The Implementation of Neural Network on Determining the Determinant Factors Towards Students' Stress Resistance

Arief Hermawan, Donny Avianto

Universitas Teknologi Yogyakarta, Indonesia

ariefdb@uty.ac.id

***Abstract*—Stress is a condition that commonly felt by almost everyone, including college student. Naturally, human beings have a stress resistance in various levels. On previous research, an artificial neural network with backpropagation algorithm has been built to predict stress resistance level among college student. The level of stress resistance was predicted using four determinant factors i.e. frustration tolerance, conflict tolerance, anxiety tolerance, and tolerance to perceive changes as a challenge. On that research, the artificial neural network can predict stress resistance among college student correctly with an accuracy reach 75% after being trained up to 10334 epochs. On this research, dimensional reduction method will be applied on the determinant factors of stress resistance to eliminate disturbance factor and increase the accuracy of artificial neural networks in predicting stress resistance among college student. After the network was trained without disturbance factor i.e. anxiety tolerance, better network obtained. Experimental result showed that artificial neural network not only has better accuracy up to 81.5% but also faster training process which is only take 5000 epochs. Based on these results, the determinant factors of stress resistance among college student are: frustration tolerance, conflict tolerance, and tolerance to perceive changes as a challenge.**

***Index Terms*— College Student; Dimensional Reduction; Neural Network; Stress Resistance.**

I. INTRODUCTION

According to the World Health Organization, stress is a significant problem of our times and affects both physical as well as the mental health of people [1]. Stress is defined as the physiological and psychological reactions to certain events in the environment [2]. For many college students, university life is a major transition in their live since they are accorded the chance to decide what to do without the undue influence of their parents [3]. Due to these changes, students can potentially experience different types of stress that can affect their mental and social health and their academic achievement [4]. College student who have experienced stressful life events also reported worse health outcomes and reduced quality of life most of the time [5].

The stress experienced by college students is often also called as academic stress. Academic stress is mental distress with respect to some anticipated frustration associated with academic failure or even unawareness to the possibility of such failure [6]. Time management issues, financial burdens, interactions with professors, personal goals, social activities, adjustments to the campus environment, and the lack of support networks are some issues that most often lead to academic stress [7].

When dealing with these issues, college student will give some different reactions. If the student takes the event positively by accepting it as a part of challenge in life and find ways to deal with it, the stress will fade away and gone when he/she gets over it [8]. However, when stress is perceived negatively or becomes excessive, it may become linked to physical and mental illness [9]. This different reaction is highly influenced by stress resistance that owned by each college student. Stress resistance is a human ability to stay calm when facing stressful condition. The better the stress resistance that owned by a person, the more positive reaction will have yielded when facing a stress condition. In other words, college students who have a good stress resistance would be easier to finish his studies. Whereas, college students who have a poor stress resistance would be harder to achieve their undergraduate degree.

The research aimed to predict stress resistance among college students using Artificial Neural Network (ANN) has been done by [10]. ANN that used in the research has 4 nodes as an input layer, 60 nodes as a hidden layer, and 1 node as an output layer. The system was built to predicts two types of stress resistance i.e. good stress resistance and poor stress resistance based on values of 4 nodes in the input layer which is represent frustration tolerance, conflict tolerance, anxiety tolerance, and tolerance to perceive changes as a challenge respectively. According to the experiment result, the system can predict stress tolerance among college students correctly and reach 75% accuracy rate after trained up to 10334 epochs. This accuracy, which did not reach 100% yet, indicates that there was a disturbing factor among the four determinant factors of stress resistance.

On this research, ANN capabilities to predict stress resistance among college students will be improved by adding a dimensional reduction method. Dimension reduction is defined as the processes of projecting high-dimensional data to a much lower-dimensional space [11]. In short, the aim is to reduce the number of dimensions of the feature variables as much as possible without influencing the problem solution, so as to simplify the neural network structure and improve the convergence and training speed [12]. In addition, the dimensional reduction method expected to increasing the accuracy of ANN when predict stress resistance level so the system can provide a more reliable output for college students.

Based on the description above, the purpose of this research is to find disturbing factor which laid on four determinant factors of stress resistance among college student i.e. frustration tolerance, conflict tolerance, anxiety tolerance, and tolerance to perceive changes as a challenge. The ANN with reduced determinant factor will be trained and tested to see the effect of performed dimensional reduction. The elimination of disturbing factor will improve the ability of ANN to predict college student stress resistance by resulting better accuracy and obtained through fewer number of iterations training.

