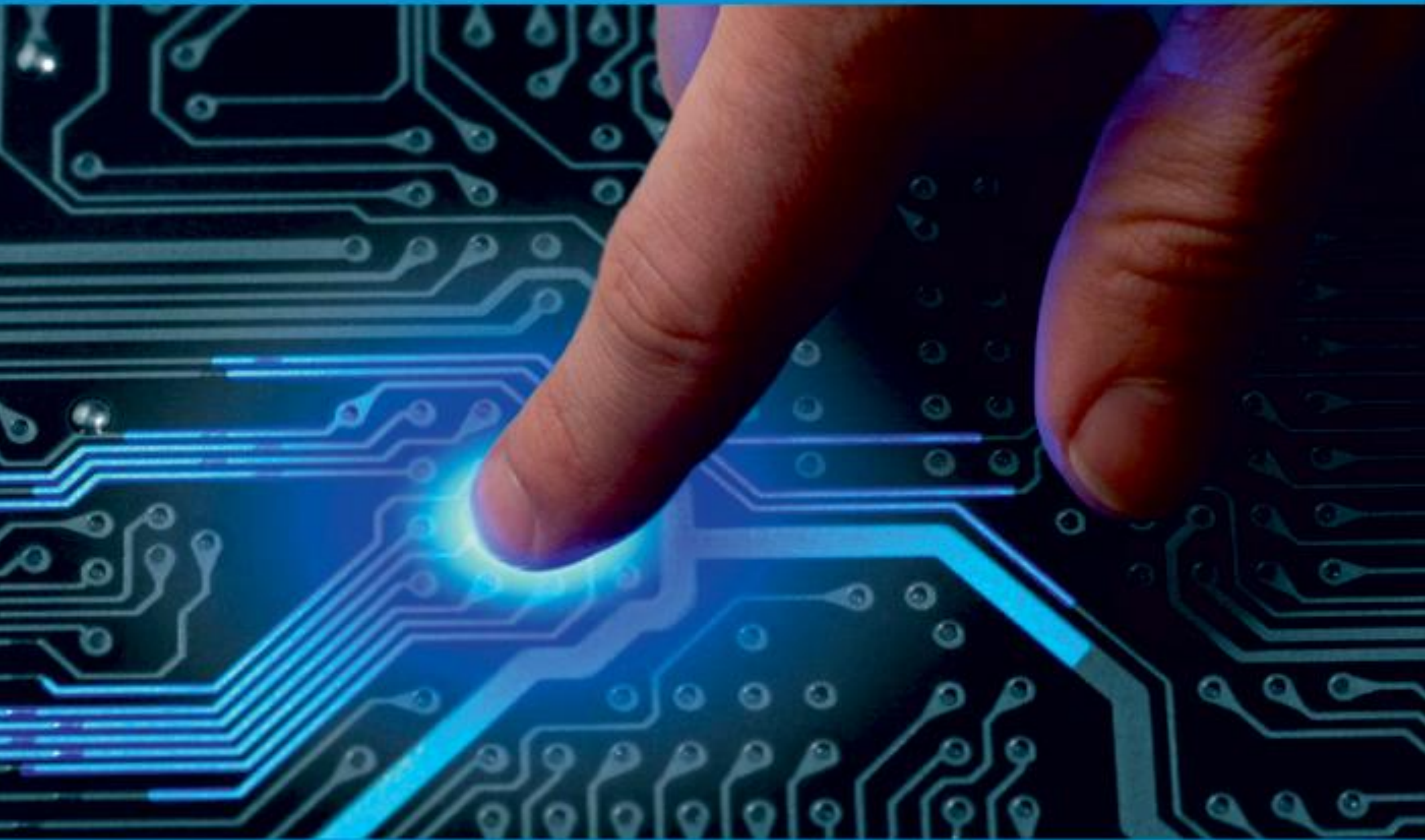
IJIRCCE

e-ISSN: 2320-9801 | p-ISSN: 2320-9798



INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN COMPUTER & COMMUNICATION ENGINEERING

