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Improved Genetic Particle Swarm Optimization and Feature Subset Selection for Extreme Learning Machine

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Abstract— Particle Swarm Optimization (PSO) is a heuristic global optimization method, which is most commonly used for feature subset selection problem. However, PSO requires the fixed number of optimal features as an input. It is a very critical task to analyze initially that how many features are relevant and non-redundant present in the given dataset. To solve the said problem this paper has proposed Improved Genetic – PSO (IG-PSO) algorithm for Extreme Learning Machine (ELM) which returns optimal features as well as an optimal number of features. The IG-PSO algorithm is experimented on six benchmarked dataset for handling medical dataset classification which improves the classification accuracy by using optimal features. Also, the simulation results demonstrate that IG-PSO algorithm has the capability to handle optimization, dimensionality reduction and supervised binary classification problems.

Keywords—Feature Subset Selection Problem, Pattern Classification Problem, Extreme Learning Machine, Particle Swarm Optimization

I. Introduction

Feature subset selection (FSS) has become the focus of research in the areas of applications like text processing of internet documents, gene expression array analysis and combinatorial chemistry. The key objective of FSS is to provide the same or improved classification accuracy with a minimum number of relevant and non-redundant features only. It is very intricate to decide the importance of and hence requirement of features without any prior information [1]. A large number of features are usually included in the input dataset, which contains all types of features like relevant, irrelevant, bad and redundant etc. However, in many real-time applications, it may be possible that the redundant or irrelevant features may become relevant while functioning jointly with other features, which makes it one of the most critical tasks to appropriately discriminate these features [2]. An optimal feature subset has the ability to collect corresponding important features [3]. One of the most important optimization techniques is particle swarm optimization (PSO). Though PSO is able to handle the big search spaces effectively and has maximum chances of a global optimal solution [4] [5], it faces several difficulties in using this approach in practice. The main reason is the use of conventional neural network classifiers that have local minima problem, over fitting problem etc. When the number of neurons is more than the required then the network faces the over-fitting problem. And in the opposite case, if the number of neurons in the neural network is less than required, then the classifier will unable to find the target classification function which leads to poor generalization performance. Even if the best optimal feature subset is used, the system degrades its performance due to the use of the poor performance classifier. Hence, in this paper ELM is performed which has established a very good performance in terms of training time, compact network size and simplification.

The main contribution of this paper is to use the Improved genetic PSO based FSS algorithm for ELM classifier with improved classification accuracy by the reduction in the number of features.

The rest of this paper is organized as follows. Section II briefly presents the basics of Extreme Learning Machine and overview of Particle Swarm Optimization. Section III describes the methodology with Improved Genetic - PSO algorithm for feature subset selection algorithm by using ELM classifier. Section IV and section V presents the experimental result and analysis to evaluate the effectiveness of the proposed algorithm respectively. Section VI concludes the work with future directions.

II. Related Work

A. Extreme Learning Machine

The extreme learning machine (ELM) was originally developed in 1992 [6] [7] and can be categorized as a supervised learning algorithm capable of solving linear and nonlinear classification problems. ELM achieves good generalization performance at extremely fast learning speed. Figure 1 shows the basic ELM architecture. To clarify, consider the input data set with N instances and the number of neurons present in the input layer, hidden layer and output layer is *n*, *m*, *k* respectively. The b_i is the bias parameter for i^{th} hidden layer neuron. An activation function g(.) is used to connect input and the output layers by using weight vectors $w_i = (w_{i;1};w_{i;2};\ldots;w_{i;n})^Y$ and $\beta_i = (\beta_{i;1};\ \beta_{i;2};\ \ldots;\ \beta_{i;n})^Y$. The output vector Y_j can be calculated as:

$$Y_j = \sum_{i=1}^{m} \beta_i g_i(x_j) \text{.....(1)}$$

$$Y_j = \sum_{i=1}^{m} \beta_i g(w_i . x_j + b_j) \quad \textit{for } j = 1;\ 2 \ldots N$$

The same equations can be rewritten briefly as:

$$H\beta = Y \text{.....(2)}$$

Where,

$$H = \begin{bmatrix} g(w_1 x_1 + b_1) & .. & g(w_1 x_1 + b_n) \\ : & .. & : \\ g(w_1 x_N + b_1) & .. & g(w_1 x_N + b_n) \end{bmatrix}_{N \times n}$$

$$\beta = \begin{bmatrix} \beta_1^Y \\ : \\ \beta_N^Y \end{bmatrix}_{n \times k} \qquad Y = \begin{bmatrix} y_1^T \\ : \\ y_N^T \end{bmatrix}_{N \times k}$$