II. RELATED LITERATURES

An ANN is a mathematical representation of the human neural architecture, reflecting its “learning” and “generalization” abilities [13]. The main characteristics of neural networks are that they have the ability to learn complex nonlinear input-output relationships, use sequential training procedures, and adapt themselves to the data [14]. Hereafter, ANN will be trained to make all the input data yielded an output as expected before [15]. Because of this ability, ANN can be widely applied in various fields, including medical.

Artificial neural networks provide a powerful tool to help doctors to analyze, model and make sense of complex clinical data across a broad range of medical applications [16]. ANN often used in medical field research for detection and diagnosis in several diseases such as: lung cancer diagnosis by [17], detection of ophthalmic artery stenosis to avoid blindness by [18], diagnosis of heart disease by [19] [20] and Parkinson’s disease diagnosis by [21].

Besides applied to the application for detecting physical illness, ANN also widely applied to detect mental disorders such as depression or stress like a research that had been done by [22]. The aim of this research is to classify depression level among adults into three groups i.e. mild, moderate, and severe. One of the ANN algorithm used in this study was a Back Propagation Neural Network (BPNN). The test results showed BPNN can predict depression level with 100% accuracy for mild group, 80% for moderate group, and 88% for severe group. BPNN algorithm also ever used to diagnose a psychosomatic disorder based on symptoms and signs were obtained through interviews with patients [23]. Based on the experimental results, the system can diagnose the disorder correctly with average of accuracy rate reach 93.3%. Another study comparing several ANN training algorithms to predict suicide desire among the Iranian college students [24]. Experimental result shows that Liebenberg-Marquardt training algorithm obtained ANN with the best accuracy up to 93.12% and took 11 seconds of training time. While Conjugate Gradient Fletcher-Powell (CUFF) algorithm has a lower accuracy i.e. 92.60%, but with a faster training time which is only took 5 seconds.

Although an ANN offers diagnostic with promising results, it does not mean that the ANN can be applied without constraints. The most common constraint is length of time for ANN to achieve convergent during training. Another constraint is low accuracy on prediction result of ANN. These things become crucial if the ANN will be used to predict someone's illness or psychiatric condition. To solve these problems, input dimensional reduction method can be performed on used ANN [25].

Several studies have shown that the dimensional reduction method can accelerate converging time while ANN training process and improves accuracy when testing process. In medical field, dimensional reduction has been applied by [26] to create smaller data in volume but still has the same analytical results as its origin. Experiment result showed that dimensional reduction significantly reduce dimension, accelerate processing time and increase cluster performance in e-coli, acute implant, blood transfusion, and prostate cancer datasets.

The vitality of a dimensionality reduction method not only depends on its performance but also on how easily people in different fields can understand it, implement it, and use it [27]. Like the research conducted by [28] in economic field, which performed dimensional reduction in ANN to predict exchange rate. The reduction applied to the economic indicators which originally consisted of 140 indicators into 12 indicators. Some of tests were performed in this study and known that the ANN can predict exchange rate with an average accuracy of 95%. Research by [29] used the dimensional reduction in natural science field to predict to model of ethylene and propylene yielded in the naphtha pyrolysis system, which is a key factor in the design and optimal operation in the furnace. Reduction was performed by elimination some input variables that used from 20 variables into only 7 variables to achieve optimum prediction result. Research on the dimensional reduction has also been done in educational field by [30]. On his research, ANN is used to identify the majors for high school students. The variables that used as input for ANN consist of five types i.e. General Competence, Mechanical Competence, Competence Numerical, Verbal Competence and Language Competence. On the initial state, with five types of input variables, ANN can predict majors for high school students with accuracy 97.5% which is obtained after training up to 28356 epochs. By reducing General Competence variable, the system can obtain same accuracy with the previous one after took 1043 epochs only.

III. RESEARCH METHOD

To achieve the research objectives, this research was conducted through several stages as shown in Figure 1.

