International Journal of Computer Applications (0975 – 8887)
Volume 181 – No. 40, February 2019

A Review of Unsupervised Artificial Neural Networks with Applications

Samson Damilola Fabiyi
Department of Electronic and Electrical Engineering, University of Strathclyde
204 George Street, G1 1XW, Glasgow, United Kingdom

ABSTRACT
Artificial Neural Networks (ANNs) are models formulated to mimic the learning capability of human brains. Learning in ANNs can be categorized into supervised, reinforcement and unsupervised learning. Application of supervised ANNs is limited to when the supervisor's knowledge of the environment is sufficient to supply the networks with labelled datasets. Application of unsupervised ANNs becomes imperative in situations where it is very difficult to get labelled datasets. This paper presents the various methods, and applications of unsupervised ANNs. In order to achieve this, several secondary sources of information, including academic journals and conference proceedings, were selected. Autoencoders, self-organizing maps, and boltzmann machines are some of the unsupervised ANNs based algorithms identified. Some of the areas of application of unsupervised ANNs identified include exploratory data, statistical, biomedical, industrial, financial and control analysis. Unsupervised algorithms have become very useful tools in segmentation of Magnetic resonance images for detection of anomalies in the body systems.

General Terms
Pattern Recognition

Keywords
Artificial Neural Networks (ANN), unsupervised ANN, Self-Organizing Maps (SOM), Magnetic Resonance Imaging (MRI), clustering, pattern recognition.

1. INTRODUCTION
Learning is a basic component needed in the creation of intelligence [1]. Humans derive their intelligence from the brains' ability to learn from experience and using that to cope when confronted with existing and new situations [2, 3]. Reproduction of human intelligence in machines and computers is the goal of artificial intelligence methods, one of which is ANN [4].

ANNs are models formulated to mimic the learning capability of human brains [4]. As in humans, training, validation and testing are important components in creating such computational models. Artificial neural networks learn by receiving some datasets (which may be labelled or unlabelled) and computationally adjusting the network's free parameters adapted from the environment through simulation [5, 6]. Based on the learning rules and training methods, learning in ANNs can be categorized into supervised, reinforcement and unsupervised learning [6, 7, 8].

In supervised learning, as its name implies, the artificial neural network is under the supervision of a teacher (say, a system designer) who uses his or her knowledge of the environment to train the network with labelled data sets [7]. Hence, the artificial neural networks learn by receiving input and target pairs of several observations from the labelled data sets, processing the input, comparing the output with the target, computing the error between the output and target, and using the error signal and the concept of backward propagation to adjust the weights interconnecting the network's neurons with the aim of minimising the error and optimising performance [6, 7]. Fine-tuning of the network continues until the set of weights that minimise the discrepancy between the output and the desired output is obtained. Figure 1 shows the block diagram which conceptualizes supervised learning in ANNs. Supervised learning methods are used to solve classification and regression problems [8]. The output of a supervised learning algorithm can either be a classifier or a predictor [9]. The application of this method is limited to when the supervisor's knowledge of the environment is enough to supply the networks with input and desired output pairs for training.

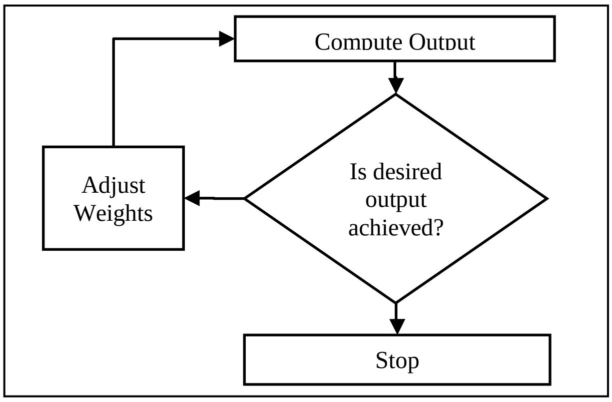

Figure 1 Supervised learning in ANNs [10]

Unsupervised learning is used when it is not possible to augment the training data sets with class identities (labels). This impossibility occurs in situations where there is no knowledge of the environment, or the cost of acquiring such knowledge is too high [11]. In unsupervised learning, as its name implies, the ANN is not under the supervision of a "teacher". Instead it is supplied with unlabelled data sets (containing only the input data) and left to find patterns in the data and build a new model from it. In this situation, ANN learns to categorize the data by exploiting the distance between clusters within it.

