Journal of Theoretical and Applied Information Technology
15th April 2018. Vol.96. No 7

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

EARLY WARNING SYSTEM FOR CERVICAL CANCER DIAGNOSIS USING RIDGE POLYNOMIAL NEURAL NETWORK AND CHAOS OPTIMIZATION ALGORITHM

[1]ROCKY YEFRENES DILLAK, [2]GLORIA CHRISTIANA MANULANGGA, [3]JANSEN LOUDWIK LALANDOS

[1, 2] Department of Electrical Engineering, Politeknik Negeri Kupang, Kupang, Indonesia

[3] Department of Obstetrics and Gynecology, Faculty of Medicine, University of Nusa Cendana, Indonesia

E-mail: [1]rocky_dillak@yahoo.com, [2]gloriamanulangga@gmail.com, [3]drjansen_fkundana@yahoo.com

ABSTRACT

Cervical cancer is one of the most dangerous cancer among women. Detecting this cancer earlier could prevent the subject from cancer. The aim of this paper is to propose a method that can be used as an early warning system for cervical cancer diagnosis. Thirteen questions about subject sexuality background were used as the significant parameters to determine whether the subject is a suspect of cervical cancer or not. These parameters also were used as the input variable to the classifier. This research hybridized Ridge Polynomial Neural Network with Chaos Optimization Algorithm as classifier. The results of this study showed that the proposed approach reached the sensitivity of 95.56%, specificity of 96.67% and accuracy of 96 %.

Keywords: *Cervical Cancer Diagnosis, Early Warning System, Ridge Polynomial Neural Network, Chaos Optimization*

1. INTRODUCTION

Cervical cancer is a primary malignant tumor of the cervix [1]. This disease is the second most types of cancer in women after breast cancer. The main cause of cervical cancer is infection Human Papilloma Virus (HPV) specific strain. In Indonesia, the estimated incidence of cervical cancer is 16 per 100,000 women. In Kupang Indonesia, One of the factors causing the high number of cases of advanced cancer is a tendency to not go to the doctor for fear of being diagnosed with cancer [2]

Medical examination of a suspect of cervical cancer patients was conducted by a pap smear test and IVA. Pap smear test is an examination of the cervix using a speculum while the IVA using a solution of acetic acid and iodine Lugol [3]. However, the lack of knowledge and awareness among women as well as culture especially in developing countries about cervical cancer, are some of the factors that contributed to this disease being diagnosed late.

One possible method that can be used to detect this cancer earlier is conducted by interviewing the subjects about their sexuality background. However with the number of questions to be asked and the number of suspects to be interviewed will causing the more resources to be needed. Hence the use of computer-aided diagnosis as an early warning system to screen cervical cancer will help in decreasing the mortality rate caused by this disease

Machine learning is a branch of science that uses artificial intelligence algorithms to solve problems such as prediction, detection, and classification [4]. It works by learning a set of data subsequently recognizing new data that are similar to data patterns that have been learned. One of the algorithms often used in machine learning is the artificial neural network (ANN) with backpropagation learning algorithm. Nevertheless, the weakness of this algorithm is easily trapped in local minima making it difficult to achieve the best recognition accuracy even been trained continuously [5].

Research conducted by Yu and Deng [6] explained that Ridge Polynomial Neural Network (RPNN) could produce recognition rate better than backpropagation algorithm. However, the process of learning pattern in RPNN requires plenty of time

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

because it uses a mathematical model that is more complex than backpropagation. Moreover, this might become more complex when the number of inputs to the model and the number of training examples becomes extremely large, the training procedure for the neural network becomes tremendously slow and tends to be trapped in local minima. Therefore algorithms that can be used to accelerate the training time of ANN are urgently needed. Sulistiyo et. al [7] proposed the approach to reduce the training time of backpropagation neural network by adding weight optimization. They used the genetic algorithm (GA) to train neural network architecture. The results of this research proved that GA could accelerate and increase the recognition rate of ANN better than without GA. However in [8], [9] and [10] proved that chaos optimization algorithm (COA) indicated a great performance in searching and optimizing rather than GA. Nevertheless, the hybrid of COA and RPNN has not been used as an early warning system for diagnosing cervical cancer.