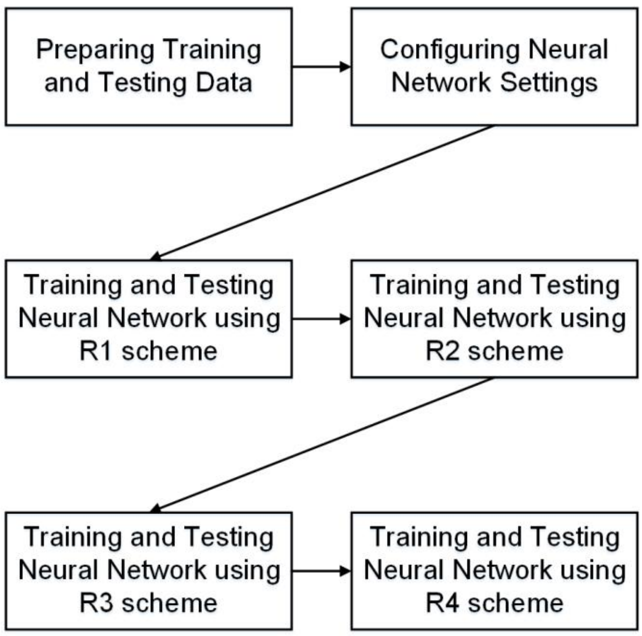

Figure 1: Flow of Research Stages

The earliest stage in this research was the preparation of the data by distributing questionnaires about stress levels to 36 college students. From a total of 36 data obtained, 20 data were used for training and 16 other data were used for testing process. Later, the answer of each student was calculated to generate input values for the four determinant factors of stress resistance i.e. frustration tolerance, conflict tolerance, anxiety tolerance, and tolerance to perceive changes as a challenge. These values would be used as an input for ANN on a next stage.

After the input data of ANN obtained, the next stage was adjusting ANN configuration that would be used. To gain the best results, this study had tried several configurations of ANN. Some configurations that had been adjusted were: the number of hidden layer nodes, the value of learning rate, and the maximum number of epoch. The number of node in hidden layer that had been used as a configuration were 10, 30, 50, and 70 nodes. For each configuration, three values of learning rate would be used i.e. 0.25, 0.50, and 0.75. The architecture of the ANN used in this study can be seen in Figure 2. After completing the configuration of the neural network would be used, the next step was to conduct ANN training and testing processes. Training and testing will be carried out in 4 schemes where at each scheme will be performed dimensional reduction of the ANN input. The detail of each scheme as shown in Table 1 below.

Table 1
Reduction Schemes

Reduction Scheme Code	Reduced Stress Factor
R1	Tolerance of Frustration (TF)
R2	Tolerance of Conflict (TC)
R3	Tolerance of Anxiety (TA)
R4	Changes As a Challenge (CAC)

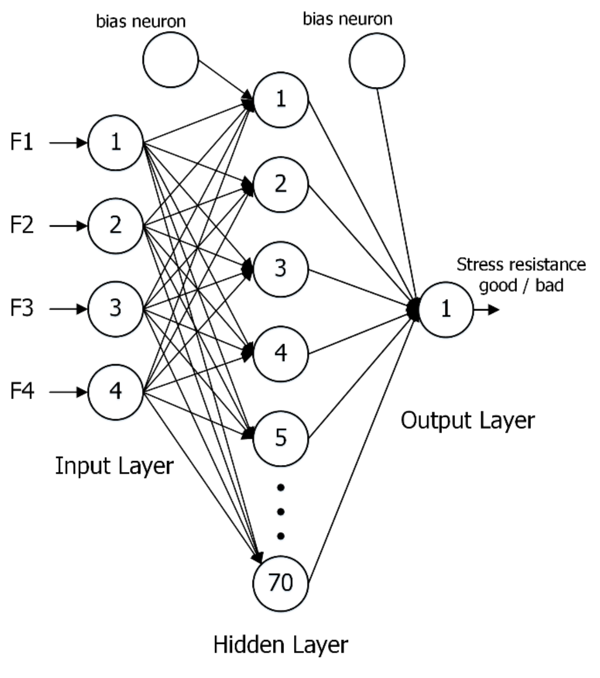

Figure 2: Neural Network Architecture

The difference between each scheme lies on the factor that was excluded or reduced. It aimed to isolate determinant factor of stress resistance that act as a disturbance factor. When the training and testing process for each of the existing scheme being done, nodes in the input layer as shown in Fig. 2 will be reduced thereby only 3 nodes in the input layer remaining. Because the output generated by ANN only has 2 possibilities i.e. good stress resistance and poor stress resistance, a node in the ANN output layer can already accommodate the needs. At the ANN training process, research will be focused to see the relationship between the dimensional reduction which is performed on the input layer and speed of ANN to achieve convergent result. While at the ANN testing process, research focus is on the relationship between dimensional reduction and ability of neural networks to predict stress resistance among college student appropriately.