Reinforcement learning is another kind of learning that involves interaction with the environment, getting the state of such environment, choosing an action to change this state, sending the action to a simulator (critic) and receiving a numerical reward or a penalty in form of a feedback which can be positive or negative with the aim of learning a policy [6, 7, 8, 12]. Actions that maximize the reward are selected by trial and error techniques [13]. Figure 2 shows the block diagram to illustrate the concept of reinforcement learning. Reinforcement and unsupervised learning differ from each other in the sense that, while reinforcement learning involves learning a policy by maximizing some rewards, the goal of unsupervised learning is to exploit the similarities and differences in the input data for categorization.

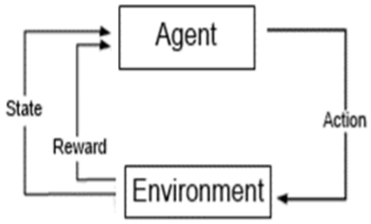

Figure 2 Reinforcement Learning [8]

This paper presents the various methods, and applications of unsupervised artificial neural networks.

2. METHODOLOGY

Academic journals, conference proceedings, textbooks, dissertations, magazines, and lecture slides are the major secondary sources of information selected for identifying various techniques and applications of unsupervised ANNs. In other to narrow down the focus of this study, only one of the unsupervised learning techniques identified known as self-organising map will be discussed in detail. In addition to identifying and discussing various applications of unsupervised artificial neural networks, some of the past work which are related to the identified applications are presented.

3. UNSUPERVISED ARTIFICIAL NEURAL NETWORKS ALGORITHMS AND TECHNIQUES

Techniques and algorithms which are used in unsupervised artificial neural networks include restricted boltzmann machines, autoencoders, self-organizing maps, etc. Self-organizing maps are presented in this section

3.1 Self-organizing maps

Self-organizing maps are basic type of artificial neural networks whose process of development is based on unsupervised learning techniques and exploitation of the similarities between data [15, 16, 17]. Self-organising maps are biologically inspired topographically computational maps that learn by self-organisation of its neurons. This inspiration came from the way different sensory inputs are organised into topographic maps in humans' brain [18, 19]. Self-organising maps, unlike supervised ANN, consists of input and output neurons with no hidden layers and are developed in such a way that only one of the output neurons can be activated. This brings about competitive learning, a process where all the output neurons compete with one another. The winner of such competition is fired and referred to as the winning neuron. With Seach of the output neurons having sets of weights which define their coordinates in the input space, one way of realising the competition between output neuron is by computing the value of discriminant function, usually Euclidean distance between them and the feature vector of the current sample being fed into the input. Selected (winning) neurons, from a group of neurons which are positioned at the nodes of a lattice, are tuned into various input patterns (structures), organising themselves, and forming a topographic map over the lattice structure. Statistical representation in the input structures are indicated by the coordinates of the neurons [18]. When supplied with input signals, self-organising maps, as their name implies, function to provide a topographic map (spatially organized arrangement of neurons over the lattice structure) which internally depicts the statistical features (properties) in input patterns of the supplied input [20].

Initialisation, competition, cooperation and adaptation are the key components involved in the self – organisation of neurons. At the initialisation stage, randomly selected small values are initially allocated as weights of output neurons. Output neurons would then compete with one another by comparing the values of discriminant function computed. The output neuron that minimizes the value of discriminant function is selected as the winner and has its weights updated such that it is drawn closer to the current observation. There is cooperation between the winning neuron those in its neighbourhood (defined by a radius) because not only is its weights updated but also the weights of those in its pre-defined neighbourhood are updated as well, with the winning neurons receiving relatively higher updates, towards the input vector. This cooperation is inspired by lateral interaction among groups of excited neurons in the humans' brain. The weight update receive by neighbouring neurons is a function of the lateral distance between them and winning neuron with the closest and farthest neurons receiving the highest and lowest weight update respectively [18, 19, 21]. The weights are updated for efficient unsupervised categorization of data [22]. The idea behind this is the need to enhance the similarity between a unit that best match the training input often referred to as the best matching unit (BMU) and those in a nearby neighbourhood to the input [18, 19, 21, 23].