Volume 12, Special Issue 1, March 2024

1st International Conference on Machine Learning, Optimization and Data Science

Organized by

Department of Computer Science and Engineering, Baderia Global Institute of Engineering and Management, Jabalpur, India

INTERNATIONAL STANDARD SERIAL NUMBER INDIA

Impact Factor: 8.379

International Journal of Innovative Research in Computer and Communication Engineering

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.379 || Monthly Peer Reviewed & Refereed Journal |

| "1st International Conference on Machine Learning, Optimization and Data Science"|

Organized by

| Department of Computer Science and Engineering, Baderia Global Institute of Engineering and Management, Jabalpur|

|| Volume 12, Special Issue 1, March 2024 ||

Comparative Analysis of Supervised and Unsupervised Learning Methods for Pattern Classification

Prof. Ranu Sahu , Prof. Khushboo Choubey

Assistant Professor, Department of CSE, Baderia Global Institute of Engineering and Management, Jabalpur, India

ABSTRACT: In the higher learning system, this article compares and contrasts supervised and unsupervised learning approaches to see which is more effective for classifying patterns. Among the most significant uses of machine learning algorithms is classification. Our research shows that, although the supervised learning algorithm, Back-propagation learning with errors, does a great deal of nonlinear real-time assignments, the unsupervised learning algorithm, Kohonen Self-Organizing Map (KSOM), performs very well in our study's classification tasks.

KEYWORDS: Categorization; Grouping; Knowledge Acquisition; Multi-Layer Perceptron; Self-Organizing Map; Guided Learning; Autonomous Learning

I. INTRODUCTION

Merging cognitive reasoning into systems for traditional computing for various problem-solving techniques such as identification of patterns, grouping, and prediction. Neural networks made artificially (ANN) provide mathematical representations of functions along with learning algorithms to imitate human behaviour. ANNs have three distinct parameters: interconnection properties (e.g., feed forward and recurrent networks), application functions (e.g., optimization, classification, association, and self-organizing models), and learning rules (e.g., supervised, unsupervised, reinforcement, etc.) [1].
Artificial neural network models offer various features and advantages, showcasing their theoretical and practical value across many applications. Due to their natural structural design and effective learning strategies, which excel in classification tasks, pattern classification has been a central focus of ANN research. The creation and training of ANN models do not rely on a single algorithm, as different learning algorithms vary in their capabilities for inference and learning. Thus, the purpose of this research is to evaluate the value of supervised and unsupervised learning techniques in categorization using specific instances [3].
The paper's structure is outlined as follows: Part II, following the introduction, delves into the different learning methods employed in artificial neural networks (ANNs) for pattern categorization, with a particular focus on supervised and unsupervised learning strategies.
In Section III, we discuss categorization and its necessary conditions, focusing on the distinctions in pattern-class knowledge between supervised and unsupervised learning. Additionally, we establish the groundwork for constructing a categorization network tailored to address our specific educational challenge. Section IV provides a detailed description of the experimental design and results of this study. The outcomes of the two algorithms employed are examined from different perspectives in Section V. Finally, Section VI concludes with reflections on the use of supervised and unsupervised learning methods for educational categorization tasks.

II. ANN LEARNING PARADIGMS

Learning can be viewed as the acquisition or enhancement of knowledge. Herbert Simon suggests that machine learning entails making adaptive system modifications to give the system permission to operate in the same work or tasks more effectively and efficiently in subsequent instances.
Artificial Neural Network (ANN) learning paradigms are categorized into three types: reinforcement learning, unsupervised learning, and supervised learning. Supervised learning involves assigning classes to training instances,

International Journal of Innovative Research in Computer and Communication Engineering

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.379 || Monthly Peer Reviewed & Refereed Journal |

| "1st International Conference on Machine Learning, Optimization and Data Science"|

Organized by

| Department of Computer Science and Engineering, Baderia Global Institute of Engineering and Management, Jabalpur|

|| Volume 12, Special Issue 1, March 2024 ||

with information about each instance's class membership provided by a presumed teacher or supervisor. In contrast, unsupervised learning employs a heuristic technique for retrieving pattern class information. Finally, Reward learning acquires knowledge by reward/penalty assignments and exchanges of trial and error with its surroundings
Although these models employ different learning approaches, the space of connections between neurons is essential to their effectiveness. Guided learning involves modifying the free parameters of an ANN, allowing learning to take place within the network as it adapts to its operating environment.