In this paper, we have proposed an early warning system for cervical cancer diagnosis using RPNN and COA

2. LITERATURE REVIEW

The use of chaos algorithm to increase the weights search of ANN was conducted by some researcher.

Khoa and Nakagawa [11] conducted a research to initialize backpropagation weights by using Chaos Optimization Algorithm. The chaos variable is the map logistics. The algorithm consists of two steps: breadth search and depth search. The breadth search interval is set to [-50, +50] and the depth search interval is set to [-2, +2]. The objective function is the least mean square error between the network output and the target output. the results obtained from this study showed that Chaos optimization algorithm always reaches global minimum and more easily to escape from local minima than other stochastic methods

Velasquez [12] studied an improved of chaos optimization algorithms using BFGS method (Broyden, Fletcher, Goldfarb, and Shanno) to optimize nonlinear functions. In traditional COA, the first search uses 5000 iterations and for a second search it uses 10,000 iterations. The initial narrowing range p is 0.1. The result of a new COA is able to find better and faster solutions than traditional chaotic optimization algorithms and other competitive techniques.

Ling, et.al [13] proposed backpropagation (BP) optimized by chaos algorithm for fault diagnosis. It was proved that BP COA could produce better accuracy than conventional BP. The similar research also conducted in [14] which they hybridized the backpropagation neural network with COA. The purpose of this research is to use COA as weights searching in order to accelerate the training time of neural network. Based on the result of this paper, COA could reduce error and training time better than standard backpropagation. The similar research was also conducted in [15]. In their research, a backpropagation was combined with COA in daily rainfall-runoff forecasting. The results show that the proposed method was better than other neural networks in providing good accuracy. Zhang, et. al [16] evaluated recurrent neural network performance with COA in image analysis. The comparison showed that the hybrid of the recurrent neural network with COA indicated superior performance to a traditional recurrent neural network. Hu, et.al [17] carried a research using elman neural network with COA to predict PM2.5. The PM2.5 is a significant parameter that is used to grade the quality of air. The result of this research showed that the proposed algorithm reached root mean square error better than standard elman neural network.

The research about Ridge Polynomial Neural Network (RPNN) in machine learning was proposed by some researcher. Since was originally introduced in [18], most recent studies indicated that this algorithm has a promising result in many areas such as forecasting, classification and detection. Waheeb et al. [19] conducted a study to predict time series data using ridge polynomial neural networks (RPNN). RPNN shows good results with fast convergence on a variety of noisy signals. The predicted results show that this algorithm generates higher profits when was compared with MLP, FLNN, and PSNN. The major complexity of using RPNN is finding the best parameters to be added sequentially to higher order pi-sigma units in the network. however, the proposed method showing the considerable expectations as a decision-making tool. The work conducted in [20] described a microwave characterization using RPNN. They evaluated this algorithm performance by comparing with BP neural network. The result showed that RPNN could produce significant accuracy than other neural network. Therefore, the use of RPNN algorithm has performed good results in many areas of science and engineering [21]

Journal of Theoretical and Applied Information Technology
15th April 2018. Vol.96. No 7

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

3. PROPOSED METHOD

3.1 Data

Data used in this study were collected from Leona Hospital, Kupang city, Indonesia. We used 400 subjects which 250 were used for training and 150 were used for testing. All of these data were observed manually by experts and each record was labeled '1' which corresponded to cervical cancer suspect and '0' which corresponded to non-suspect

Each subject was evaluated by thirteen (13) questions that also were used as input variables to RPNN. The variables used and its corresponding value as shown in Table 1.