The five stages involved in self-organized maps algorithm are initialization, sampling (drawing of training input vector), finding the winning neuron whose weight vector best matches the input vector, updating the weights of the winning neuron, and those in the neighbourhood using equation (1), and returning to the sampling stage until no changes can be implemented in the feature map [18, 19].

$$\Delta w_{ji} = ŋ T_{j,I(X)} (t)(x_i - w_{ji}) \qquad (1)$$

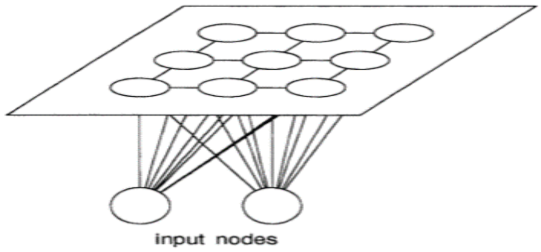

Figure 3 Feature map of the Kohonen network [23].

Kohonen network is a type of self-organized maps [23]. The Kohonen network's feature map is shown in Figure 3. Self-organizing maps artificial neural networks are mainly applied for clustering and brain-like feature mapping and are most suitable for application in the areas of exploratory data, statistical, biomedical, industrial, financial and control analysis [22, 24, 25].

4. APPLICATIONS OF UNSUPERVISED ARTIFICIAL NEURAL NETWORK

While supervised learning leads to regression and classification, unsupervised learning performs the tasks of pattern recognition, clustering and data dimensionality reduction.

Unsupervised learning is aimed at finding some patterns in the input data. Recognition of patterns in unlabelled datasets leads to clustering (unsupervised classification). Clustering involves grouping of data with similar features together. One of the key stages of recognition systems is pattern recognition. Pattern recognition has found application in diagnosing diseases, data mining, classification of documents, recognizing faces, etc [22, 26]. Data mining, as its name implies, involves automatically or semi-automatically mining (extracting) useful information from massive datasets [27, 28]. Self-organizing maps are artificial neural network algorithms for data mining [29]. Massive data can be analysed and visualized efficiently by self-organising maps [25]. In [30], unsupervised neural networks, based on self-organising map, was used for clustering of medical data with three subspaces namely patients' drugs, body locations, and physiological abnormalities [30]. In [31], self-organising map was used to analyse and visualize yeast gene expression, and identified as an excellent, speedy and convenient techniques for organization and interpretation of massive datasets like that of yeast gene expression [31].

Unsupervised learning also performs the task of reducing the number of variables in high-dimensional data, a process known as dimensionality reduction. Data dimensionality reduction task can be further classified into feature extraction and feature selection [32]. Feature selection involves selecting a subset of relevant variable from the original dataset [32, 33]. Transformation of the dataset in high dimensional space to low dimensional space is referred to as feature extraction [32]. Principal component analysis is one of the best techniques for extracting linear features [34]. High dimensional data can be easily classified, visualized, transmitted and stored thanks to the dimensionality reduction task which can be facilitated by unsupervised artificial neural network algorithms [35]. In [35], auto-coders with weights initialized effectively was presented as a better tool than principal components analysis for data dimensionality reduction [35]. Dimensionality reduction of data is usually performed at the pre-processing stages of other tasks to reduce computational complexity and improve performance of machine learning models. In [36], Performance component analysis, an unsupervised learning algorithm, was used to reduce the dimension of the data before classification for improvement in performance and better computational speed [36].

5. UNSUPERVISED NEURAL NETWORKS IN SEGMENTATION OF MAGNETIC RESONANCE IMAGES

Clustering can also be used for image segmentation [37]. Image segmentation, a very important aspect of image processing, involves dividing an image into simpler units or regions with similar features [38]. Detection of anomalies in body systems requires analysis of medical images. Segmentation is a prelude for analysing medical images [39]. Magnetic resonance imaging is one of the imaging techniques used in detection of such irregularities. Others are Computerized Tomography (CT) scan, ultrasound imaging, X-rays, mammogram, etc [39, 40]. For instance, brain disorder like schizophrenia or dementia can be identified by segmentation of MR brain images [42]. Conditions like tumours and infections can be detected by MRI [40]. Use of these imaging techniques enhance the accuracy of decisions to be reached by radiographers when determining the presence or absence of irregularities in medical images which are under analysis for correct diagnosis [39, 40]. MRI is non-invasive and known for providing detailed information for tissue identification [40, 41]. Unlike supervised segmentation, unsupervised segmentation of MRI images is automatic or semi-automatic. It does not require prior knowledge or intervention of an expert. Hence, it consumes less time and effort [41].