Making the distinction between supervised, unsupervised, and other learning methods requires this parameter alteration. A variety of learning criteria, shown in Figure 1 [2], also support these algorithms.

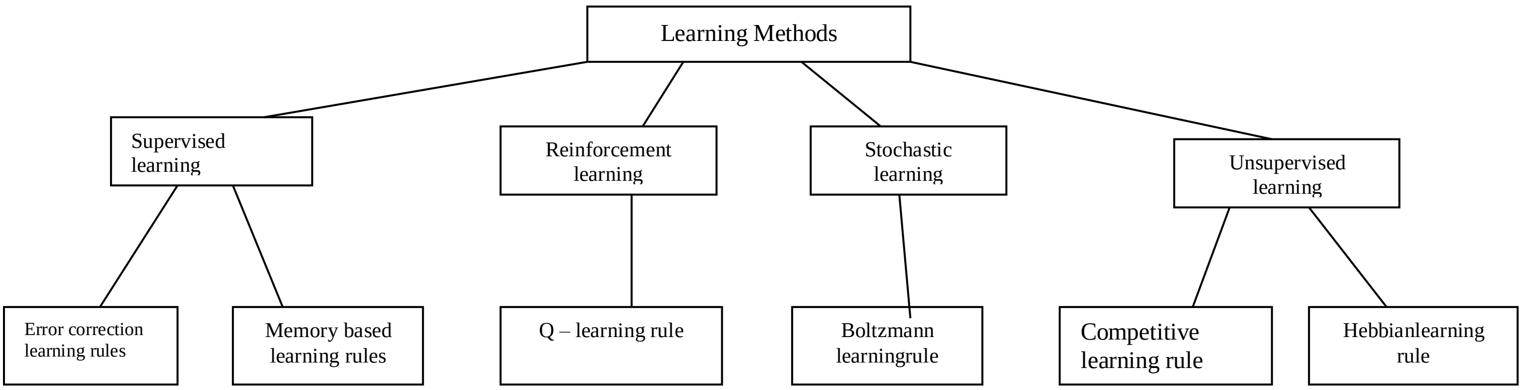


Fig. 1. Learning Rules Of ANN

A. Supervised Learning
Supervised learning is the process of learning on a dataset where each data point has an accurate categorization assigned to it beforehand. These methods are frequently applied to feed forward or Multilayer Perceptron (MLP) models, which are distinguished by three characteristics:
1. Hidden neurons are incorporated into the network's layers besides the input and output layers, allowing the network to effectively handle complex situations.
2. Neural activity exhibits differentiable nonlinearity.
Combining these qualities with training makes it possible to solve a wide range of difficult tasks. The training procedure in a supervised Artificial Neural Network (ANN) model is commonly known as the error back-propagation algorithm. The difference between the expected and computed outputs is represented by error signals, which are found using input-output samples. This algorithm helps with error correction learning. It then modifies the weights of neurons at synapses according the input synaptic weight multiplied by and the error signal. This idea leads to the two stages of mistake back-propagation learning:
In the Forward Pass, the network is introduced to the input vector. Neuron by neuron, this input signal travels through the network until it reaches the output end, where it manifests as the output signal, $y(n) = \varphi(v(n))$. Here, The generated local field of a neuron is represented by $v(n)$, which is defined as $v(n) = \Sigma\, w(n)y(n)$. The error, $e(n)$, for that neuron is then found by comparing the output, which is calculated at the output layer as $o(n)$, with the desired response, $d(n)$. The synaptic weights of the network do not change throughout this pass.
The layer's output neuron generates an error signal that travels backward through the network during the Backward Pass. This procedure calculates the local gradient for every neuron in every layer, allowing the network's synaptic weights to be adjusted in accordance with the delta rule, which is represented as follows: $\Delta w(n) = \eta * \delta(n) * y(n)$.
Until the network converges, this iterative procedure consists of a forward pass followed by a backward pass for each input pattern [4–7].Many linear and non-linear issues, including robotics, plant control, robotic categorization, forecasting, and prediction, can be effectively tackled by an ANN using its supervised learning technique. [7-9]