IV. Research Finding and Discussion

After the whole schemes tested on ANN, it is known that there is a factor that act as a disturbance factor. The experiment results from ANN training process in each scheme are shown in Table 2 through Table 5.

Table 2
Experiment Results for R1 Scheme

Hidden Layer's node	Learning rate	MSE	Accuracy
10	0.25	0.086	68.75%
	0.50	0.126	68.75%
	0.75	0.122	68.75%
30	0.25	0.016	62.50%
	0.50	0.009	56.25%
	0.75	0.009	37.50%
50	0.25	0.003	37.50%
	0.50	0.010	68.75%
	0.75	0.049	56.25%
70	0.25	0.099	62.50%
	0.50	0.156	50.00%
	0.75	0.239	75.00%

Table 3
Experiment Results for R2 Scheme

Hidden Layer's node	Learning rate	MSE	Accuracy
10	0.25	0.044	43.75%
	0.50	0.075	62.50%
	0.75	0.103	50.00%
30	0.25	0.001	43.75%
	0.50	0.011	43.75%
	0.75	0.061	50.00%
50	0.25	0.001	50.00%
	0.50	0.065	56.25%
	0.75	0.090	56.25%
70	0.25	0.068	43.75%

	0.50	0.127	56.25%
	0.75	0.129	62.50%

Table 4
Experiment Results for R3 Scheme

Hidden Layer's node	Learning rate	MSE	Accuracy
10	0.25	0.092	75.00%
	0.50	0.087	81.25%
	0.75	0.092	81.25%
30	0.25	0.038	50.00%
	0.50	0.078	56.25%
	0.75	0.113	62.50%
50	0.25	0.011	62.50%
	0.50	0.005	62.50%
	0.75	0.003	56.25%
70	0.25	9.389×10^{-4}	62.50%
	0.50	0.119	62.50%
	0.75	0.188	62.50%

Table 5
Experiment Results for R4 Scheme

Hidden Layer's node	Learning rate	MSE	Accuracy
10	0.25	0.051	62.50%
	0.50	0.039	68.75%
	0.75	0.030	62.50%
30	0.25	0.003	62.50%
	0.50	0.077	50.00%
	0.75	0.144	56.25%
50	0.25	5.240×10^{-5}	56.25%
	0.50	3.522×10^{-4}	68.75%
	0.75	0.084	62.50%
70	0.25	3.799×10^{-5}	62.50%
	0.50	0.038	56.25%
	0.75	0.094	68.75%

All data above were obtained after ANN training process up to 5000 epochs. Based on trials, training over 5000 epochs did not leave a significant impact on the accuracy of ANN and instead may drop ANN accuracy when making predictions on training data. Hence 5000 epochs were used as a basis in this research.

The changes in learning rate value, based on the above data, gave various effect for Mean Squared Error (MSE) resulted from training process. Most of the data from the test results shown the movement of learning rate from 0.25 through 0.75 are also followed by increasing the value of MSE generated by ANN. But in some neural network architectures, as shown in Table 4 where the hidden layer has 50 nodes, an increasing of learning rate is followed by a MSE decrease. In addition, the smaller the MSE does not guarantee the higher accuracy result of ANN.

The experiment of R1 scheme shown a fluctuating trend results, especially when the number of hidden layer nodes is 70, have ever reached 75% of accuracy rate. Overall, the average accuracy produced by reducing the frustration tolerance is 59.3%. This may be an indication that the frustration tolerance factor is an influential factor in determining stress resistance among college student.

The experiment of R2 scheme also provides quite fluctuating results. However, the average accuracy in predicting ANN stress resistance among college students in this scheme is lower than R1 scheme which is only reach 51.5%. This also indicate that conflict tolerance is one of the most influencing factor for college students stress resistance.

At R3 scheme's experiment, more consistent output and better ANN accuracy was obtained. The accuracy, which reach 81.25%, were produced from ANN with 10 nodes on hidden layer. This configuration also produced a robust neural network because increasing of learning rate over 0.5 would no longer have a significant impact for the accuracy of ANN on predicting stress resistance. The evident can be seen when the learning rate = 0.75. On that situation, ANN obtained same accuracy with when the learning rate = 0.5. Thereby, the anxiety tolerance, which is reduced on this scheme, is indicated as disturbance factor because without this factor, the ANN can achieve a better accuracy than before.