Features of MRI images are usually extracted for classification using unsupervised neural networks. In [42], two different approaches, neural network and fuzzy clustering used in segmentation of MRI images of human brain were compared from different perspectives, some of which are learning methods (supervised vs unsupervised), time complexity, etc. Magnetic resonance images of a brain section were segmented using fuzzy clustering methods and supervised neural network. Though the results obtained using both methods were similar, a visual inspection of the unsupervised fuzzy clustering algorithm indicates a better result [42]. In [43], unsupervised neural network approach for classification of MRI images of human brain in detection of brain tumour was proposed. After pre-processing and feature extraction (using independent component analysis for dimensionality reduction), unsupervised neural classifiers, SOM and k-means clustering algorithms were used to classify MRI images into normal and abnormal images with 98.6 % accuracy. The proposed technique was considered to have outperformed other techniques like probabilistic neural network (PNN), Back propagation (BPN), Bayesian, etc. with accuracies of 87%, 76% and 79.3% respectively [43].

In [44], an unsupervised neural network approach for segmentation of kidney in MRI images was proposed. Iterative segmentation of each slice, which gave the proposed method relatively high robustness and efficiency, involved obtaining segmented kidney by clustering of pixels values in each image using K-means [44]. In [45], comparisons between performance of supervised ANNs algorithms, back propagation and cascade correlation, and that of unsupervised algorithm (clustering), fuzzy c-means (FCM) in segmentation of MR images for characterization of tissues was carried out. While classification by the supervised algorithms involved training and testing with significantly higher speed attained, classification by supervised algorithms required only the testing phase but with longer time requirement. Finding ways for significant reduction in time requirement for FCM was recommended [45]. In [41], an unsupervised algorithm using self-organising maps for segmentation of MRI images was proposed. SOM classifier was used for brain tissue classification, following pre-processing of acquired MR brain images, feature extraction and feature selection with principal component analysis. The proposed technique achieved good segmentation results. Besides, the use of principal component analysis was helpful in achieving optimum results and reducing the time required for segmentation [41].

6. CONCLUSION

Unsupervised artificial neural networks are networks which are left to learn by looking for patterns in inputs and are used in situations where getting labelled datasets becomes very difficult. This paper has identified some unsupervised artificial neural networks algorithms including autoencoders and self-organizing maps. Unsupervised artificial neural networks can perform the tasks of pattern recognition, clustering and data dimensionality reduction. Application of unsupervised neural networks in data mining, diagnosing of diseases, image segmentation and dimensionality reduction will continue to make them dominant and indispensable models in exploratory data, statistical, biomedical, industrial, financial and control analysis. Unsupervised algorithms have become very useful tools in segmentation of Magnetic resonance images for detection of anomalies in the body systems.

7. REFERENCES

[1] S. Russell, 'Machine Learning', in Artificial Intelligence A volume in Handbook of Perception and Cognition, Waltham: Academic Press, 1966, 89–133.

[2] R. M. E. Sabbatini, 'The Evolution of Human Intelligence', Brain and Mind, no. 12, p. 2, 2001.

[3] S. Twardosz, 'Effects of Experience on the Brain: The Role of Neuroscience in Early Development and Education', Early Education & Development, vol. 23, no. 1, p. 96-119, 2012.

[4] D. J. Livingstone, Artificial Neural Networks Methods and Applications. Totowa: Humana Press, 2008, p. v.

[5] R. Rojas, Neural Networks A Systematic Introduction. Berlin: Springer-Verlag, 1996, p. 101.

[6] R. Sathya and A. Abraham, 'Comparison of Supervised and Unsupervised Learning Algorithms for Pattern Classification', International Journal of Advanced Research in Artificial Intelligence, vol. 2, no. 2, p. 34 - 38, 2013.