The output matrix of the hidden layer is *H* with respect to inputs $x_1, x_2, \ldots x_N$ and Each output weight β is represented as:

$$\beta = H^{\mp} Y \text{.....(3)}$$

$$H^{\mp} Y = (H^Y H)^{-1} H^Y Y \text{.....(4)}$$

ELM has various advantages over back propagation algorithm and SVM in terms of speed, reliability and generalization [8][9]. Though, ELM is unable to handle the uncertain dataset in which it is difficult to assign the exact input to one of the target classes [10]. Such category of the problems; which contain some uncertainty in the input dataset, by itself belongs to the weighted classification problem. The conventional ELM lacks the ability to resolve such type of problem. One of the alternative solutions is F-ELM.

B. Particle Swarm Optimization : An Overview

The PSO is a population based technique developed by Eberhat and Kennedy [11]. PSO is valued global search technique [12] which is suitable to address feature selection problems due to: easy encoding of feature, global search facility, being reasonable computationally, less parameters and easier implementation [13]. The principal space is the search space through which a subset of principal components or principal features were explored and selected via PSO. In PSO, the particles represent candidate solutions in the search space particles and form a population which is also known as a swarm. The swarm of the particle is generated by distributing 1 s and 0 s randomly. For every particle, if the principal component is 1, it is selected and the principal component with 0 is ignored. Thus, every particle indicates a different subset of principal components. The particles swarm is initialized randomly and then it moved in the search space or principal space to search the optimal subset of features by updating its position and velocity. The current position of particle i and its velocity are expressed in (5) and (6):

$$x_i = \{x_{i1}, x_{i2}, x_{i3} \ldots\ldots x_{iD}\} \text{.....(5)}$$

where D is the dimension of the principal search space,

$$v_i = \{v_{i1}, v_{i2}, v_{i3} \ldots\ldots v_{iD}\} \text{.....(6)}$$

The velocity and position of the particle i are calculated by,

$$v_{id}^{t+1} = w * v_{id}^{t} + c_1 * r_{1i} * (p_{id} - x_{id}^{t}) + c_2 * r_{2i} * (p_{gd} - x_{id}^{t}),$$

$$x_{id}^{t+1} = x_{id}^{t} + v_{id}^{t+1},$$

where t is used to show t^{th} iteration and d is used to denote the d^{th} dimension in the search space. Weight is described by w and acceleration constants are illustrated by c_1 and c_2. r_{1i} and r_{2i} are random values uniformly distributed in between [0, 1]. *pbest* and *gbest*, p_{id} and p_{gd} represent the elements of in the d^{th} dimension.

The position and velocity values of each particle are continuously updated to search for the best set of features until stopping criterion is met which can be a maximum number of iterations or a satisfactory fitness value.

III. Methodology

A. Datasets

In this research work, six different datasets are used to evaluate the effectiveness of proposed GPSO like Pima Indian Diabetes (PID), Heart-Statlog (SHD), Ionosphere (IS), Breast Cancer (BC), Australian (AS) and German (GN) [18]. Table 1 summarizes the details of the dataset.

Table 1. Dataset Information [14]

Dataset	Features	Instances	Class1	Class2
PID	8	768	500	268
SHD	13	270	150	120
IS	34	351	126	225
BC	10	699	458	241
AS	14	690	383	307
GN	20	915	644	271

B. Preprocessing

Pre-processing is one of the important tasks for building any efficient model. Data normalization and Feature Subset Selection are used as the pre-processing methods. Data normalization [15] is a key step for various machine learning algorithms, including ELMs. Various attributes present in the dataset have the different scale, due to which the higher range features are dominant over the lower range features. Therefore, it is necessary to convert all features from vector space to unit space, i.e. [0,1].

C. Proposed IG-PSO Algorithm for FSS

Genetic Algorithm is an important technique for FSS which returns optimal feature subset. GA works iteratively with a set of candidate solutions which are also known as population [19]. In each iterative step, three processes are executed like evaluation, selection and recombination process with the help of genetic operators - selection, crossover and mutation. The iteration is repeated till it reaches to some termination condition. Hence, GA has faced the optimal population size problem. As the population size changes, the feature subset is also changed. To solve this problem I-GA algorithm is used [25] which returns the optimal features.

