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Application of Cat Swarm Optimization for Recognition of Handwritten Numerals

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***Abstract*—**Accurate recognition of optical handwritten numeral is still an open and demanding problem in present digital world. The basic objective of the present work is to develop a novel method for recognition of off line unconstrained handwritten Odia numeral using curvature feature and functional link artificial neural network (FLANN) based cat swarm optimization (CSO) technique. In this paper preprocessing and feature extraction steps are carried out before the recognition of numerals. For feature extraction curvature based approach is applied. For recognition of handwritten Odia numeral hybrid architecture has been proposed where the classification task is performed by FLANN classifier and cat swarm optimization is used for finding a suitable set of weights for the FLANN classifier. The proposed model is evaluated on database consisting of 4000 number of handwritten Odia numerals. The combined effect of curvature based feature extraction approach and FLANN based cat swarm optimization technique yielded a high accuracy which exhibits the effectiveness of CSO based FLANN optimization model (FLANN-CSO) for recognition of Odia handwritten numerals.

***Keywords*—** Odia numeral recognition, FLANN, CSO, Preprocessing, Feature extraction, classification.

I. INTRODUCTION

Recognition of unconstrained handwritten numerals has significant effect in various applications related to postal code verification, business sector, banking sector, digital library, document analysis, passport verification and many more. It is very difficult to develop a method for recognition of unconstrained hand written numerals due to their variations and lots of constraints associated with the numerals. In recent years, a number of hybrid techniques [20-24] have been applied to solve a number of complex problems. In hybrid system one or more techniques are combined to solve a complex problem. Hybrid system works by the integration of various techniques to obtain a better solution so as to overcome the weakness of one technique with the strength of other technique. In this paper, a cat swarm based FLANN hybrid model is presented for recognition of handwritten Odia numerals.

A number of schemes have been reported in literature for classification of unconstrained handwritten numeral. Mostly they differ in feature extraction and classification strategies. A multilayered feed forward neural network has been reported by A. Desai in [2] for recognition of Gujarati handwritten digits. In [3], a model is proposed for recognition of Arabic numerals using Hidden Markov Model (HMM) and Nearest Neighbour Classifier (NNC). Recognition accuracy of 97.99 % and 94.35 % is achieved with HMM and NNC respectively. A novel model has been proposed in [4] for the recognition of Persian / Arabic handwritten zip code. B.Majhi et.al [5] proposed a low complexity classifier with gradient and curvature based feature for recognition of Odia numerals. A recognition accuracy of 98% is achieved with gradient based feature extraction and 94% accuracy is achieved with curvature based feature extraction. T.K. Mishra et.al [6] has proposed a model for recognition of handwritten numerals using Discrete Cosine Transform (DCT) and Discrete Wavelet Transform. In [7] the authors have proposed a character recognition system for Devnagari script using SVM (Support Vector Machine) and particle swarm optimization. A comparative study has been carried out between the two techniques. An accuracy of 90 % has been achieved with particle swarm optimization (PSO). In [9] the authors have applied neuroevolution for automatic design of convolutional neural network (CNN) topologies. The proposed system is applied on MNSIT handwritten digit dataset and obtained a satisfactory result. A hybrid evolutionary approach with genetic algorithm and convolutional neural network (CNN) has been proposed in [10] for recognition of Devnagri handwritten numeral. Joseph Tarigan et.al [11] has developed a plate recognizer system using genetic algorithm and back propagation neural network. The accuracy of the model is found to be 1.35 % better than non-optimized backpropagation neural network.

From literature review, evolutionary approaches: Genetic algorithm (GA) and particle swarm optimization (PSO) have been mostly used for recognition of Odia numerals. Cat swarm optimization is an evolutionary technique which has been successfully applied to solve many complex problems. But the optimization has not been applied to Odia numeral in literature. In this paper a new hybrid approach is presented for the recognition of unconstrained handwritten Odia numerals using cat swarm optimization based FLANN model. In this work curvature based feature extraction approach is used for extraction of features. After feature extraction the features are reduced further by using principal component analysis (PCA). A combination of curvature approach for feature extraction and cat swarm based FLANN model for recognition has not been attempted before. Experiments have shown that this combination scheme has the effect of increasing the performance of recognition system. Figure 1 shows a block diagram of proposed system.

