6] the authors have proposed a neural network approach for identification of skilled and unskilled forgeries. PSO algorithm has been used for training the neural network. In [7], the authors have developed an optimization technique to optimize input and output weights of a single layer feed forward network (SLFN). The model is applied on MNIST and United States postal service (USPS) database. In [8], to train FLANN Particle swarm based optimization (PSO) technique has been proposed. L. M. Al-zoubaidy [9] has proposed a method for feature selection in unsupervised learning for recognition of Arabic handwritten character. Multiobjective genetic algorithm has been proposed to improve the recognition speed and accuracy of the system. Differential evolution has been successfully applied for solving many optimization techniques for many applications such as parametric identification of seismic isolation [10], functionally graded beam [11], noisy multi objective optimization[12], complementary metal oxide-conductor (CMOS) inverter design [13], time series forecasting [14], neural network stagnation problem [15] etc. From literature it is noticed that the DE optimization technique has not been applied to Odia vowel recognition. Hence in this paper this problem is addressed and suitable solution is proposed for recognition of the handwritten Odia vowels.

As compared to multi layer perceptron, FLANN classifier has low computational complexity. Character recognition task mostly deals with highly non linear data. The FLANN provides nonlinear solution to such type of problems by functionally extending its input vector. There are several applications of FLANN model such as noise control [16] , modeling of intelligent pressure sensor [17], stock market prediction [18][19], detection of impulsive noise in images [20], data classification [21] and channel equalization [22] etc. The FLANN model has been successfully applied to many classification problems with low computational complexity with better solution. Thus in this paper the FLANN model is chosen for the recognition of handwritten Odia vowels.

Feature extraction is an important phase of character recognition which significantly affects the recognition phase. In literature several authors have employed successfully various feature extraction techniques to extract important features from the input pattern. From the literature it is observed that the SLT has been successfully applied to many fields like electric power quality detection [23], exchange rate prediction [24], and classification of current in power system [25], brain image classification [26], reversible water marking scheme [27], and nonlinear dynamic systems [28]. Being motivated by these applications SLT has been employed in this paper to extract important features from handwritten Odia vowels.

The chapter is organized as follows. Section II outlines the proposed system, section III describes preprocessing phase, section IV describes feature extraction technique using Slantlet transform and feature extraction using PCA. Section V presents the structure of FLANN model followed by the basics of general DE algorithm. The proposed DE-FLANN model is discussed in Section VII. Experimental study is carried out in Section VIII followed by conclusion.

II. PROPOSED SYSTEM

For the proposed system 1440 handwritten Odia Vowels are collected from NIT Rourkela, 120 for each vowel in .jpg format. Each sample is categorized into one out of twelve classes ranging from 1-12. The images are preprocessed before feature extraction and recognition phase. After preprocessing SLT transform is applied on the images to extract the feature vector. The features extracted are further reduced using PCA. The reduced features are applied to FLANN classifier for recognition of vowels. The weights of FLANN are optimized with DE optimization technique. Figure 2 shows a block diagram of proposed system.

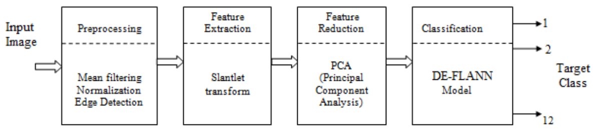

Fig.2. Block diagram of proposed system

III. PREPROCESSING

Pre-processing is the initial step of character recognition. In this step all type of irregularities present in the vowel images are removed. It includes the operations like background noise reduction, filtering, slant correction, normalization, original image restoration etc.

A. *Dataset used for the propose study*

The development and performance evaluation of the proposed model is done using standard Odia handwritten vowels data set collected from NIT, Rourkela. This database contains 1440 samples of Odia handwritten vowels. All samples of the dataset are categorized into twelve classes from ranging from (1-12). Each vowel appears 120 times in the database. Figure 1 shows one sample of Odia handwritten vowels (1-12).