For any model, the wrong input definitely degrades the quality of the system. Hence, it becomes very important to provide an accurate input. Though PSO is one of the best optimization techniques, it initially requires the number of optimal feature as an input which is impossible to simply guess. To overcome the problem, this paper proposes an Improved Genetic PSO algorithm for ELM classifier in which IGA based number of optimal features given as an input to the PSO algorithm. The IG-PSO flow for feature selection is shown in Figure 1.

D. Classification

Classification is a vital process in machine learning and and mining, which is used to categorize every instance in the input dataset into various classes [16]. As classifier plays an important role in system generalization performance; the ELM classifier is used. Table 2 shows the parameters of ELM which are required for experimentation.

Algorithm 1 : Proposed IG-PSO-ELM

Input: A given dataset $X = X_1, X_2, \ldots X_n$
Learner: Classification algorithm = ELM
FSSAlgSet:= IGA(FSSAlg1) and PSO(FSSAlg2), Set of 2 FSS Algorithm
Output: Feature Subset from $S_1, S_2, \ldots S_m$ where m < n and

Begin
Step 1 : (swarm initialization). Randomly initialize the position and velocity of each particle.
nf=IGA() //number of optimal features
Step 2: (particle fitness evaluation)
if fitness of $x_i > pbest_i$
$pbest_i = x_i$
if fitness of $pbest_i > gbest_i$
$gbest_i = pbest_i$
end
Step3 Update the velocity of particle *i*

$$v_{id}^{t+1} = w * v_{id}^{t} + c_1 * r_{1i} * (p_{id} - x_{id}^{t}) + c_2 * r_{2i} * (p_{gd} - x_{id}^{t}),$$

Update the position of particle *i*

$$x_{id}^{t+1} = x_{id}^{t} + v_{id}^{t+1},$$

Step4 If stopping criterion is not met, continue Steps 2 and 3
Step5 Return *gbest* and its fitness values.

Algorithm 1 Proposed IG-PSO-ELM

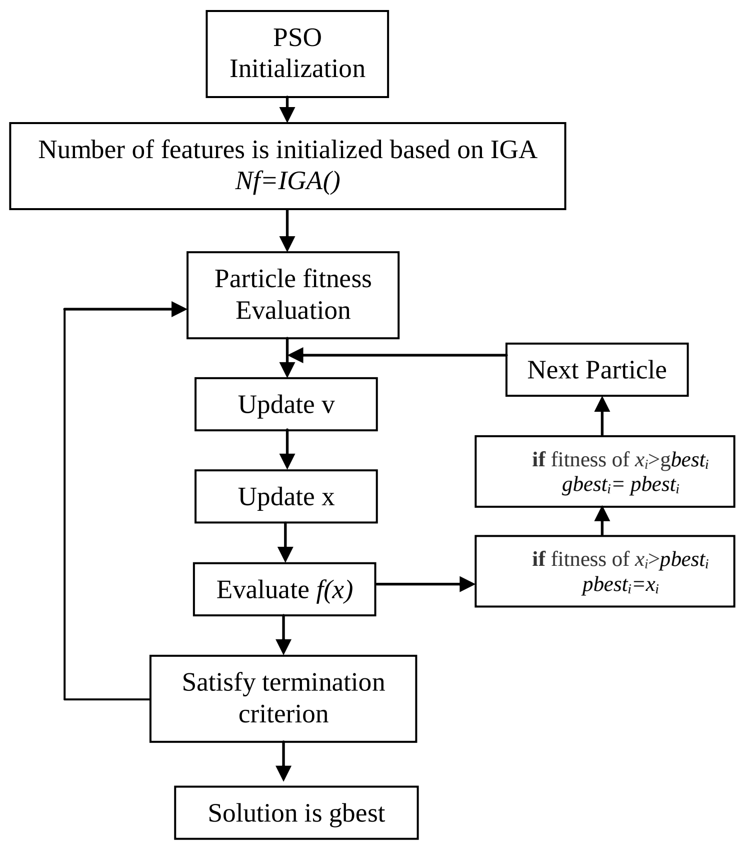

Figure 1. The flow of IG-PSO for Feature Selection

Table 2. Parameters for ELM

Parameter	*Features*
Input Layer Neuron	Same as input features
Output Layer Neuron	2
Hidden Layer Neuron	1:5:200
Activity Function	Sigmoidal
Dataset Division	Training (70%)-Testing (30%)