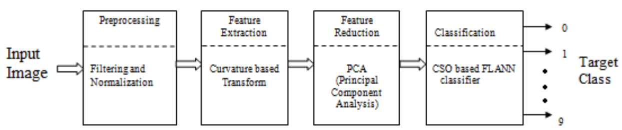

Figure.1. Block diagram of proposed system

The paper is organized into six sections. Section II describes preprocessing and feature extraction phase. Section III describes functional link artificial neural network, the CSO algorithm is described in section IV. Section V describes the weight optimization of FLANN model using CSO algorithm. Section VI describes the experimental results. Conclusion is described in section VII.

II. Preprocessing and Feature Extraction

In this work the handwritten numerals are considered to be unconstrained and isolated. The images of the numerals are preprocessed to remove noise and variability in images. A median filtering- based approach is used for filtering and the images of the Odia numerals are normalized to 64 X 64 pixels to convert the random sized image into a standard sized image. Curvature based approach is used for feature extraction and PCA is applied to reduce the features further. Figure 2 shows one sample of Odia handwritten numerals (0-9).

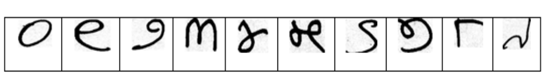

Figure.2. Handwritten Odia numerals from the database

A. Feature extraction using curvature feature

The feature extraction process using Curvature approach is based on bi quadratic interpolation method [1][5]. The calculation of curvature feature depends on the eight neighbourhood pixels of a pixel. The neighbourhood of a pixel u_0 and their corresponding pixel value f_k is shown in Figure 3.

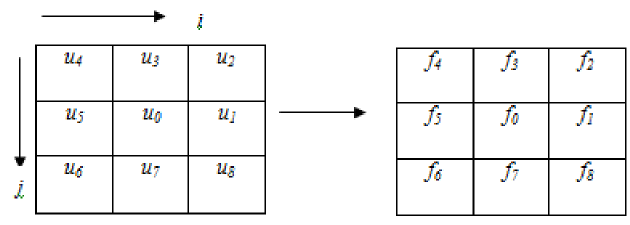

Figure.3. Eight neighbourhoods of pixel u_0 and their corresponding pixel values

The curvature c at u_0 in a gray scale image [5] is defined using (1)

$$c = -2(a_{01}^2 a_{02} - a_{01}a_{10}a_{11} + a_{01}^2 a_{02})/(a_{10}^2 + a_{01}^2)^{3/2} \quad (1)$$

where

$$a_{10} = \frac{f_1 - f_5}{2},\ a_{20} = \frac{f_1 + f_5 - 2f_0}{2},\ a_{01} = \frac{f_3 - f_7}{2},$$
$$a_{02} = (f_3 + f_7 - 2f_0)/2,\ a_{11} = (f_2 - f_8) - (f_4 - f_6)/4 \quad (2)$$

The coefficients a_{10} and a_{20} are, respectively, the first and the second order partial derivatives of $f(u, v)$ regarding u; a_{01} and a_{02} are similar partial derivatives regarding v, and a_{11} is the one regarding to u and v.

B. Generation of Curvature Feature

The steps for generation of curvature vector is as follows

(a) The curvature c detected by equation (1) quantized to 32 levels with uniform interval.
(b) The normalized numeral image is divided into 81 (9 horizontal × 9 vertical) blocks.
(c)The strength of the gradient is accumulated separately in each of 32 directions, in each block, to produce 81 local spectra of direction.

III. Functional Link Artificial Neural Network (FLANN) Model for Recognition

As FLANN [11-17] model has no hidden layer and it has low computational complexity, in this paper FLANN based classification model is designed for the recognition of numerals. The numerals are represented by feature vectors based on curvature approach and the dimension of the feature vector is further reduced by using PCA. The reduced features are applied as inputs to the FLANN model. The dimension of input vectors of FLANN model is increased trigonometrically. A diagrammatic representation of the architecture of FLANN model with trigonometric expansion is shown in figure 4. The input Z_i trigonometrically expanded into five terms is represented as

$$Z_i = [z_i \quad \sin(\pi z_i) \quad \cos(\pi z_i) \quad \sin(3\pi z_i) \quad \cos(3\pi z_i)] \tag{3}$$