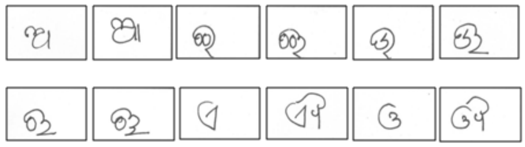

Fig.1. Handwritten Odia vowels from the database

The images are also normalized to a standard pixel size of 64x64 to get uniform images of each vowel. Then the gray scale images of the data are generated by using mean filtering method.

B. *Edge detection*

Edge detection is the process of finding sharp contrasts in the intensities of an image. It preserves most important structural features and reduces the amount of data in an image. In this paper Canny edge detection method is proposed for detecting edges from the images [30][31][32]. For smoothing, removing noise and unwanted details Gaussian filter $G\sigma(x,y)$ is applied to the image $f(x,y)$ by using equation 1.

$$\left.\begin{array}{c} g(x,y) \;=\; G\sigma(x,y) * f(x,y) \\ where\ G\sigma(x,y) is\ given\ as \\ G\sigma(x,y) = \frac{1}{\sqrt{2\pi\sigma^2}}\ \exp\left[-\frac{x^2+y^2}{2\sigma^2}\right] \end{array}\right\} \qquad (1)$$

The first derivative in horizontal (g_x) and vertical direction (g_y) is calculated by filtering the image with Sobel Kernel. From this the magnitude $M(x,y)$ and direction $\theta(x,y)$ for each pixel by is calculated b using equation 2.

$$\left.\begin{array}{c} M(x,y) = \sqrt{g_x{}^2(x,y) + g_y{}^2(x,y)} \\ and \\ \theta(x,y) = tan^{-1}[g_y(x,y)/g_x(x,y)] \end{array}\right\} \qquad (2)$$

Non-maxima suppression is calculated by using equation 3

$$\mathrm{M_T}(\mathrm{x,y}) = \begin{cases} M(x,y) & if\ \ M(x,y) > T \\ 0 & otherwise \end{cases} \qquad (3)$$

Where the threshold T is chosen, such that all edge elements are kept, most of the noise is suppressed. The non-maxima pixels in the edges of $\mathrm{M_T}$ obtained above are suppressed to thin the edge ridges. Each non-zero $\mathrm{M_T}\ (x,y)$ which is greater than its two neighbors along the gradient direction $\theta(x,y)$ is checked and $\mathrm{M_T}\ (x,y)$ remains unchanged. The output of non-maxima suppression sometimes contains the local maxima created by noise. To get rid of this hysteresis is carried out to find real edges. Figure 3 shows one set of vowels with detected edge using Canny edge detection method.

Fig. 3. Edge of the vowels using Canny edge detection method.

IV. FEATURE EXTRACTION USING SLANTLET TRANSFORM

This step is carried out to extract important features from the vowels. In this paper Slantlet transform (SLT) based approach is used for feature extraction. The Slantlet transform [25],[26] is an orthogonal discrete wavelet transform with two zero moments and with improved time localization. The construction of the Slantlet is based on a filter bank approach than the traditional tree based approach, with filters of different lengths at different scales. It is an orthonormal transform that defines a continuous function over L2 space with shorter support. The filters used for construction of Slantlet filter bank are $g_i(n) f_i(n) and\ h_i(n)$. For l scales, let $g_i(n) f_i(n) and\ h_i(n)$ be the filters employed in scale i to analyze the signal, where each of these filters has an exact support of 2^{i+1} . The l scale Slantlet has $2l$ number of channels. The low pass filter bank (LPF) which is the first filter has transfer function $h_i(n)$. The low pass filter is paired with its adjacent filter with transform function $f_i(n)$, where each filter is followed by a downsampling by 2^l. Each of the other $(l-1)$ channel pairs constitutes of a $g_i(n)$ filter and its shifted time-reversed version $(i = 1,2, \dots, l-1)$, followed by a down sampling by 2^{i+1}. The filter banks in the Slantlet analysis is determined by solving variables (parameters) in equation 4.