B. Unsupervised Learning
To find hidden patterns in unlabelled input data, self-organizing neural networks use an unsupervised learning

International Journal of Innovative Research in Computer and Communication Engineering

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.379 || Monthly Peer Reviewed & Refereed Journal |

| "1st International Conference on Machine Learning, Optimization and Data Science"|

Organized by

| Department of Computer Science and Engineering, Baderia Global Institute of Engineering and Management, Jabalpur|

|| Volume 12, Special Issue 1, March 2024 ||

technique. Unsupervised learning is the ability to organize and learn without being given an error signal to evaluate possible solutions. In unsupervised learning, having no instruction for the learning algorithm can be helpful since it allows the system to investigate patterns that it might not have noticed before. Self-Organizing Maps (SOM) have the following main qualities

1. It dynamically transforms one- or two-dimensional maps from incoming signal patterns of different dimensions.
2. The network uses a feed-forward design with one computational layer made up of neurons arranged in columns and rows.
3. At every stage of representation, each input signal is kept inside its own context.
4. Neural connections allow nearby neurons that process similar input to communicate with one another.

Because of the competition amongst the neurons in the computational layer for activation, it is also known as the competitive layer. As such, we refer to this learning algorithm as a competitive algorithm. There are three stages that the SOM unsupervised algorithm goes through.

During the calculation of the inner product with synaptic weight w, competition phase, upon introducing each input pattern x to the network. After then, neurons in the competitive layer identify a discriminate function that sets off rivalry between them. The competition winner is the synaptic weight vector that is, in terms of Euclidean distance, closest to the input vector. The best matching neuron, represented by the notation x = arg min - w - ∑x; is this neuron.

The cooperative neuroscience's victorious neuron phase designates the hub of a topological neighborhood h made up of cooperating neurons. The cooperative neurons' lateral interactions with one another promote this process. This topological region steadily shrinks in size over time.

In the adaptive phase, synaptic weights are modified by enhancing the winning neuron and the neurons nearby their individual discriminate function values concerning the input pattern ($\Delta w = \eta h(x)(x - w)$.

As the neighborhood undergoes updates and the training patterns are repeatedly introduced, the synaptic weight vectors gradually align with the input pattern distribution. Consequently, the ANN gains knowledge autonomously, without the need for supervision [2].

Self-organizing models are useful for a variety of real-world applications, including texture segmentation, speech recognition, clustering, vector coding, and others. These models naturally mimic neurobiological processes. [11–13].

III. CLASSIFICATION

"Classification" is a typical decision-making task in human activity. It arises from the necessity of classifying an object according to its observed attributes and placing it in a predefined category. Numerous business activities, including character identification, weather forecasting, medical diagnosis, bankruptcy forecast, stock market prediction, and voice recognition, are known to involve classification challenges [14–18]. These classification tasks can be addressed with mathematical and nonlinear methods. Mathematically handling such problems presents a difficulty in terms of ensuring correctness and addressing the capacity of the model as well as the distribution of data attributes [19].

Recent improvements have shown that Artificial Neural Networks (ANN) are helpful as classification models due to their nonlinear, adaptive, and functional approximation principles. In an ANN, the output activation determines the classification of a given object. A Multilayer Perceptron (MLP) uses nodes in its hidden layers to extract pattern features when it is shown a series of input patterns. For example, nodes in the first hidden layer of a two-layered artificial neural network (ANN) generate boundaries between pattern classes, whereas nodes in the second layer define decision regions based on the hyper planes the previous layer created. After that, the nodes of the output layer logically merge decision regions from the hidden layers to classify objects into the right classes and lower the average error over training cases.