where $0 \leq i \leq n$

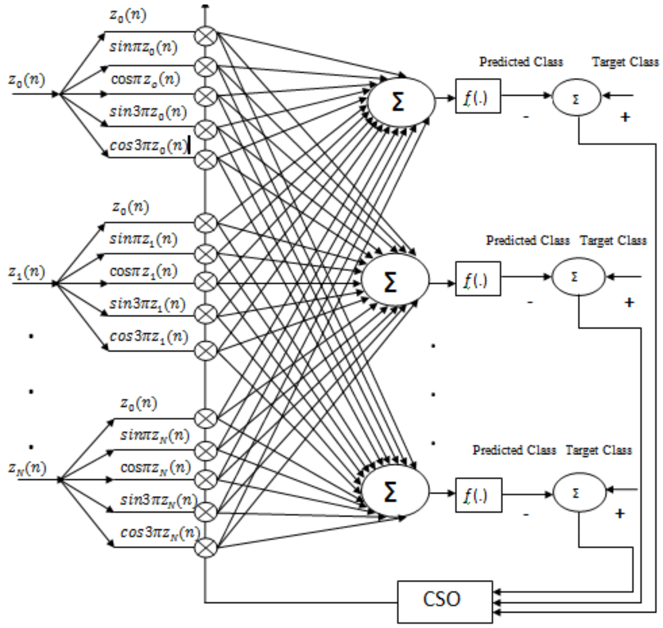

Figure. 4 An input trigonometric expansion based FLANN adaptive model using CSO

IV. Cat Swarm Optimization (CSO) Algorithm

Cat swarm optimization [18][19] is an evolutionary technique which is based on the natural behaviour of cats. Most of the time cats are found in resting condition. In resting condition cats undergoes very slow movement but they remain alter every times. This characteristic of cat represents seek mode. When the cats found any prey, they trace to catch the prey very fast with lots of energy. This characteristic of cat represents trace mode. The two modes of cats: seeking and tracing modes are modelled mathematically to solve very complex optimization problems.

A. Seeking mode:

Seeking mode is a global search technique in optimization problem. Seeking memory pool (SMP) is the number of copies of a cat in seeking mode. The steps of seeking mode are as follows

Step1: Corresponding to i^{th} cat create N number of copies of the cat.

Step2: Update the position of each copy of the cat basing on Counts of dimension to change (CDC) value by randomly adding or subtracting seeking range of selected dimension (SRD) percents to the present position of cat.

Step3: Calculate the fitness of all copies of the cats.

Step4: Choose the best cat from the N copies and replace the i^{th} cat with the best cat.

B. Tracing mode:

Tracing mode is a local search technique in optimization problem. In this mode the chasing of cat is mathematically represented as a number of changes in its positions. The position of i^{th} cat in D dimension is represented as

$Pos_i = [Pos_{i1}, Pos_{i2}, \ldots, Pos_{iD}]$

The velocity of i^{th} cat is represented in D dimension as

$Vel_i = [Vel_{i1}, Vel_{i1}, \ldots, Vel_{iD}]$

Where $d(1 \leq d < D)$ represents the dimension

The global best position of the cat is represented as

$Pos_{gbest} = [Pos_{gbest1}, Pos_{gbest2}, \ldots, Pos_{gbestD}]$

The position and velocity of cats are updated as follows

$Pos_{id} = Pos_{id} + Vel_{id}$

$Vel_{id} = w * Vel_{id} + cons * rand * (Pos_{gbestd} - Pos_{id})$

Where w represents the inertia of weight, cons represents the acceleration constant and rand is a random number distributed uniformly within the range [0 1]

CSO based optimization technique uses two group of cats: cats in seeking mode and cats in tracing mode. These two groups of cats are combined to solve the optimization problem. A mixed ratio (MIXR) is used to represent the ratio of number of cats in tracing mode to the number of cats in seeking mode.

C. Steps of CSO algorithm:

Step1: Initialization of position in D dimension: Randomly initialize the position Pos_{id} of the i^{th} cat in d^{th} dimension.

Step2: Initialization of velocity: Randomly initialize the velocity Vel_{id} of each cat in d^{th} dimension.

Step3: Calculate the fitness function of each cat. Obtain the best fitness Pos_{bestm} where $m = 1,2, \ldots, D$

Step4: Set the flag of the cats to seeking mode and tracing by picking the cats randomly from the population using MIXR.

Step5: Apply the steps of seeking or tracing mode according to the flag of the i^{th} cat.