[7] M. Bennamoun, 'Neural Network Learning Rules', University of Western Australia, Australia.

[8] V. Stankovic, 'Introduction to Machine Learning in Image Processing', University of Strathclyde, Glasgow, 2017.

[9] J. Si, A. Barto, W. Powell and D. Wunsch, 'Reinforcement Learning and Its Relationship to Supervised Learning', in Handbook of Learning and Approximate Dynamic Programming, Hoboken: John Wiley & Sons, Inc., Hoboken, NJ, USA, 2004, p. iii.

[10] M. Dalvi, 'Artificial Neural Networks', Visvesvaraya National Institute of Technology, Nagpur, 2014.

[11] A. F. Atiya, 'An Unsupervised Learning Technique for Artificial Neural Networks', Neural Networks, vol. 3, no. 3, p. 707-711, 1990.

[12] A. Gosavi, 'Neural Networks and Reinforcement Learning', Missouri University of Science and Technology Rolla.

[13] F. Woergoetter and B. Porr, 'Reinforcement learning', Scholarpedia, vol. 3, no. 3, p. 1448 ,2008.

[14] A. Ghanbari, Y. Vaghei, and S. M. R. S. Noorani, 'Reinforcement Learning in Neural Networks: A Survey', International journal of Advanced Biological and Biomedical Research, vol. 2, no. 5, p. 1399, 2014.

[15] G. Pölzlbauer, 'Survey and Comparison of Quality Measures for Self-Organizing Maps', in Proceedings of the Fifth Workshop on Data Analysis (WDA'04), Sliezsky dom, Vysoké Tatry: Elfa Academic Press, 2004, 67-82.

[16] J. Djuris, S. Ibric and Z. Djuric, 'Neural computing in pharmaceutical products and process development', in Computer-Aided Applications in Pharmaceutical Technology, Oxford: Woodhead Publishing, 2013, p. 91–175.

[17] K. Roy, S. Kar and R. N. Das, 'Newer QSAR Techniques', in Understanding the Basics of QSAR for Applications in Pharmaceutical Sciences and Risk Assessment, Tokyo: Academic Press, 2015, p. 319–356.

[18] S. Haykin, Neural Networks and Learning Machines, 3rd ed. New York: Pearson Prentice Hall, 2009, p. 425 – 466.

[19] J. A. Bullinaria, 'Self Organizing Maps: Fundamentals', Birmingham, 2004.

[20] T. Kohonen, 'The Self-Organizing Map', in Proceedings of the IEEE, vol. 78, no. 9, p. 1464 – 1480, 1990.

[21] M. Köküer, R. N.G. Naguib, P. Jančovič, H. B. Younghusband and R. Green, 'Towards Automatic Risk Analysis for Hereditary Non-Polyposis Colorectal Cancer Based on Pedigree Data', in Outcome Prediction in Cancer, Elsevier, 2007, p. 319–337.

[22] J. K. Basu, D. Bhattacharyya and T. Kim, 'Use of Artificial Neural Network in Pattern Recognition', International Journal of Software Engineering and Its Applications, vol. 4, no. 2, p. 23 – 34,2010.

[23] R. Beale and T. Jackson, Neural Computing: An Introduction. Bristol: IOP Publishing Ltd, 1990, p. 107 – 109.

[24] T. Kohonen, 'Essentials of The Self-Organizing Map', Neural Networks, vol. 37, no. 2013, p. 52 – 65, 2012.

[25] P. Toronen, M. Kolehmainen, G. Wong and E. Castren, 'Analysis of Gene Expression Data Using Self-Organizing Maps', Federation of European Biochemical Societies, vol. 451, no. 1999, p. 142 – 146, 1999.

[26] B. D. Ripley, Pattern recognition and neural networks. Cambridge University Press, 2008.

[27] N. Jain and V. Srivastava, 'Data Mining Techniques: A Survey Paper', International Journal of Research in Engineering and Technology, vol. 2, no. 11, p. 116 – 119, 2013.

[28] T. Silwattananusarn1 and K. Tuamsuk, 'Data Mining and Its Applications for Knowledge Management: A Literature Review from 2007 to 2012', International Journal of Data Mining & Knowledge Management Process, vol. 2, no. 5, p. 13 – 24, 2012.