Through a case study, the article aims to investigate the effectiveness of these algorithms in the educational area and to clarify the theory behind popular Pattern categorization using supervised and unsupervised learning approaches. Group assignment in a course for academic advancement can be viewed as a classification issue since any classification system seeks to build a functional relationship between group association and object features [20–22]. Higher education is becoming more and more vital in a competitive atmosphere, thus both educational institutions and students must evaluate performance and rankings. Schools search for possible pupils and their skill sets, categorizing them in accordance with standards in order to maintain or improve their reputation in the education sector. The core of observation-based learning is the foundation of any model for classification problems using Artificial Neural Networks (ANNs). As the intention of. The purpose of this work is to examine the properties of pattern classification for the two previously mentioned techniques. We developed Unsupervised ANN and Supervised ANN models for the given problem in order to achieve this. We utilized a dataset of ten primary variables that are considered essential for pursuing an MCA degree at a university or other educational institution. Among these criteria are the students' academic standing, their previous math proficiency, and the outcomes of eligibility examinations administered by the institution. Input observations were used to define three student group classes [3]. The training and structural design of the ANN models are covered in the following sections of the paper.

IV. EXPERIMENTAL OBSERVATION

A. Supervised ANN

An 11-4-3 Multi-Layer Perceptron (MLP) was constructed using anmistake back-propagation technique for learning. Around thirty datasets from the domain were utilized to train the ANN, while the remaining fifty were used for system testing and validation. For each randomly selected pattern, the desired output at the output layer and bias are presented to the input layer. Initially, the synaptic weight vectors of each neuron are randomly assigned from the interval [-1,1]. These vectors are then updated during the backward pass based on the local error, and their values are normalized at each epoch.

The hyperbolic tangent function is employed as the activation function for nonlinearity. The sequential backpropagation learning technique was utilized, and various learning rates were experimented with before settling between [0.05 - 0.1]. The average squared error per epoch, ranging from 0.01 to 0.1, was used to gauge the convergence of the learning algorithm. Three output patterns were differentiated from the input patterns within the output layer. The ANN architecture was devised through an iterative trial-and-error process, as detailed in Table I.

TABLE I: SUPERVISED LEARNING OBSERVATION

No. of hidden neurons	No. of Epochs	Meansquared error	Correctness on training	Correctness on Validation
3	4000- 9000	0.21-0.32	78%	78%
4	4000- 9000	0.29	82-86%	88%
5	4000- 9000	0.31-0.41	85-89%	89%

B. Unsupervised ANN

Ten input neurons and three output neurons are used in the construction of Kohonen's Self-Organizing Model (KSOM), an unsupervised ANN. To train the network, the dataset used in the supervised model is deployed. Synaptic weights are first initialized to guarantee a unit length; they are then set to 1/√ (number of input characteristics) and then changed according to adaptability.

The way the presentation patterns are arranged in the input vector affects the network's results, especially when there isn't much training data. As a result, the neural network receives the training patterns one after the other.

The winning neuron was identified at each repetition by computing the Euclidean distance measure. The starting value of the learning rate parameter was set to 0.1, and it was progressively reduced over time, never going below 0.01. It remained at 0.01 during the convergence phase [11]. The neighbourhood parameter has little effect on activation because the competitive layer is made up of a one-dimensional vector containing three neurons. The point at which notable adaption changes stopped was identified as network convergence. The outcomes are shown in the table that follows:

TABLE II. UNSUPERVISED LEARNING OBSERVATION

Learning rate parameter	No. of Epochs	Correctness on training	Correctness on Validation
0.3 – 0.01	1000 - 2000	85%	86%
0.1 -0.01	1000 - 3000	85-89%	92%

V. OUTCOMES AND TALKING

We observed that throughout the categorization phase, both learning models grouped students according to particular attributes. For example, students with similar eligibility and academic scores were put together, students from disadvantaged families were placed in a different class, and students with mediocre academic performance were placed in a different category.