Step6: Obtain the fitness of each cat and store the position of the cat with best fitness value Pos_{bestm} where $m = 1,2, \ldots, D$

Step7: Compare the fitness of Pos_{gbest} and Pos_{bestm} and update Pos_{gbest} .

Step8: Terminate the process if a termination criterion is reached otherwise repeat step 4 to step 7

V. Weight Updation of FLANN Model using CSO Algorithm

The steps for optimization of weights of FLANN model using CSO are

Step1: Randomly initialize the weights of the FLANN model within the range 0 to 1. Each weights of the FLANN model represent the cat positions.
Step2: Randomly initialize the velocity of each cat Vel_{ij} of i^{th} cat in j^{th} dimension.
Step3: for $t = 1\ to\ itr$ where itr represents the maximum number of iterations.
Generate random integers T_q within the range 1 to Length where
$q = 1,2, \dots, L/(1 + MIXR)$
The number T represents the cats that will undergo the tracing mode and seeking mode.
For $k = 1\ to\ L$ength
The weights of the FLANN model are represented with k^{th} row of the population P.
Apply all input samples to the FLANN model and obtain the error$e(n)$. Where $n = 1,2, \dots, N$ using actual and calculated outputs.
Evaluate the fitness of k^{th} cat.
$Fit_k = 1/N \sum_{n=1}^{N} e^2(n)$ Which represents mean square error (MSE) corresponding to k^{th} solution.

$$Fit_{min} = minimum(MSE)$$

Corresponding to Fit_{min} store the position of cat as Pos_l .
Step4: if $Fit_{min} < Fit_t$, then $Fit_t = Fit_{min}$ and $Pos_{\ gbest} = Pos_l$
Step5: P_{gbest} gives the optimized weight of the FLANN model.

VI. Simulation Study for FLANN-CSO Model

The proposed hybrid recognition system FLANN-CSO is implemented using MATLAB. The handwritten Odia numerals database consisting 4000 numerals are used for the experimental work. The system is trained with 3600 number of samples. The numerals are categorized into at most ten categories. The classification model is tested with the rest of ten percent of samples. The model is trained using the training set of data and the recognition accuracy is calculated for the test data. Fivefold cross validation is used for training the data. The images are normalized and median filtering is applied in preprocessing step. Curvature based approach is used to generate feature vector. The feature vector is further reduced using PCA to reduce the dimension. The reduced features are applied as inputs to the FLANN model based on trigonometric expansion. Sigmoid activation function is used for the outputs. The error terms are calculated based on the actual and calculated outputs. The weights of the FLANN model are optimized using CSO algorithm. Mean square error (MSE) is computed using the error terms. The population size of cats is taken as 50, MIXR=0.75, SMP=5, SRD=0.75, CDC=0.25, inertia weight = 0.5, rand = 0.5, number of generation taken is 1000. Figure 5 shows the confusion matrix obtained during validation of FLANN-CSO model which exhibits the improved recognition accuracy of the model. The recognition accuracy of FLANN-CSO model is also compared with other hybrid models: Differential evolution based FLANN (FLANN-DE) model, Particle swarm based FLANN (FLANN-PSO) model, Clonal selection based FLANN (FLANN-CSA) model and Genetic algorithm based FLANN (FLANN-GA) model. Table 1 shows comparison of recognition accuracy of FLANN-CSO model with four adaptive models: FLANN-DE, FLANN-PSO, FLANN-CSA and FLANN-GA during validation. From the experiment it is noticed that the proposed FLANN-CSO model provides highest accuracy as compared to other FLANN based optimization model for recognition of Odia handwritten numerals. Figure 6 shows comparison of FLANN-CSO model with other adaptive models.

Class	0	1	2	3	4	5	6	7	8	9
0	40	0	0	0	0	0	0	0	0	0
1	0	38	0	0	1	0	0	1	0	0
2	0	0	39	0	0	0	0	1	0	0
3	0	0	2	36	0	0	0	0	2	0
4	1	1	0	0	38	0	0	0	0	0
5	0	0	0	0	0	40	0	0	0	0
6	1	0	0	0	0	0	37	0	2	0
7	0	0	1	0	0	0	0	38	0	1
8	0	0	0	0	0	0	0	0	39	1
9	2	0	0	0	0	0	1	0	0	37

Figure.5 Confusion Matrix achieved for all classes for the FLANN-CSO Model with test data

Table 1 Comparison of recognition accuracy of FLANN-CSO model with four adaptive models during validation