[29] J. Vesanto, 'Neural Network Tool for Data Mining: Som Toolbox', in Proceedings of Symposium on Tool Environments and Development Methods for Intelligent Systems (TOOL-MET2000), Oulun yliopistopaino, Oulu, Finland, 2000, pp. 184–196.

[30] D. Shalvi and N. DeClaris, 'An unsupervised neuralnetwork approach to medical data mining techniques', in Neural Networks Proceedings, 1998. IEEE World Congress on Computational Intelligence. The 1998 IEEE International Joint Conference, Anchorage, AK, USA, 2002, p. 171 – 176.

[31] P. Törönen, M. Kolehmainen, G. Wong and E. Castrén, 'Analysis of Gene Expression Data Using Self-Organizing Maps', FEBS Letters, Volume 451, Issue 2, p. 142-146, 1999.

[32] M. Sabitha and M. Mayilvahanan, 'Application of Dimensionality Reduction techniques in Real time Dataset', International Journal of Advanced Research in Computer Engineering & Technology, vol. 5, no. 7, p. 2187 – 2189, 2016.

[33] C. O. S. Sorzano, J. Vargas, and A. P. Montano, “A survey of dimensionality reduction techniques”, ArXiv14032877 Cs Q-Bio Stat, 2014.

[34] S. Munder and D.M. Gavrila, ‘An Experimental Study on Pedestrian Classification’, IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 28, no. 11, p. 1863 – 1868, 2006.

[35] G. E. Hinton and R. R. Salakhutdinov, ‘Reducing the Dimensionality of Data with Neural Networks’, Science, vol. 313, no. 5786, p. 504-507, 2006.

[36] N. Pinto, D. D. Cox and J. J. DiCarlo, ‘Why is Real-World Visual Object Recognition Hard?’, PLoS Computational Biology, vol. 4, no. 1, p. 0151 – 0156, 2008.

[37] K.-L. Du, ‘Clustering: A Neural Network Approach’, Neural Networks, vol. 23, no. 2010, p. 89-107, 2009.

[38] M. Awad, ‘An Unsupervised Artificial Neural Network Method for Satellite Image Segmentation’, The International Arab Journal of Information Technology, vol. 7, no. 2, p. 199 – 205, 2010.

[39] S. N. Sulaiman, N. A. Non, I. S. Isa and N. Hamzah, "Segmentation of brain MRI image based on clustering algorithm," 2014 IEEE Symposium on Industrial Electronics & Applications (ISIEA), Kota Kinabalu, 2014, pp. 60-65.

[40] J. T. Vaughan et al., "Current and Future Trends in Magnetic Resonance Imaging (MRI)," 2006 IEEE MTT-S International Microwave Symposium Digest, San Francisco, CA, 2006, pp. 211-212.

[41] P. K. Prajapati and M. Dixit, "Un-Supervised MRI Segmentation Using Self Organised Maps," 2015 International Conference on Computational Intelligence and Communication Networks (CICN), Jabalpur, 2015, pp. 471-474.

[42] L. 0. Hall, A. M. Bensaid, L. P. Clarke, R. P. Velthuizen, M. S. Silbiger, and J. C. Bezdek, ‘A Comparison of Neural Network and Fuzzy Clustering Techniques in Segmenting Magnetic Resonance Images of the Brain’, IEEE Transactions on Neural Networks, vol. 3, no. 5, p. 672 – 682, 1992.

[43] S. Goswami and L. K. P. Bhaiya, "Brain Tumour Detection Using Unsupervised Learning Based Neural Network," 2013 International Conference on Communication Systems and Network Technologies, Gwalior, 2013, pp. 573-577.

[44] N. Goceri and E. Goceri, "A Neural Network Based Kidney Segmentation from MR Images," 2015 IEEE 14th International Conference on Machine Learning and Applications (ICMLA), Miami, FL, 2015, pp. 1195-1198.

[45] A. M. Bensaid, L. O. Hall, L. P. Clarke and R. P. Velthuizen, "Mri Segmentation Using Supervised and Unsupervised Methods," *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society Volume 13: 1991*, Orlando, FL, USA, 1991, pp. 60-61