The two results are analyzed, and the analysis shows that unsupervised learning algorithms perform better for classification tasks than supervised algorithms in terms of accuracy %. Adding another hidden layer might improve the supervised algorithm's accuracy, even when the differences aren't significant enough to warrant a comparison at first. It is noteworthy, therefore, that building the network took longer than with KSOM. We furthermore ran into and resolved a number of back propagation algorithm-related problems, such as:

Network Size: A hidden layer is usually not required for a linear classification issue. Nevertheless, we progressively discovered by trial and error that 1 hidden layer was appropriate because the input patterns needed to be classified into 3 categories. The count of neurons in the buried layer was also difficult to ascertain. The results indicate that the optimal choice of 4 hidden neurons was obtained when evaluating the system's performance in relation to the number of neurons in the hidden layer, as indicated in Table I.

Local Gradient Descent: Gradient descent uses iterative weight adjustments to minimize output error. This modification could, however, cause the error to become trapped in a specific range, or "local minima." By randomly initializing weight vectors and modifying them based on the error of the current pattern after each iteration, we were able to avoid this issue.

Termination Criteria: An ANN model usually stops training when it has correctly learned every pattern, which is determined by total mean squared error. Unfortunately, further reduction proved difficult, with the classification error for the model with 4 hidden neurons reaching 0.28. Validation error increased as a result of attempts to reduce the error. As a result, we chose to stop the system based on the validation data's accuracy, which was 89% as shown in Table I. As can be observed in the last row of Table I, adding a neuron to the hidden layer decreased performance on validation datasets but raised the danger of overfitting on training datasets..

Finding and lowering the learning rate parameter was the sole difficulty found during KSOM training. After experimenting with various parameter configurations and applying an exponential reduction over time, we finally settled on a training rate of 0.1 and 0.01 at convergence, as shown in Table II.

Moreover, the unsupervised KSOM uses single-pass learning, which may be quicker and more accurate than the multi-pass supervised methods used in MLP classification models. This justification emphasizes how well-suited the KSOM unsupervised algorithm is for classification-related issues.

In the context of education, classification could help organizations mentor students and improve their performance through focused attention and instruction, as classification is one of the most dynamic decision-making processes in human activity. Additionally, it helps students pinpoint their areas of weakness and strengthen their abilities, which is advantageous to the school as well as the students.

VI. CONCLUSION

Building a categorization network according to predetermined patterns is an example of observational learning. The discovery of new classes or the assignment of already-existing ones may result from such observations. New theories and information that are included into the input patterns are encouraged to arise as a result of this classification process. Neural network models' learning behavior improves their categorization capabilities. This work examines the effectiveness of two learning algorithms—supervised and unsupervised—in categorizing postgraduate candidates according to their admissions period performance. Our results show that while the error back-propagation supervised learning approach is quite effective for many nonlinear real-time applications, the KSOM unsupervised model performs better when it comes to student categorization.

REFERENCES

[1] L. Fu., Neural Networks in Computer Intelligence, Tata McGraw-Hill, 2003.

[2] S. Haykin, Neural Networks- A Comprehensive Foundation, 2nd ed., Pearson Prentice Hall, 2005

International Journal of Innovative Research in Computer and Communication Engineering

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.379 || Monthly Peer Reviewed & Refereed Journal |

| "1st International Conference on Machine Learning, Optimization and Data Science"|