3.2 Chaos Optimization Algorithm

The aim of using COA is to find the most optimum weights of RPNN in order to accelerate the training and increase the accuracy of recognition the patterns

1) *Set the number of iteration k=1, a temporary error and initialize:*
   $\gamma_i(k) = \mu\gamma_i(k-1)(1-\gamma_i(k-1))$
2) $x_i(k) = a_i + \gamma_i(k)(b_i - a_i)$
3) *Compute Objective function f(x) based on least mean square error* $E = \frac{1}{2}\sum_{p=1}^{N}(d_p - y_p)^2$

Check if f(x) reaches b_error, obtains x^* *as a temporary optimum and go to step 4) otherwise repeat step 1)*

4) *Decrease current error slightly into tolerated error*

Current_error = η * b_error

Where η *is decreased factor*

5) $\gamma_i(k) = \mu\gamma_i(k-1)(1-\gamma_i(k-1))$
6) $x_i(k) = x^* + a_i + \gamma_i(k)(b_i - a_i)$
7) *Compute Objective function f(x) based on least mean square error* $E = \frac{1}{2}\sum_{p=1}^{N}(d_p - y_p)^2$

Check if f(x) reaches current_error go to step 9) otherwise, go to step 8)

8) *Check if reaches limit iteration, it is not a global optimum go to step 1) otherwise go to step 5)*
9) *Check if reaches d_error, obtains* x^* *as global optimum otherwise go to step 4)*

3.3 Ridge Polynomial Neural Network

The architecture of the classifier used in this paper as shown in Fig 1

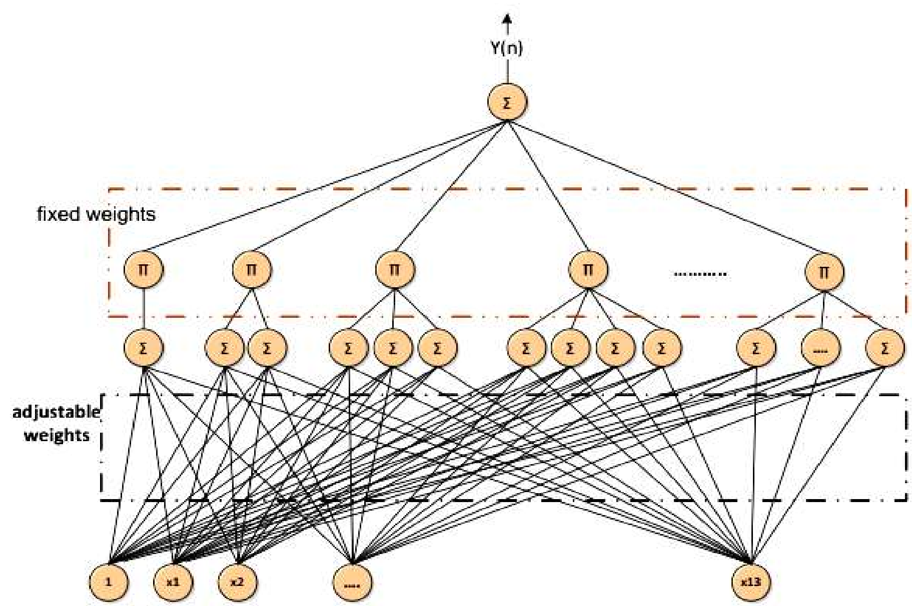

Figure 1: Architecture of RPNN

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

RPNN is the artificial neural network that consists of 3 layers namely input layer with adjusTable weights, Pi-Sigma Network (PSN) with fixed weights and output layer. The RPNN algorithm is summarized as follows:

1) Set the N =1 (the order of PSN)
2) Train and update the weights and biases using COA for each pattern
3) Observe the error of PSN, if it has reached threshold th, then increase the order N

$$\left| \frac{e_{(n)} - e_{(n-1)}}{e_{(n-1)}} \right| < \text{th}$$

4) Reduce threshold th and learning rate n by multiplying with dec_th and dec_n
5) Repeat steps 2 to 4 until the maximum iteration is reached

Meanwhile, we summarized the following algorithm to train and update the RPNN classifier :