The experiment results from R4 scheme also showed quiet consistent results. It can be seen from the average accuracy generated in this scheme which reached 61.5%. On this scheme the smallest MSE value was obtained as well. The smallest MSE i.e. 3.799 × 10-5 obtained from ANN using 70 hidden layer nodes and learning rate = 0.75 configuration. The best accuracy result in this scheme which reached 68.75%, indicating the tolerance to perceive changes also give an affect to stress resistance among college students although the affect is less than frustration tolerance and conflict tolerance factors.

V. CONCLUSION AND FUTURE WORK

ANN has been widely applied in the medical field applications and most of them were used to predict or diagnose disease. This research showed that ANN not only can be used to predict the physical diseases but also disease such as mental disorders like stress. In this research, ANN is used to predict stress resistance among college students. This research also used the dimensional reduction method to obtain better result from previous research. Several schemes have been performed and obtain promising results. By eliminating disturbance factors i.e. anxiety tolerance, the ANN can predict stress resistance with better accuracy than earlier one which is up to 81.25% accuracy rate and obtained after 5000 epochs in training process. This research also unveiled the sequence of determinant factors of stress resistance among college student from the most influence are as follows: conflict tolerance, frustration tolerance, tolerance to perceive changes as a challenge, and anxiety tolerance.

This research is still likely to continue in the future. Future work can be done by adding other factors which is indicated may affect human stress resistance and testing its effect. With the addition of new influential factor, expected rate accuracy of the system can be significantly increased so the resulted system can give more reliable and accurate prediction of stress resistance.

REFERENCES

[1] L. Varvogli and C. Darviri, "Stress Management Techniques: evidence-based procedures that reduce stress and promote health", Health Science Journal. Insight Medical Publishing., vol. 5, no. 2, pp. 74-89, 2011.

[2] T. D. Joseph, "Work Related Stress", European Journal of Business and Social Sciences, vol. 1, no. 10, , pp. 73-80, 2013.

[3] G. Nakalema and J. Ssenyonga, "Academic Stress: Its Causes and Results at a Ugandan University", African Journal of Teacher Education, SPREAD Corporation, vol. 3, no. 3, pp. 1-21, 2013.

[4] A. M. Thawabieh and L. M. Qaisy, "Assessing Stress among University Students", American International Journal of Contemporary Research, Center for Promoting Ideas (CPI), vol. 2, no. 2, pp. 110-116, 2012.

[5] K. U. D. Khan, S. Gulzar, F. Yahya, "Crucial Factors Affecting Stress: A Study Among Undergraduates in Pakistan", International Journal of Asian Social Science, Asian Economic and Social Society, vol. 3, no. 2, pp. 428-442, 2013.

[6] K. Lal, "Academic Stress Among Adolescent in Relation to Intelligence and Demographic Factors", American International Journal of Research in Humanities, Arts and Social Sciences, The International Association of Scientific Innovation and Research, vol. 5, no. 1, pp. 123-129, 2014.

[7] S. E. Wilks, "Resilience amid Academic Stress: The Moderating Impact of Social Support among Social Work Students", Advances in Social Work, Indiana University School of Social Work, vol. 9, no. 2, pp. 106-125, 2008.

[8] H. Elias, W. S. Ping, M. C. Abdullah, "Stress and Academic Achievement among Undergraduate Students in University Putra Malaysia", Proceedings of The 2nd International Conference on Education and Educational Psychology, Selangor Darul Ehsan, Malaysia, (2011) October 19-22.

[9] R. Shkulaku, "Student's Stress in Higher Education Institutions: A Critical Review of Foreign Literatures and The Ones in Albania", European Scientific Journal, European Scientific Institute, August Special Edition, pp. 40-48, 2015.

[10] D. Yudhawati, A. Hermawan, N. I. Fadilah, "Implementasi Jaringan Saraf Tiruan untuk Mendeteksi Daya Tahan Terhadap Stres pada Mahasiswa Tingkat Akhir dengan Menggunakan Metode Backpropagation", Jurnal Psikologi, vol. 10, no. 1, pp. 1-15, 2014.

[11] A. Sarveniazi, "An Actual Survey of Dimensionality Reduction", American Journal of Computational Mathematics, Scientific Research Publishing, vol. 4, no. 2, pp. 55-72, 2014.

[12] W. Jia, D. Zhao, T. Shen, S. Ding, Y. Zhao, C. Hu, "An optimized classification algorithm by BP neural network based on PLS and HCA", Applied Intelligence, Springer International Publishing, vol. 43, no. 1, pp. 176-191, 2014.