IV. EXPERIMENTAL RESULTS

Experiments have been conducted using MATLAB cR2014a. The observations are obtained by considering true negatives (TN), true positives (TP), false positives (FP) and false negative (FN) [17]. The accuracy of the classification model on a given test is the percentage of test set that is correctly classified by the classifier [18]. Precision is the measure of correctness of positive labeled examples. Recall is the measure of completeness or accuracy of positive examples that how many examples of the positive class are labeled correctly[19]. In the statistical analysis of binary classification, the F-score or F-measure is a measure of a test's accuracy. F-measure is the harmonic mean of Recall and Precision while the G-measure is the geometric mean [20]. Accuracy, precision, recall (sensitivity), F-measure and G-measure are calculated as per in equations 11 to 15 respectively :

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \quad .....(11)$$

$$\text{Pr}ecision = \frac{TP}{TP + FP} \quad .....(12)$$

$$\text{Re}call = \frac{TP}{TP + FN} \quad .....(13)$$

$$F - measure = 2 * \frac{\text{Pr}ecision * \text{Re}call}{\text{Pr}ecision + \text{Re}call} \quad .....(14)$$

$$G - measure = \sqrt{\text{Pr}ecision * \text{Re}call} \quad .....(15)$$

Figure 2 and Figure 3 depict the IG-PSO results of PID and SHD in terms of the number of iteration and best cost respectively. PID and SHD are reached to the best cost at 13^{th} and 12^{th} iteration respectively. Table 3 shows the results in terms of evaluation metrics accuracy, precision, recall, f-measure and g-measure for all and selected features using proposed IGPSO-ELM. It is indicated that the IG-PSO-ELM is superior to another regarding the aspects of all evaluation measures and it also provides increased generalization performance as compared to traditional ELM.

Figure 4 show the relationship between the features selected using ELM and GPSO-ELM. It is observed that, the proposed - GPSO-ELM selects less features (minimum 20% and maximum 70%) for further analysis or to build a classifier and have the computational advantage of binary classification. Table 4 shows the performance comparison of ELM and IG-PSO ELM with reduction rate of features. With the results, it is inferred that due to the selection of optimal features which are relevant and non-redundant, the classification accuracy is improved.