$$g_i(n) = \begin{cases} a_{0,0} + a_{0,1}n & for \quad n = 0, \dots, 2^i - 1 \\ a_{1,0} + a_{1,1}n & for \quad n = 2^i, \dots, 2^{i+1} - 1 \end{cases}$$
$$h_i(n) = \begin{cases} b_{0,0} + b_{0,1}n & for \quad n = 0, \dots, 2^i - 1 \\ b_{1,0} + b_{1,1}n & for \quad n = 2^i, \dots, 2^{i+1} - 1 \end{cases} \quad (4)$$
$$f_i(n) = \begin{cases} c_{0,0} + c_{0,1}n & for \quad n = 0, \dots, 2^i - 1 \\ c_{1,0} + c_{1,1}n & for \quad n = 2^i, \dots, 2^{i+1} - 1 \end{cases}$$

The objective is to determine the parameters as, bs and cs, to design $g_i(n), f_i(n) and\ h_i(n)$ filters for each i^{th} scale, which is based on formulation of constraints which satisfy orthogonality and two vanishing moments [29].

C. Feature reduction using PCA

The principal component analysis (PCA) is a mathematical procedure that uses an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components. By using the SLT 2519 numbers of features are generated for each vowel. The number of features generated is large. To reduce the computational complexity of the classifier the number of features is further reduced from 2519 to 32 by using the principal component analysis (PCA) method. These features are then fed to the FLANN model for training purpose and the weights of the FLANN is optimized with DE algorithm.

V. FUNCTIONAL LINK ARTIFICIAL NEURAL NETWORK MODEL FOR CLASSIFICATION

ANN can solve highly non linear problems. But, the complexity of ANN increases with the increase in number of layers. It needs more time to adjust the weight vector. Hence a FLANN model is suggested in this paper for the recognition of handwritten vowels. The FLANN [17][18][19] is a single layer neural network with no hidden layer. It has the capability to solve non linear classification problems with low complexity and provides better convergence rate. FLANN uses gradient descent algorithm iteratively to obtain a solution based on the training samples. In FLANN, the dimension of input pattern is expanded by a set of linearly independent function. The extended inputs are fed to the classifier for recognition purpose. Various mathematical functions such as sine, cosine, and log are used to functionally expand the input vector. Figure 4 shows the architecture of FLANN model. In this paper the reduced features are fed to the FLANN model for generating the enhanced intermediate pattern. The input z_i is trigonometrically expanded into five terms as

$$Z_i = [z_i \quad \sin(\pi z_i) \quad \cos(\pi z_i) \quad \sin(3\pi z) \quad \cos(3\pi z_i)]$$

where $0 \le i \le n$ (5)

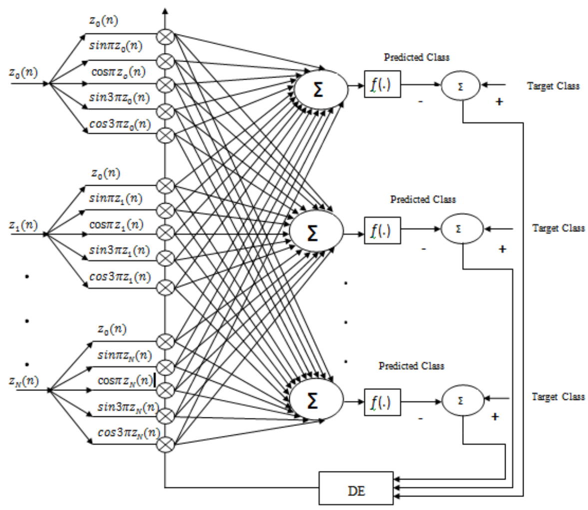

Fig. 4 A five input trigonometric expansion based DE-FLANN adaptive model

VI. DIFFERENTIAL EVOLUTION (DE)

Differential Evolution (DE) is a stochastic; population based heuristic approach suitable for optimization technique. It has been successfully applied in many optimization problems. DE is used to solve many complex problems analytically when the function is non differentiable, non-continuous, non-linear, noisy, flat, multi-dimensional or has many local minima and having constraints in the variables. In DE algorithms, the difference between selected individuals is used to generate a third individual called target vector, obtaining a new trial solution. A standard DE goes through four main operations: initialization, mutation, crossover, and selection.

Basic steps of DE algorithm

Step1: Select NP number of individuals $\vec{X}_{i,G}$ randomly, where $\vec{X}_{i,G}$ is the i^{th} individual of G^{th} generation.