1) Set all parameters of RPNN such as stopping criteria, number of PSN order and learning rate
2) Set N (the order of Pi-Sigma)
3) Assign weights and biases obtained from COA
4) For each pattern, repeat steps 5 to 7
5) compute PSN layer using formula

$$h_j = \sum_k w_{kj} x_k + \Theta_j$$

$$y_{PSN} = f\left(\prod_j h_j\right)$$

6) Compute delta weights and biases of PSN using equation :

$$\delta_l = \eta (d - y) y' \prod_{\substack{z = 1 \\ z \neq l}}^{j} h_z$$

$$\Delta w_{kl} = \delta_l x_k$$

$$\Delta w_{0l} = \delta_l$$

7) Update weights and biases
8) Compute MSE using the following formula:

$$e^2 = \frac{1}{2 * p} \sum_p (d^p - y^p)^2$$

If e <= expected error, go to step 9 otherwise perform steps 4 to 8
9) Calculate output layer of RPNN using the equation :

$$y_{RPNN} = \sum_{j=1}^{N} \prod_{i=1}^{j} \left(\sum_{k=1}^{n} w_{ijk} x_k + \theta_{ji} \right)$$

10) Repeat steps 3 to 8 until reached maximum number of PSN order (N)

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Table 1: Variables used

Variable	Attribute	Possible outcomes	Values
x1	The current age of subject		$\frac{0,8(x-x_{\min})}{(x_{\max}-x_{\min})}$ (1)
x2	The age when subject became sexuality active	< 18 years	1
		> 18 years	0
x3	Cervical cancer history in subject family	yes	1
		no	0
x4	Active smoker	yes	1
		no	0
x5	Had different sexual partners	yes	1
		no	0
x6	The use of hormonal contraception	always	0
		occasionally	0,5
		Never used	1
x7	Number of children	<> 3 children	1
		> 3 children	0
x8	vaginal discharge	yes	1
		no	0
x9	Bleeding outside the menstrual period	yes	1
		no	0
x10	Bleeding after sex	yes	1
		no	0
x11	Pain in the pelvis	yes	1
		occasionally	0,5
		no	0
x12	Urinating disorders	yes	1
		no	0
x13	Tenderness around vagina	yes	1
		occasionally	0,5
		no	0
t	Output	suspect	1
		non-suspect	0

From Table 1, x1 was normalized using equation (1) which x_{min} and x_{min} represent the maximum age and minimum age of the data set. The examples of data used in this paper as shown in Table 2

Journal of Theoretical and Applied Information Technology
15th April 2018. Vol.96. No 7

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Table 2 : The Examples of data used in training phase

ID	x1	x2	x3	x4	x5	x6	x7	x8	x9	x10	x11	x12	x13	t
DT-0003	0,748	1	0	1	1	0	0	0	1	1	0.5	1	1	1
DT-0014	0,708	1	1	1	1	1	1	0	1	1	0.5	1	1	1
DT-0156	0,515	1	1	1	0	0.5	0	0	1	1	0.5	1	0,5	1
DT-0015	0,789	1	0	0	1	1	0	0	1	0	1	0	0,5	0
DT-0016	0,778	1	1	1	1	0	1	1	1	0	0.5	1	1	1
DT-0017	0,677	1	1	1	1	0.5	1	0	1	0	0.5	1	1	1
DT-0018	0,556	1	1	1	1	0	0	1	0	1	1	1	0,5	1
DT-0019	0,586	1	0	0	1	0.5	1	0	1	1	0.5	1	0	1
DT-0020	0,525	1	1	1	0	0	1	1	1	1	1	0	0	1
DT-0026	0,697	1	1	1	1	0	1	0	0	1	1	0	0	0
DT-0027	0,627	1	0	1	0	0.5	1	0	0	0	0.5	0	0	0
DT-0028	0,151	1	1	1	1	1	1	1	0	0	0	1	1	1
DT-0004	0,556	1	1	1	1	0	1	1	1	1	0.5	1	1	1
DT-0029	0,414	1	1	0	1	0.5	0	1	0	0	0	0	0	0
DT-0030	0,566	1	0	0	0	0	0	0	0	0	0	0	0	0
DT-0031	0,728	1	0	1	0	1	0	0	1	0	1	1	0	0
DT-0032	0,677	1	1	0	0	1	0	0	0	0	0	0	0	0
DT-0033	0,404	1	1	1	1	1	1	1	1	0	1	1	0,5	1
DT-0034	0,252	1	0	0	0	0.5	0	1	0	1	0	0	0,5	0
DT-0035	0,242	1	1	0	1	0	0	1	0	0	0	0	0,5	0
DT-0036	0,566	1	0	0	0	0	0	0	0	1	0	0	0	0
DT-0037	0,586	1	0	0	0	0	0	0	0	0	1	0	0	0
DT-0038	0,556	1	0	1	0	0.5	0	0	0	0	0	0	0	0
DT-0006	0,434	1	1	1	1	1	0	1	0	1	0.5	1	0,5	1
DT-0039	0,535	1	0	1	0	1	0	0	0	1	0.5	0	0	0