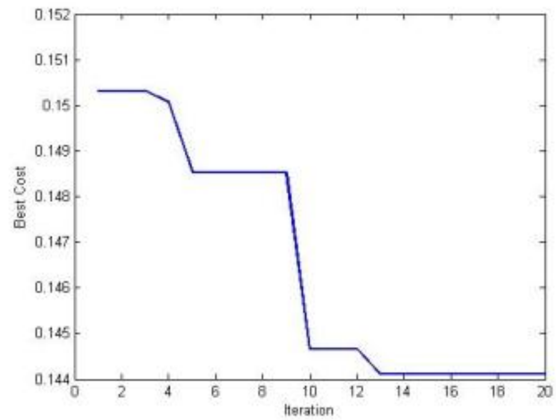

Figure 2 Results of PSO for PID

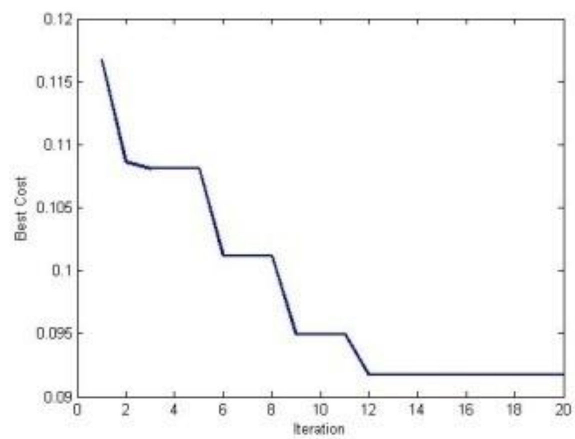

Figure 3 Results of PSO for SHD

V. RESULTS AND DISCUSSION

For benchmark problem, IGA-PSO-ELM algorithm is compared with previously available traditional FSS methods for PID and SHD datasets as shown in Table 5 and Table 6 respectively. The existing traditional classifier and FSS methods like multilayer NN (MLNN) [24], Improved GA [21], Hybrid approach for FELM [22], Mean selection method (MS) [23], Half selection method (HS) [23], NN for threshold selection (NN for TS) [23], PNN [24], Particle Swarm Optimization (PSO)-ELM [25], Self Regularized PSO-ELM [25], Evolutionary product-unit neural networks EPUNN [26], ESNN [26] and Multi-logistic Regression EPUNN [27]. It is observed that the classification accuracy, specificity and sensitivity of the proposed algorithm gives increased generalization performance.

Table 3 Evaluation Metrices

Dataset	*Accuracy*		*Precision*		*Recall*		*F-measure*		*G-measure*	
	ELM	*IG-PSO-ELM*	*ELM*	*GPSO-ELM*	*ELM*	*GPSO-ELM*	*ELM*	*GPSO-ELM*	*ELM*	*GPSO-ELM*
PID	69.8885	80.56	91.404	91.35	70.7317	80.87	79.75	85.7911	80.4062	85.9504
SHD	77.7778	90.48	85.5769	94.23	76.7241	89.09	80.9091	91.5879	81.0297	91.624
BC	85.102	95.92	83.7288	96.95	90.8088	96.3	87.1252	96.6239	87.197	96.6245
IS	84.898	96.3	75.4098	95.9	92.9293	96.69	83.2579	96.2934	83.7125	96.2942
AS	73.706	94	81.6479	93.63	73.6486	95.42	77.4423	94.5165	77.5452	94.5208
GN	71.5625	80.16	94.6903	94.24	73.0375	80.8	82.4663	87.004	83.1622	87.2616

Table 4 Performance comparison of ELM and GA-ELM with reduction rate of features

Datasets	**ELM (%)**	**IG-PSO-ELM(%)**	**Improved Accuracy(%)**	**Total Number of features present in the dataset**	**Total Number of features present in the optimal feature subset**	**Reduction in Number of features (%)**	**Use of number of features (%)**
PID	69.8885	80.56	10.68	8	3	63	37
SHD	77.7778	90.48	12.71	13	5	62	38
Ionosphere	85.102	95.92	10.82	34	7	80	20
BC	84.898	96.3	11.41	10	7	30	70
Australian	73.706	94	20.3	14	4	72	28
German	71.5625	80.16	8.6	20	7	65	35
Average			**12.41**	-	**5.5**	**62**	**38**

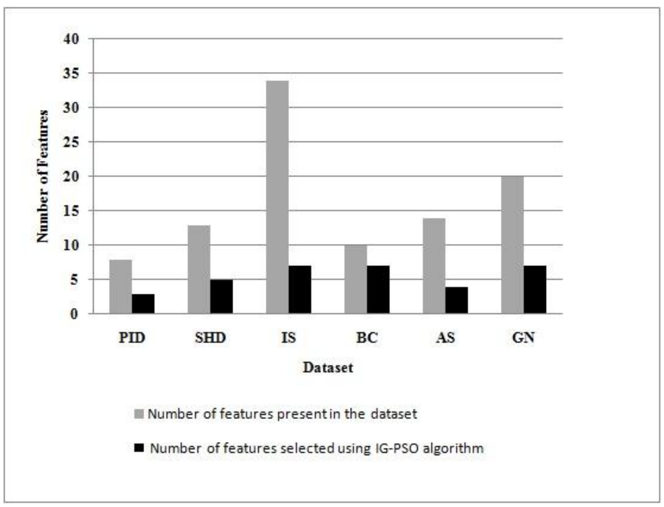

Figure 4 Features selection using proposed IGA-PSO for ELM

Figure 5 describes the relationship between the ELM and IGPSO-ELM for all datasets. It is noticed that IGPSO-ELM provides improved performance as compared to others ELM.