Organized by

| Department of Computer Science and Engineering, Baderia Global Institute of Engineering and Management, Jabalpur|

|| Volume 12, Special Issue 1, March 2024 ||

[3] R. Sathya and A. Abraham, "Application of Kohonen SOM in Prediction", In Proceedings of ICT 2010, Springer-Verlag Berlin Heidelberg, pp. 313–318, 2010.
[4] R. Rojas, TheBackpropagation Algorithm, Chapter 7: Neural Networks, Springer-Verlag, Berlin, pp. 151-184, 1996.
[5] M. K. S. Alsmadi, K. B. Omar, and S. A. Noah, "Back Propagation Algorithm: The Best Algorithm Among the Multi-layer Perceptron Algorithm", International Journal of Computer Science and Network Security, Vol.9, No.4, 2009, pp. 378 – 383.
[6] X. Yu, M. O. Efe, and O. Kaynak, "A General Backpropagation Algorithm for Feedforward Neural Networks Learning", IEEE Trans. On Neural Networks, Vol. 13, No. 1, 2002, pp. 251 – 254.
[7] Jin-Song Pei, E. Mai, and K. Piyawat, "Multilayer Feedforward Neural Network Initialization Methodology for Modeling Nonlinear Restoring Forces and Beyond", 4th World Conference on Structural Control and Monitoring, 2006, pp. 1-8.
[8] Awodele, and O. Jegede, "Neural Networks and Its Application in Engineering", Proceedings of Informing Science & IT Education Conference (InSITE) 2009, pp. 83-95.
[9] Z. Rao, and F. Alvarruiz, "Use of an Artificial Neural Network to Capture the Domain Knowledge of a Conventional Hydraulic Simulation Model", Journal of HydroInformatics, 2007, pg.no 15-24.
[10] T. Kohonen, O. Simula, "Engineering Applications of the SelfOrganizing Map", Proceeding of the IEEE, Vol. 84, No. 10, 1996, pp.1354 – 1384
[11] R. Sathya and A. Abraham, "Unsupervised Control Paradigm for Performance Evaluation", International Journal of Computer Application, Vol 44, No. 20, pp. 27-31, 2012.
[12] R. Pelessoni, and L. Picech, "Self Organizing Maps - Applications and Novel Algorithm Design, An application of Unsupervised Neural Netwoks in General Insurance: the Determination of Tariff Classes".
[13] P. Mitra, "Unsupervised Feature Selection Using Feature Similarity", IEEE Transaction on Pattern Analysis and Machine Intelligence", Vol.24, No. 4, pp. 2002
[14] Moghadassi, F. Parvizian, and S. Hosseini, "A New Approach Based on Artificial Neural Networks for Prediction of High Pressure Vapor-liquid Equilibrium", Australian Journal of Basic and Applied Sciences, Vol. 3, No. 3, pp. 1851-1862, 2009
[15] R. Asadi, N. Mustapha, N. Sulaiman, and N. Shiri, "New Supervised Multi Layer Feed Forward Neural Network Model to Accelerate Classification with High Accuracy", European Journal of Scientific Research, Vol. 33, No. 1, 2009, pp.163-178.
[16] Pelliccioni, R. Cotroneo, and F. Pung, "Optimization Of Neural Net Training Using Patterns Selected By Cluster Analysis: A Case-Study Of Ozone Prediction Level", 8th Conference on Artificial Intelligence and its Applications to the Environmental Sciences", 2010.
[17] M. Kayri, and Ö. Çokluk, "Using Multinomial Logistic Regression Analysis In Artificial Neural Network: An Application", Ozean Journal of Applied Sciences Vol. 3, No. 2, 2010.
[18] U. Khan, T. K. Bandopadhyaya, and S. Sharma, "Classification of Stocks Using Self Organizing Map", International Journal of Soft Computing Applications, Issue 4, 2009, pp.19-24.
[19] S. Ali, and K. A. Smith, "On learning algorithm selection for classification", Applied Soft Computing Vol. 6, pp. 119–138, 2006
[20] L. Schwartz, K. Stowe, and P. Sendall, "Understanding the Factors that Contribute to Graduate Student Success: A Study of Wingate University's MBA Program"

INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN COMPUTER & COMMUNICATION ENGINEERING

9940 572 462 6381 907 438 ijircce@gmail.com

www.ijircce.com

Scan to save the contact details