Variable t from Table 2 denotes output for the neural network. Value ‘0’ means that the record is a non-suspect of cervical cancer and value ‘1’ means that the record is a suspect of cervical cancer.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

4. RESULTS AND DISCUSSION

In this experiments, we varied the number of PSN order from 4 to 7. Meanwhile, the decreased factor of learning rate was set to 1.7 and the decreased factor of threshold error was set to 10. Thus the threshold error will be multiplied by 10 at each epoch. In the training phase, we adjusted parameters such as learning rate and the network order of the neural network (N) to find the best structure that shall be used in the next steps. We used error threshold of 0,0002 to search the best structure and learning rate of the RPNN

Table 3: The results obtained from architecture 13-4-1

Learning rate	MSE
0.1	0.00022416
0.2	0.00024059
0.3	0.00022227
0.4	**0.00021045**
0.5	0.00078841
0.6	0.000278854
0.7	0.000278853
0.8	0.00022559
0.9	0.000278853

Table 4: The results obtained from architecture 13-5-1

Learning rate	MSE
0.1	0.00022453
0.2	**0.00022096**
0.3	0.000278850
0.4	0.000278851
0.5	0.000278853
0.6	0.000278829
0.7	0.000278848
0.8	0.000278852
0.9	0.000278644

Table 5: The results obtained from architecture 13-6-1

Learning rate	MSE
0.1	**0.0022093**
0.2	0.002212
0.3	0.0022131
0.4	0.00278852
0.5	0.0104362
0.6	0.0022164
0.7	0.0278853
0.8	0.0278851
0.9	0.0278855

Table 6: The results obtained from architecture 13-7-1

Learning rate	MSE
0.1	0.000278849
0.2	0.0002510
0.3	**0.0001019**
0.4	0.000278854
0.5	0.00022166
0.6	0.000278846
0.7	0.00022357
0.8	0.000278800
0.9	0.000278848

Based on the results from Table 3, Table 4 Table 5 and Table 6, it can be seen that the structure of 6-7-1 and learning rate of 0,3 produced MSE smaller than others. Therefore these parameters shall be used to train and test the neural network in order to measure the performance of the proposed approach

We evaluated the performance of RPNN + COA with RPNN approach by comparing their errors and CPU time during training. The results as shown in Table 2 and Table 3

Table 7: Training Error Comparison of Different Structure

N	Algorithms	E1	E2	E3	E4	E5
4	RPNN	0,001	0,008	6E-04	0,002	6E-04
	RPNN + COA	2E-05	1E-04	4E-05	5E-04	3E-05
5	RPNN	0,0011	2E-04	2E-05	1E-04	7E-04
	RPNN + COA	8E-05	1E-04	6E-05	3E-05	6E-06
6	RPNN	0,0007	9E-04	7E-04	6E-04	8E-05
	RPNN + COA	2E-05	5E-06	2E-05	9E-05	1E-04
7	RPNN	0,0007	2E-05	6E-05	2E-04	1E-04
	RPNN + COA	4E-06	7E-06	3E-05	4E-05	3E-06

From Table 7, the average error obtained from network order model N=7 better than others. Therefore this network structure shall be used to perform testing phase

Table 8: Average Error and Training Time Comparison

Algorithms	Avg Error	Training Time
RPNN	0,000208	32,81
RPNN + COA	1,79E-05	26,66

Based on Table 7 and Table 8, the average error and training time of the proposed model produced a better result. RPNN without COA only reached MSE of 0,0002 meanwhile RPNN + COA reached MSE smaller than RPNN namely 1,79E-05. At the same time, CPU time consuming of the proposed approach also showed the significant result when reached convergence. The comparison of the proposed method and traditional method errors during training as depicted in Fig 2.