Table 5. Classification results with PID

Methodology	*Accuracy (%)*	*Sensitivity (%)*	*Specificity (%)*	*Selected Features*
IGA-PSO-ELM	**80.56**	**80.87**	**79.72**	**2,6,8**
IGA-ELM [21]	77.82	-	-	2,5,6
MS[23]	76.04	71	78	2,6,8
HS[23]	75.91	69	79	1,2,6,8
NNfor TS[23]	76.04	71	78	2,6,8
PNN [24] (10*FC)	78.05	71	70.5	2,6,8
MLNN with LM [24] (10*FC)	79.62	70	70.31	1,2,6,8

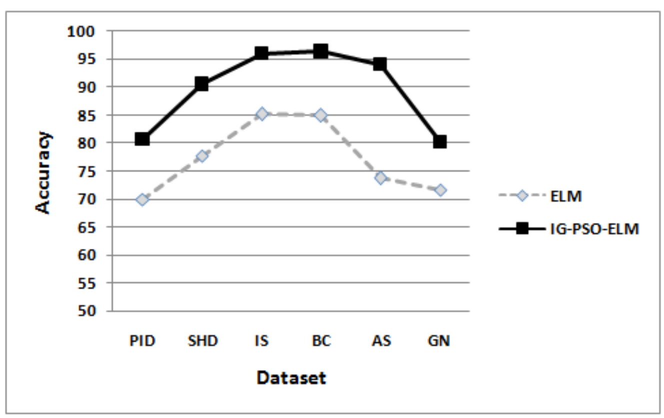

Figure 5 Benchmark Comparison of ELM and proposed IGPSO-ELM

Table 6. Classification results with SHD

Methodology	*Accuracy (%)*	*Sensitivity (%)*	*Specificity (%)*	*Selected Features*
IGA-PSO-ELM	**90.48**	**89.09**	**92.4**	**3,7,10,12,13**
IGA-ELM [21]	83.95	-	-	1,2,3,9,12
SRLPSO – ELM [25]	89.96	87.79	88.42	11,12,13
PSO-ELM [25]	85.88	86.00	86.03	3,11,12,13
MS[23]	84.44	85	84	3,8,9,11,12,13
HS[23]	84.81	85	84	3,8,9,10,11,12,13
NN for TS [23]	85.19	85	86	3,11,12,13
ESUNN[26]	83.22	84.32	81.65	3,8,9,11,12
EPUNN[26]	81.89	83.67	84.91	8,9,11,12
MR + EPUNN[27]	83.12	78.15	80.59	8,9,11,12, 13

VI. CONCLUSION

In this paper, feature selection by Improved Genetic Particle Swarm Optimization for ELM classifier (IG-PSO-ELM) is introduced. IG-PSO-ELM is able to improve the classification accuracy by minimizing the number of features. The proposed algorithm performs satisfactorily on several datasets with the key advantages of less learning (training) time, high speed, optimal feature selection and better generalization performance. For the benchmark, the IG-PSO-ELM is compared with ELM, IG-ELM and PSO-existing classifier. The proportional average analysis shows that on an average 12.41% classification accuracy is increased by reducing 62% number of features. Presently, the results are evaluated for binary classification problem. In future, the same work will be extended to multiclass classification and one-class classification problem.

REFERENCES

[1] L. Yu and H. Liu, "Efficient feature selection via analysis of relevance and redundancy", Journal of machine learning research, pp. 1205-1224, 2014.

[2] Kittler,J. and aan den Rijn, Netherlands, "Feature Set Search Algorithms", , Pattern Recognition and Signal Processing, Chapter pp. 41-60, 1978.

[3] D. Koller and M. Sahami, Toward optimal feature selection, Tech.rep. Stanford InfoLab, 1996.

[4] Zhi-Hui Zhan, Jun Zhang, Yun Li and Henry Shu-Hung Chung, " Adaptive Particle Swarm Optimization", IEEE Trans. On Systems, Man, and Cybernetics- Part B, vol. 39,no. 6, December 2009.

[5] Iftikhar Ahmad,"*Feature Selection Using Particle Swarm Optimization in Intrusion Detection*",International Journal of Distributed Sensor Network, January 2015.

[6] G.-B. Huang, Q.-Y. Zhu and C.-K. Siew, "*Extreme learning machine: a new learning scheme of feedforward neural networks*", In proceedings. IEEE International Joint Conference., vol. 2., pp. 985-990, 2004.

[7] G.-B. Huang, Q.-Y. Zhu and C.-K. Siew, "*Extreme learning machine:theory and applications*", Neurocomputing 70 (1), pp. 4

[8] 89501, 2006.