Step 2: Let $f_i = f(\vec{X}_{i,G})$ represents the fitness value of i^{th} individual solution at G^{th} generation, for $i = 1$ to NP .

Step 3: Repeat steps 4 to 10 while stopping criteria is not reached

Step 4: For i=1 to NP repeat steps 5 to 10

Step 5: Select three random indices $r_0 = best,\ r_1,\ r_2$ between 1 to $NP(i \neq r_0 \neq r_1 \neq r_2)$

Step 6: Compute the mutant vector as

$$\vec{V}_{i,G} = \vec{X}_{best,G} + F(\vec{X}_{r_1,G} - \vec{X}_{r_2,G}) \quad (6)$$

where F is a real value within the range [0.0, 1.0]

Step 7: For $j = 1\ to\ n$ repeat steps 8 to 9

Step 8: Select a random number r_j where $(0 \leq r_j < 1)$ and j_{rand} index $(1 \leq r_{rand} < n)$

Step 9: If $r_j \leq C_r$ or $j = j_{rand}$ then $u_{j,i,G} = v_{j,i,G}$ else $u_{j,i,G} = x_{j,i,G}$ where C_r is a real valued crossover factor in the range [0.0, 1.0]. Construct the trial vector $\vec{U}_{i,G}$ using $u_{j,i,G}$

Step 10: Selection process is carried out as, if $f(\vec{U}_{i,G}) \leq f_i$ then $\vec{X}_{i,G+1} = \vec{U}_{i,G}$ and $f_i = f(\vec{U}_{i,G})$ else $\vec{X}_{i,G} = \vec{X}_{i,G}$

Figure 5 shows the flowchart of basic DE algorithm.

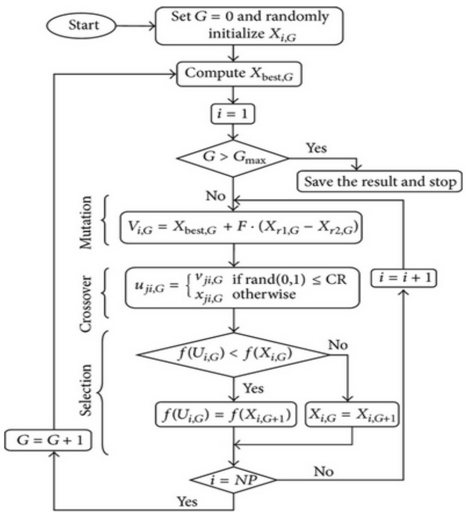

Fig.5. Flow Chart of Differential Evolution Algorithm

VII.DEVELOPMENT OF DE-FLANN HYBRID MODEL FOR RECOGNITION OF ODIA HANDWRITTEN VOWELS

FLANN is a derivative based algorithm which, sometimes suffer from local minima problem. The choice of initial parameter such as weight significantly affects the learning quality in recognition phase. So to improve the learning quality, the weights of the FLANN model is optimized with DE evolutionary algorithm. In this paper the DE based learning scheme is proposed to overcome the limitation FLANN model. The steps involved in DE based weight optimization model are

(a) Initialise the population M of FLANN-DE model. Each m^{th} individual of the population represents the coefficients or weights of the FLANN model. N number of weights of the FLANN model corresponds to each individual of the population.

(b) Generate K numbers of input patterns, each containing 32 features extracted from handwritten vowels. Expand each input trigonometrically to five non linear values.

(c) Multiply each element of the expanded input feature vector with each element of the member of population and then add together the partial sums to determine the estimated outputs y_i as

$$y_i = \sum_{n=1}^{N} w_n x_n \quad (7)$$

(d) Generate K errors by comparing the i^{th} predicted output of the DE-FLANN model with the corresponding actual outputs. The i^{th} error is represented as

$$e_i(n) = d_i(n) - y_i(n) \quad (8)$$

(e) Calculate the MSE (Mean Square Error) for finding fitness value of each member. Determine the MSE for a set of parameters corresponding to i^{th} member using equation 9. Repeat it for M times.

$$MSE(i) = \frac{\sum_{k=1}^{K} {e_i}^2}{K} \quad (9)$$

(f) Minimize the MSE using the DE.