After being trained continuously, in the testing phase, the proposed method was tested with 150 records to measure the performance of the model in recognizing records whether is a suspect or non-suspect data. The results of this experiment were assessed using sensitivity, specificity, and accuracy.

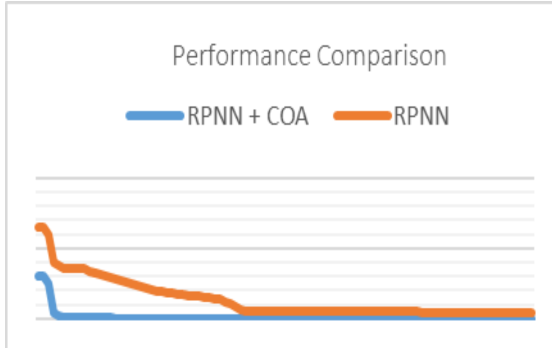

Figure 2: Error Comparison

The formula for these measurements as follows [22] :

$$Sensitivity = \frac{TP}{TP + FN} \quad (2)$$

$$Specificity = \frac{TN}{TN + FP} \quad (3)$$

$$Accuracy = \frac{TN + TP}{TN + TP + FN + FP} \quad (4)$$

Where TP: True Positive, TN: True Negative, FP: False Positive, and FN: False Negative.

Table 9: Results of TP TN FP and FN

Algorithms	TP	TN	FP	FN
RPNN	83%	50%	10%	7%
RPNN + COA	86%	58%	2%	4%

From Table 9 and using equation 2, 3 and 4, we obtained sensitivity, specificity, and accuracy as shown in Table 5

Table 10: Sensitivity, Specificity, and Accuracy

Algorithms	Sensitivity	Specificity	Accuracy
RPNN	92,22%	83,33%	88,67%
RPNN + COA	95,56%	96,67%	96%

Table 10 showed that the proposed method achieved the accuracy of 96% higher than conventional approach 88.67%. The significant result also indicated by specificity, which the RPNN + COA produced 96,67% higher than RPNN 83,33 %

5. CONCLUSION

In this study, we have developed a method as early warning system for cervical cancer diagnosis. Based on experiments, the use of Chaos optimization algorithm could accelerate the convergence speed of Ridge Polynomial Neural Network. This hybridized model has produced better results comparing to the previous method RPNN without COA. Therefore, the method could be used as an early warning system for the cervical cancer diagnosis. The further study will be focused on postprocessing methods to reduce the input variables of the RPNN

ACKNOWLEDGMENT: The work of this paper is supported by The Ministry of Research, Technology and Higher Education of the Republic of Indonesia under scheme **Junior Lecturer Grant 2017 (ID: 42d/PL23.2/PL/2017)**

REFERENCES:

[1] Rasjidi, I., 2010a. *Epidemilogi Kanker pada Wanita.* Jakarta: CV Sagung Seto

[2] The Ministry of Health of Republic of Indonesia, 2015. Buletin Kanker. [Online] available at: http://www.depkes.go.id/resources/download/pusdatin/buletin/buletin-kanker.pdf

[3] Rasjidi, I., 2010b. *Imaging Ginekologi Onkologi.* Jakarta: CV Sagung Seto

[4] Camastra F., Vinciarelli A. (2015) Machine Learning. In: Machine Learning for Audio, Image and Video Analysis. Advanced Information and Knowledge Processing. Springer, London

[5] Samarasinghe, S. (2006). Neural Networks for Applied Sciences and Engineering. New York: Auerbach Publications.

[6] Yu, X. & Deng, F. Neural Comput & Applic (2013) 22(Suppl 1): 333. doi:10.1007/s00521-012-0915-4

[7] Mahmud Dwi Sulistiyo, R. N. Dayawati and Nurlasmaya, "Evolution strategies for weight optimization of Artificial Neural Network in time series prediction," *2013 International Conference on Robotics, Biomimetics, Intelligent Computational Systems*, Jogjakarta, 2013, pp. 143-147

[8] Xiaolan Wu and Guifang Guo. "A hybrid global optimization algorithm based on parallel chaos optimization and outlook algorithm". *J. Chem. Pharm*. Res., 2014, 6(7):1884-1889