[9] G.-B. Huang, L. Chen, and C.-K. Siew, "*Universal approximation using incremental constructive feedforward networks with random hidden node*", IEEE Tranactions on. Neural Network, vol. 17., no. 4., pp. 879-892, 2006.

[10] G.-B. Huang, H. Zhou, X. Ding and R. Zhang, "*Extreme learning machine for regression and multiclass classification*", IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics) 42 (2), pp. 513-529, 2012.

[11] G.-B. Huang, "*An insight into extreme learning machines: Randomneurons, random features and kernels*", Cognit. Computat, vol. 6., no.3., pp. 376-390, 2014.

[12] R. Eberhart and J. Kennedy, "*New optimizer using particle swarm theory*," In Proceedings International Symposium on Micro Machine and Human Science, pp. 39–43,October 1995.

[13] B. Xue, M. Zhang, and W. N. Browne, "*Particle swarm optimization for feature selection in classification: amulti-objective approach*," IEEE Transactions on Cybernetics, vol. 43, no. 6, pp. 1656–1671, 2013.

[14] B. Xue, M. Zhang, and W. N. Browne, "*Particle swarm optimisation for feature selection in classification: novel initialisation and updating mechanisms*", Applied Soft Computing Journal, vol. 18, pp. 261–276, 2014.

[15] M. Lichman, UCI machine learning repository. URL http://archive.ics.uci.edu/ml, 2013. UCI repository

[16] Akusok, A., Bj¨ork, K.-M., Miche, Y., Lendasse, A., "*High-performance extreme learning machines: a complete toolbox for big data applications*". IEEE Access 3, 1011–1025, 2015.

[17] G. Karakaya, S. Galelli, S. D. Ahipa sao glu and R. Taormina, "*Identifying (quasi) equally informative subsets in feature selection problems for classification: a max-relevance min-redundancy approach*", IEEE transactions on cybernetics 46 (6), pp. 1424-1437,2016.

[18] Nahato, K. B., Nehemiah, K. H., Kannan, A, " *Hybrid approach using fuzzy sets and extreme learning machine for classifying clinical datasets*", Elsevier Journal of Informatics in Medicine Unlocked 2, 1–11, 2016.

[19] Han, J., Pei, J., Kamber, M., 2011. Data mining: concepts and techniques. Elsevier.

[20] Mahdiyah, U., Irawan, M. I., Imah, E. M., *"Integrating data selection and extreme learning machine for imbalanced data"*. Procedia Computer Science 59, 221–229, 2015.

[21] Parikh, R., Mathai, A., Parikh, S., Sekhar, G. C., Thomas, R., *Understanding and using sensitivity, specificity and predictive values*. Indian journal of ophthalmology 56 (1), 45, 2008.

[22] Archana Kale and Shefali Sonavane, "*Optimal Feature Subset Selection for Fuzzy Extreme Learning Machine using Genetic Algorithm with Multilevel Parameter Optimization*", IEEE International conference on Signal and Image Processing Applications pp.445-450, Septmber 2017.

[23] A. Kale and S. Sonavane, "*Hybrid Feature Subset Selection Approach for Fuzzy-Extreme Learning Machine*", Springer journal of Computational Intelligence and Complexity - Data Enabled and Discovery Applications, September 2017.

[24] D. C¸ alis¸ir, E. Do˘gantekin, "*An automatic diabetes diagnosis system based on LDA-wavelet support vector machine classifier",* Expert Syst. Appl. 38(7), 8311–8315, 2011.

[25] H. Temurtas, N. Yumusak, F. Temurtas, "*A comparative study on diabetes disease diagnosis using neural networks*". Expert Syst. Appl. **36**(4), 8610–8615, 2009.

[26] C.V. Subbulakshmi, S.N. Deepa, "*Medical dataset classification: a machine learning paradigm integrating particle swarm optimization with extreme learning machine classifier*", Scientific World Journal 2015.

[27] F.J. Marti´ınez-Estudillo, C. Herv´as-Mart´ınez, P.A. Guti´errez, A.C. Mart´ınez-Estudillo, "*Evolutionary product-unit neural networks classifier"s*. Neurocomputing **72**(1), 548–561, 2008.

[27] C. Herv´as-Mart´ınez, F.J. Mart´ınez-Estudillo, M. Carbonero-Ruz, "*Multilogistic regression by means of evolutionary product-unit neural networks"*. Neural Netw. **21**(7), 951–961, 2008.

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