		FLANN-CSO		FLANN-DE		FLANN-PSO		FLANN-CSA		FLANN-GA	
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 %	No. of Correct Prediction	Accuracy in %	No. of Correct Prediction	Accuracy in %

0	40	40	100	38	95	38	95	34	85	32	80
1	40	38	95	36	90	40	100	36	90	36	90
2	40	39	97.5	35	87.5	36	90	37	92.5	38	95
3	40	36	90	36	90	40	100	35	87.5	32	80
4	40	38	95	35	87.5	35	87.5	38	95	37	92.5
5	40	40	100	40	100	37	92.5	36	90	32	80
6	40	37	92.5	34	85	36	90	34	85	32	80
7	40	38	95	34	85	38	95	36	90	35	87.5
8	40	39	97.5	37	92.5	36	90	36	90	32	80
9	40	37	92.5	36	90	36	90	37	92.5	33	82.5
		Overall accuracy in % = 95.5		Overall accuracy in % = 90.25		Overall accuracy in % = 93		Overall accuracy in % = 89.5		Overall accuracy in % = 84.75	

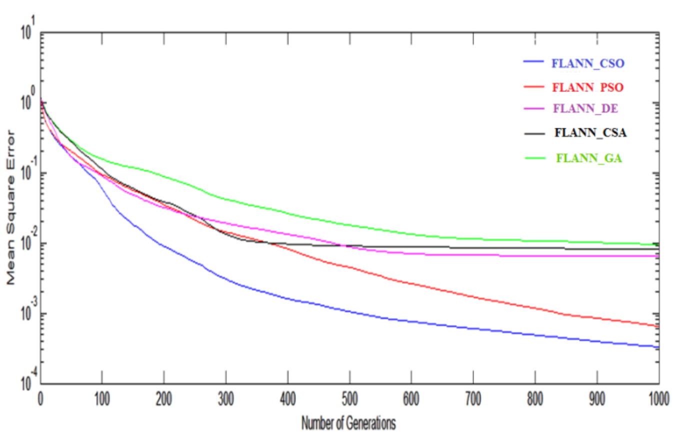

Figure. 6 Comparison of convergence characteristics of FLANN-CSO model with other adaptive models during training period

VII. Conclusion

This paper is concerned with the problem of recognition of unconstrained handwritten Odia numerals. The novelty of the work is the combination of curvature based feature extraction approach and cat swarm based FLANN hybrid optimization technique for recognition of numerals. Experimental result shows that the accuracy of the proposed model is 95.5%. The result demonstrates that the model can be used to develop solutions for the recognition of handwritten Odia numerals. The experimental result shows that the proposed model exhibits well as compared to other models. The recognition accuracy is found to be between 92.5 % and 100 % for different handwritten Odia numerals. The errors in recognition errors were due to the variations in writing and similarity among numerals. The performance of the recognition method can be improved by using ensemble model and with other evolutionary techniques like bacterial foraging optimization (BFO), ant colony optimization (ACO) etc.

References

[1] M. Shia, Y. Fujisawab, T. Wakabayashia, F. Kimuraa, “Handwritten numeral recognition using gradient and curvature of gray scale image,” Journal of Pattern Recognition, Vol. 35, pp. 2051 – 2059, 2002

[2] A. Desai, “Gujarati handwritten numeral optical character reorganization through neural network” , The Journal of Pattern Recognition, Vol. 43, pp. 2582–2589, 2010.

[3] S. Mahmoud, “Recognition of writer-independent off-line handwritten arabic (indian) numerals using hidden Markov

models," Journal of Signal Processing, Vol. 88, pp. 844–857, 2008.

[4] Z. Kamranian, S.A. Monadjemi and N. Nematbakhsh, "A novel free format persian/arabic handwritten zip code recognition system," Journal of Computers and Electrical Engineering, Vol. 39, pp:1970–1979, 2013.

[5] B. Majhi, J. Satpathy and M. Rout, "Efficient recognition of odia numerals using low complexity neural classifier," In Proceedings of IEEE International Conference on Energy, Automation and Signal , pp. 140-143, 2011.

[6] T.K.Mishra, B. Majhi, S. Panda, "A comparative analysis of image transformations for handwritten Odia numeral recognition," In Proceedings of IEEE International Conference on Advances in Computing, Communications and Informatics (ICACCI), 2013, pp. 790-793.