[9] Adeli H. (2010) Wavelet-Chaos-Neural Network Models for EEG-Based Diagnosis of Neurological Disorders. In: Kim T., Lee Y., Kang BH., Slezak D. (eds) Future Generation Information Technology. FGIT 2010. Lecture Notes in Computer Science, vol 6485. Springer, Berlin, Heidelberg

[10] Pradeepkumar D., Ravi V. (2014) FOREX Rate Prediction Using Chaos, Neural Network and Particle Swarm Optimization. In: Tan Y., Shi Y., Coello C.A.C. (eds) Advances in Swarm Intelligence. ICSI 2014. Lecture Notes in Computer Science, vol 8795. Springer, Cham

[11] Khoa T. Q. D. dan Nakagawa M., 2007, Neural Network Learning based on Chaos, International Journal of Computer and Information Engineering 1:2 2007

[12]Velasquez, J. D., 2010, An Enhanced Hybrid Chaotic Algorithm using Cyclic Coordinate Search and Gradient Techniques, revista de ingenieria. Universidad de los Andes. Bogota, Colombia. rev.ing. ISSN. 0121-4993. Julio – Diciembre de 2010, pp.45-53.

[13] Ling L., Huang Y., Qu L. (2010) Research on Fault Diagnosis Based on BP Neural Network Optimized by Chaos Ant Colony Algorithm. In: Tan Y., Shi Y., Tan K.C. (eds) Advances in Swarm Intelligence. ICSI 2010. Lecture Notes in Computer Science, vol 6145. Springer, Berlin, Heidelberg

[14] Zhou F., Lin X. (2014) Research of Training Feedforward Neural Networks Based on Hybrid Chaos Particle Swarm Optimization-Back-Propagation. In: Huang DS., Han K., Gromiha M. (eds) Intelligent Computing in Bioinformatics. ICIC 2014. Lecture Notes in Computer Science, vol 8590. Springer, Cham

[15] M. Chettih, K. Chorfi and K. Mouattah, "Combining a neural network with deterministic chaos theory using phase space reconstruction for daily rainfall-runoff forecasting," 2015 12th International Symposium on Programming and Systems (ISPS), Algiers, 2015, pp. 1-7. doi: 10.1109/ISPS.2015.7244983

[16] Zhang, Y., Liu, M., Ma, B. et al. Neural Comput & Applic (2017) 28: 1611. doi:10.1007/s00521-015-2129-z

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

[17] Z. Hu, W. Li and J. Qiao, "Prediction of PM2.5 based on Elman neural network with chaos theory," 2016 35th Chinese Control Conference (CCC), Chengdu, 2016, pp. 3573-3578. doi: 10.1109/ChiCC.2016.7553908

[18] Shin, Y., Ghosh, J., 1991, "Approximation of Multivariate Functions Using Ridge Polynomial Networks", *Department of Electrical and Computer Engineering, The University of Texas at Austin, 1991*

[19] Waheeb W, Ghazali R, Herawan T (2016) Ridge Polynomial Neural Network with Error Feedback for Time Series Forecasting. *PLOS ONE* 11(12): e0167248. https://doi.org/10.1371/journal.pone.0167248

[20] T. Hacib, Y. Le Bihan, M. K. Smail, M. R. Mekideche, O. Meyer and L. Pichon, "Microwave Characterization Using Ridge Polynomial Neural Networks and Least-Square Support Vector Machines," in *IEEE Transactions on Magnetics*, vol. 47, no. 5, pp. 990-993, May 2011. doi: 10.1109/TMAG.2010.2087743

[21] N. K. S. Behera and H. S. Behera, "Firefly based ridge polynomial neural network for classification," 2014 IEEE International Conference on Advanced Communications, Control and Computing Technologies, Ramanathapuram, 2014, pp. 1110-1113. doi: 10.1109/ICACCCT.2014.7019270

[22] M. Cheffena, "Fall Detection Using Smartphone Audio Features," in *IEEE Journal of Biomedical and Health Informatics*, vol. 20, no. 4, pp. 1073-1080, July 2016. doi: 10.1109/JBHI.2015.2425932