[13] F. Amato, A. Lopez, E. M. Pena-Mendez, P. Vanhara, A. Hampl, J. Havel, "Artificial Neural Networks in Medical Diagnosis", Journal of Applied Biomedicine, Elsevier, vol. 11, no. 2, pp. 47-58, 2013.

[14] J. K. Basu, D. Bhattacharyya, T. Kim, "Use of Artificial Neural Network in Pattern Recognition", International Journal of Software Engineering and Its Applications, SERSC, vol. 4, no. 2, pp. 23-34, 2010.

[15] A. Hermawan, Author, "Jaringan Saraf Tiruan", Andi Publishers, Yogyakarta, 2006.

[16] Q. K. Al-Shayea, "Artificial Neural Networks in Medical Diagnosis", International Journal of Computer Science Issues, IJCSI, vol. 8, no. 2, pp. 150-154, 2011.

[17] N. Ganesan, K. Venkatesh, M. A. Rama, "Application of Neural Networks in Diagnosing Cancer Disease Using Demographic Data", International Journal of Computer Applications, Foundation of Computer Science, vol. 1, no. 26, pp. 76-85, 2010.

[18] I. Guler and E. D. Ubeyli, "Detection of Ophthalmic Artery Stenosis by Least-Mean Squares Backpropagation Neural Network", Computers in Biology and Medicine, Elsevier, vol. 33, no. 4, pp. 333-343, 2003.

[19] R. Das, I. Turkoglu, A. Sengur, "Effective Diagnosis of Heart Disease Through Neural Networks Ensembles", Expert Systems with Applications, Elsevier, vol. 36, no. 4, pp. 7675-7680, 2009.

[20] E. B. Olaniyi, O. K. Oyedotun, "Heart Diseases Diagnosis Using Neural Networks Arbitration", International Journal of Intelligent Systems and Applications, MECS Publisher, vol. 12, no. 1, pp. 75-82, 2015.

[21] M. Can, "Neural Networks to Diagnose the Parkinson's Disease", Southeast Europe Journal of Soft Computing, International University of Sarajevo, vol. 2, no. 1, pp. 68-75, 2013.

[22] S. Chattopadhyay and R. Acharya, "Neural Network Approaches to Grade Adult Depression", Journal of Medical Systems, Springer, vol. 36, no. 5, pp. 2803-2815, 2012.

[23] P. Aruna, N. Puviarasan, B. Palaniappan, "An Investigation of Neuro-Fuzzy Systems in Psychosomatic Disorders", Expert Systems with Applications, Elsevier, vol. 28, no. 4, pp. 673-679, 2005.

[24] S. Ayat, H. A. Farahani, M. Aghamohamadi, M. Alian, S. Aghamohamadi, Z. Kazemi, "A Comparison of Artificial Neural Networks Learning Algorithms in Predicting Tendency for Suicide", Neural Computing and Applications, Springer, vol. 23, no. 5, pp. 1381-1386, 2012.

[25] S. Muknahallipatna, B. H. Chowdhury, "Input Dimension Reduction in Neural Network Training - Case Study in Transient Stability Assessment of Large Systems", Proceedings IEEE International Conference on Intelligent System Application to Power Systems, Orlando, USA, January 28-February 2, 1996.

[26] R. W. Sembiring, J. M. Zain, A. Embong, "Dimension Reduction of Health Data Clustering", International Journal on New Computer Architectures and Their Applications, The Society of Digital Information and Wireless Communications, vol. 1, no. 3, pp.1041-1050, 2011.

[27] X. Zhang, "Nonlinear Dimensionality Reduction of Data by Deep Distributed Random Samplings", Proceeding of Asian Conference on Machine Learning, Nha Trang City, Vietnam, November 26-28, 2014.

[28] D. S. Antić, M. B. Milovanović, S. L. Perić, S. S. Nikolić, M. T. Milojković, "Input Data Preprocessing Method for Exchange Rate Forecasting via Neural Network", Serbian Journal of Electrical Engineering, faculty of Technical Sciences Čačak, vol. 11, no. 4, pp. 597-608, 2014.

[29] Z. Qunxiong, L. Chengfei, "Dimensionality Reduction with Input Training Neural Network and Its Application in Chemical Process Modelling", Chinese Journal of Chemical Engineering, Elsevier, vol. 14, no. 5, pp. 597-603, 2006.

[30] A. Hermawan, "The Dimensional Reduction to Improve the Speed and Accuracy of Neural Network in Identifying the Senior High School Students' Major", International Journal of Applied Engineering Research, Research India Publications, vol. 11, no. 7, pp. 4758-4762, 2016.