[7] Prashant M. Kakde, S. M. Gulhane, " A comparative analysis pf particle swarm optimization and support vector machines for Devnagri character recognition: An android application", Procedia Computer Science, Proceedings of International conference on communication, computing and virtualization (ICCCV) 2016, volume 79, 2016, Pages 337-343

[8] Alejandro Baldominos , Yago Saez, Pedro Isasi, Evolutionary convolutional neural networks: An application to handwritten recognition", Neuro Computing, Volume 283, 29 March 2018, Pages 38-52

[9] Adarsh Trivedi, Siddhant Srivastava, Aproova Mishra, Anupam Shukla, Ritu Tiwari," Hybrid evolutionary approach for Devanagari handwritten numeral recognition using convolutional neural network", Procedia Computer Science, Volume 125, 2018, Pages 525-532

[10] Joseph Tarigan, Nadia, Ryanda Diedan, Yaya Suryana, " Plate recognition using backpropagation neural network and genetic algorithm", Procedia Computer Science, Volume 116, 2017, Pages 365-372

[11] W-D Weng, C-S Yang and R-C Lin, A channel equalizer using reduced decision feedback Chebyshev functional link artificial neural networks, Information Sciences, Elsevier, vol.177, issue 13, pp.2642-2654, July 2007. (FLANN)

[12] B. Naik, J. Nayak and H. S. Behera, A global-best harmony search based gradient descent learning FLANN (GbHS-GDL-FLANN) for data classification, Egyptian Informatics Journal, Elsevier,21 October 2015(In press). (FLANN)

[13] C.M.Anish and B. Majhi, Hybrid nonlinear adaptive scheme for stock market prediction using feedback FLANN and factor analysis, Journal of the Korean Statistical Society, July 2015 (in press). (FLANN)

[14] R. Majhi, G. Panda and G. Sahoo, Development and performance evaluation of FLANN based model for forecasting of stock markets, Expert Systems with Applications, Elsevier, vol.36, pp. 6800-6808, June 2012. (FLANN)

[15] B. Majhi and P. K. Sa, FLANN-based adaptive threshold selection for detection of impulsive noise in images, AEU- International Journal of Electronics and Communications, Elsevier, vol. 61, issue 7, pp.478-484, July 2007. (FLANN)

[16] J. C. Patra and A. Bos, Modelling of an intelligent pressure sensor using functional link artificial neural networks, ISA transactions, Elsevier, vol.39, issue 1, pp.15-17, February 2000. (FLANN)

[17] S. K. Behera, D. P. Das and B. Subudhi, Functional link artificial neural network applied to active noise control of a mixture of tonal and chaotic noise, Applied soft computing, Elsevier, vol. 23, pp. 51-60, October 2014. (FLANN)

[18] Chu, S.-C., & Tsai,P.-W, Computational intelligence based on the behavior of cats. International journal of innovative computing, Information and control, 3, pp.163-173

[19] G. Panda, P.M.Prahan, B. Majhi, IIR system identification using cat swarm optimization, Expert system with applications, 38(2011), pp.12671-12683

[20] A.D. Parkins, A.K. Nandiembers, "Genetic programming techniques for hand written digit recognition", Signal Processing, Volume 84, Issue 12, pp: 2345-2365, December 2004.

[21] Moayad Yousif Potrus, Umi Kalthum Ngah, Bestoun S. Ahmed, "An evolutionary harmony search algorithm with dominant point detection for recognition-based segmentation of online Arabic text recognition", Ain Shams Engineering Journal, Volume 5, Issue 4, pp. 1129-1139, December 2014.

[22] Saurabh Shrivastava, Manu Pratap Singh, "Performance evaluation of feed-forward neural network with soft computing techniques for hand written English alphabets", Applied Soft Computing, Volume 11, Issue 1, pp: 1156-1182, January 2011.

[23] C. De Stefano, F. Fontanella, C. Marrocco, A. Scotto di Freca, "A GA-based feature selection approach with an application to handwritten character recognition", Pattern Recognition Letters, Volume 35, Pages 130-141, 1 January 2014

[24] M. Kherallah, F. Bouri, A.M. Alimi, "On-line Arabic handwriting recognition system based on visual encoding and genetic algorithm", Engineering Applications of Artificial Intelligence, Volume 22, Issue 1, pp: 153-170, February 2009.

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