(g) Using equation (6) obtain the mutant vector.

(h) Using step 9 of section IV perform crossover operation and generate trial vectors.

(i) Based on minimum MSE criterion select the members for the next generation. Repeat the whole process for desired number of generations.

(j) Obtain learning characteristics of the classification model by plotting relation between the minimum MSE (MMSE) and the number of generations. When the MMSE has reached the possible minimum value and almost remains constant the training process is stopped. At this stage all the members of the population almost acquire same value which represents the best possible weights of the FLANN model.

VIII. SIMULATION STUDY

To measure the performance of the DE-FLANN model simulation is carried out using Matlab software. The handwritten Odia vowels from NIT Rourkela comprising of 1440 handwritten vowels belonging to twelve target classes (1-12) are used for recognition purpose. Each class contains 120 samples. The images are normalized to a standard size of 64x64 pixels. Then the mean filtering technique is applied to convert the images into gray scale images. Canny edge detection method is applied on the images to detect the edge of the vowels. Slantlet transform is employed to each image to extract feature vectors. Further the features are reduced by using PCA from 2519 to 32 numbers to reduce computational complexity. Trigonometric FLANN is chosen as classifier and its weights are updated with DE based optimization algorithm. Out 1440 number of samples 1152 samples each with 32 attributes is used for training the weights of the FLANN and the remains are used for testing purpose. Each feature of the sample is trigonometrically expanded to five terms. Log sigmoid function is used as activation function. The estimated output for each input sample is compared with the desired output to calculate error term. Mean square error (MSE) is computed from the set of error terms. In the present simulation study the MSE is considered as the fitness function which is progressively minimized by varying the weight vector of the population using DE based optimization technique. The parameters of DE used in the simulation study are: population size = 750, F=0.1, C_r=0.9, number of generations = 1000 and number of independent run =10. The experimental results are also obtained for GA-FLANN and PSO-FLANN models under similar condition for comparison. The comparison of convergence characteristics of all three adaptive models is shown in Figure 6. From the figure it is observed that the DE-FLANN model gives minimum MMSE level as compared to other two models. The confusion matrix obtained during training and testing of DE-FLANN model is given in Table 1 and Table 2 respectively. Table 3 shows the accuracy of individual class for DE-FLANN model during training and testing phase. Table 4 shows the comparison of recognition accuracy of the three models during validation. The recognition accuracy obtained is 91.31%, 84.72% and 82.29% for DE-FLANN, PSO-FLANN and GA-FLANN model respectively. From the simulation results it is noticed that the proposed DE-FLANN model is a better model in comparison to the other two models for recognition of handwritten Odia vowels.

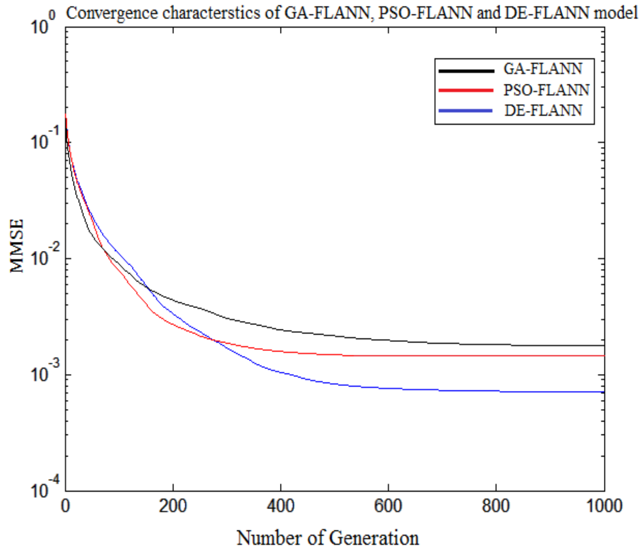

Fig. 6 Comparison of convergence characteristics of three adaptive models during training period

Table1.Confusion matrix of training dataset using DE-FLANN model

Class	1	2	3	4	5	6	7	8	9	10	11	12
1	94	2	0	0	0	0	0	0	0	0	0	0
2	1	95	0	0	0	0	0	0	0	0	0	0
3	0	0	94	1	0	0	1	0	0	0	0	0
4	0	0	1	95	0	0	0	0	0	0	0	0
5	0	0	0	0	95	1	0	0	0	0	0	0
6	0	0	0	0	0	96	0	0	0	0	0	0
7	0	0	0	0	0	0	96	0	0	0	0	0
8	0	0	0	0	0	0	0	94	2	0	0	0
9	0	0	0	0	0	0	0	1	95	0	0	0
10	0	0	0	0	0	0	0	0	0	96	0	0
11	0	0	0	0	0	0	0	0	0	0	96	0
12	0	0	0	0	0	0	0	0	0	0	0	96

Table2.Confusion matrix of testing dataset using DE-FLANN model

Class	1	2	3	4	5	6	7	8	9	10	11	12
1	21	1	0	0	1	0	0	0	0	0	1	0
2	1	23	0	0	0	0	0	0	0	0	0	0
3	0	0	22	1	0	0	1	0	0	0	0	0
4	0	0	1	21	0	0	1	1	0	0	0	0
5	0	0	0	1	22	0	1	0	0	0	0	0
6	0	0	0	0	0	23	1	0	0	0	0	0
7	0	0	0	0	1	1	21	1	0	0	0	0
8	0	0	0	1	0	0	1	22	0	0	0	0
9	0	0	0	0	0	0	0	1	23	0	0	0
10	0	0	0	0	0	0	0	0	1	22	0	1
11	0	0	0	0	1	0	0	0	0	0	22	1
12	0	0	0	0	0	0	0	0	0	1	2	21

Table3. Accuracy of each class using DE-FLANN model for training and testing dataset

Class	Training			Testing		
	Total Sample	Correct Class	Accuracy in %	Total Sample	Correct Class	Accuracy in %
1	96	94	97.92	24	21	87.5
2	96	95	98.96	24	23	95.83
3	96	94	97.92	24	22	91.67
4	96	95	98.96	24	21	87.5
5	96	95	98.96	24	22	91.67
6	96	96	100	24	23	95.83
7	96	96	100	24	21	87.5
8	96	94	97.92	24	22	91.67
9	96	95	98.96	24	23	95.83
10	96	96	100	24	22	91.67
11	96	96	100	24	22	91.67
12	96	96	100	24	21	87.5
Total Accuracy			95.17 %	Total Accuracy		91.32 %

Table4. Comparison of recognition accuracy during validation of three adaptive models

		DE-FLANN		PSO-FLANN		GA-FLANN	
Class	No of samples in all cases	No. of Correct Prediction	Accuracy in %	No. of Correct Prediction	Accuracy in %	No. of Correct Prediction	Accuracy in %
1	24	21	87.5	20	83.33	21	87.5
2	24	23	95.83	21	87.5	18	75
3	24	22	91.67	20	83.33	19	79.17
4	24	21	87.5	21	87.5	20	83.33
5	24	22	91.67	21	87.5	20	83.33
6	24	23	95.83	20	83.33	19	79.17
7	24	21	87.5	21	87.5	20	83.33
8	24	22	91.67	19	79.17	20	83.33
9	24	23	95.83	20	83.33	21	87.5
10	24	22	91.67	22	91.67	20	83.33
11	24	22	91.67	20	83.33	19	79.17
12	24	21	87.5	19	79.17	20	83.33
		Overall accuracy in % = 91.32		Overall accuracy in % = 84.72		Overall accuracy in % = 82.29	

IX. CONCLUSION

This paper has proposed a hybrid soft computing approach DE-FLANN model using FLANN as classifier and DE as optimization technique for recognition of handwritten Odia vowels. All generic phases of character recognition are carried out. The feature vector is generated using Slantlet transform and further reduced using PCA. The system is also compared with PSO-FLANN and GA-FLANN model. From the experimental result DE-FLANN model has achieved a recognition accuracy of 91.32% on test dataset which is highest than the other models. The present work is an attempt to use evolutionary based approach for recognition of handwritten vowels. Different feature extraction and classification techniques can be applied to the system to increase the recognition accuracy.

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