REST Journal on Emerging trends in Modelling and Manufacturing
Vol: 6(4), 2020
REST Publisher
ISSN: 2455-4537

Website: www.restpublisher.com/journals/jemm

Evaluation of Artificial Neural Network, using Evaluation based on Distance from Average Solution

Parwani Dhiraj Mahesh
SSt College of Arts and Commerce, Maharashtra, India.
dhirajparwani@sstcollege.edu.in

Abstract

Computer systems based on artificial neural networks, often known as neural networks or neural nets, are modeled after the organic neural networks seen in animal brains. Artificial neurons are a group of interconnected units or nodes that serve as the foundation of an ANN and are meant to approximate the function of biological brain neurons. This article contains a survey of practical uses for neural networks. It offers a taxonomy of Artificial Neural Networks (ANNs), in-forms the reader of recent and upcoming developments in ANN applications research, and highlights research areas of interest. This paper also discusses the difficulties, contributions, comparative effectiveness, and important methodologies in ANN applications. The study examines a wide range of ANN applications in numerous disciplines, including computing, science, engineering, medicine, the environment, agriculture, mining, technology, climate, business, and the arts similar to nanotechnology. This study analyses performance assesses ANN contributions and criticizes techniques. The study discovered that artificial neural networks with feedforward and feedback propagation do well when applied to solving human problems. Therefore, based on data analysis characteristics such as accuracy, processing speed, latency, fault tolerance, volume, scalability, convergence, and efficiency, we presented feed-forward and feedback propagation ANN models for research centers. A computational model known as an artificial neural network (ANN) is composed of many processing elements that accept inputs and produce outputs by their specified activation functions. This article will make other articles in this computer magazine easier to grasp for those who know little or nothing about ANNs. We go over the reasons for creating ANNs, the fundamentals of a biological neuron and an artificial computer model, network designs, learning mechanisms, and some of the most widely used ANN models. A successful ANN character recognition application brings us to a close. EDAS Evaluation Based on Distance from Average Solution method for Notebook(n1), Notebook(n2), Notebook(n3), Notebook(n4), Notebook(n5). Notebook (n1), Notebook (n2), Notebook (n3), Notebook (n4), Notebook (n5). Speed (MHz), RAM (Mbytes), Display (inches), Price (Euro). Notebook (n5) has the highest rank whereas Notebook (n1) has the lowest rank. The need for hybrid systems, Optical Neural Networks, EDAS Method.

1. Introduction

Artificial neural networks (ANNs) have recently gained popularity and proved to be effective models for prediction, pattern recognition, grouping, and classification in a variety of domains. A type of machine learning (ML) model, ANNs are now somewhat competitive with traditional regression and utility statistical models. Information and communication technology is currently dominated by artificial intelligence (including machine learning, neural networks, deep learning, and robotics), information security, big data, cloud computing, the internet, and forensic science (ICT). In terms of data analysis parameters including accuracy, processing speed, latency, efficiency, fault tolerance, volume, scalability, and convergence, entire ANN applications can be assessed. Due to its great characteristics of self-learning, adaptability, fault tolerance, linearity, and improved input-to-output mapping, ANNs are now frequently employed as global function approximations in numerical paradigms. ANNs are highly connected massively parallel computing systems with a lot of simple processors that were inspired by biological brain networks. A few "organizational" ideas thought to apply to humans are attempted to be used by ANN models. In one kind of network, nodes are viewed as "artificial neurons." ANNs are primarily utilized in sectors that involve information processing because it is their primary role. However, there are ANNs used for engineering objectives such as pattern recognition, prediction, and data summarization. Inputs (such as synapses) are essentially multiplied by weights in these. The information flow is represented by the weights given to each arrow. These weights are computed using a mathematical formula that assesses the neuron's activity. The output of the artificial neuron is calculated by another function (perhaps identity) (sometimes dependent on a certain threshold). This network's neurons merely add their inputs. Given that input neurons only get one input, their output is equal to the input times

Copyright@ 2022 REST Publisher

a weight. Artificial neural nets base their structures on a dense interconnection of basic computational units rather than executing a program made up of a series of instructions, as in a von Neumann computer. To attain high-performance speeds, artificial neurons, or simply "neurons," operate enormous computing components in parallel. The nervous system assists the human body in performing work. An enormous network of interconnected neurons makes up a neural network. These coupled neurons enable all parallel processing within the human body, making the human body the ideal example of parallel processing. A neuron is a specialized biological cell that uses certain electrical and chemical changes to process information from one neuron to another. It is made up of a cell body, or soma, and two different kinds of outwardly extending branches that resemble trees: axons and dendrites. The cell body is made up of a nucleus that houses genetic material and plasma that houses the production resources or molecular machinery required by neurons. Artificial neural networks' capacity to recognize or accurately classify patterns that haven't been previously presented in the network is one of their primary advantages. In their capacity to detect new inputs by using key properties extracted from a training set, neural networks appear to be unique. It is unknown how the network's size or organizational structure influences this quality. Through back-propagation of feed-forward networks, this working layer learns the classification task. We want to look into the connection between the training set's network topology and the network's capacity for generalization. We looked at how network structure and generalization were impacted by noise in the training set as well as the effects of network size. Because trained networks can not always utilize all of their hidden units successfully, trained networks of various sizes cannot complete this second task.

2. Materials and Methods

The need for hybrid systems: By outlining some significant flaws in empirical learning systems and hand-built classifiers, we further promote the creation of hybrid systems. The list of factors that make hybrid systems a hot topic for machine learning research is followed by a quick summary.

Hand-built classifiers: Classifiers created by hand are not learning systems (unless they are later modified by hand). They follow instructions and don't engage in intellectual learning. Even though they seem straightforward, such systems give their creators a lot of trouble. Hand-built classifiers typically assume that their domain theory is whole and accurate. Completeness and accuracy are highly challenging, if not impossible, to achieve for the majority of real-world jobs. Indeed, coping with vague and imperfect domain theories is one of the key issues with explanation-based learning. Domain theorems cannot be applied. It may be essential to write thousands of interconnected, perhaps recursive rules to make a domain theory as accurate and thorough as feasible. Such rules would be too slow to be applied.

Empirical learning: Systems of experiential learning infer generalizations from particular examples. As a result, they only need a limited amount of theoretical understanding of the issue area and instead, rely heavily on a huge example library. They completely ignore key elements of induction because they have little knowledge of problem-specific theory. Among the most crucial issues are: Any item can be described using an infinite number of features. Because of this, a computer and a cookie may appear extremely similar or quite different depending on a user's preferences. Learning is greatly facilitated by complex characteristics that are constructed from simple aspects. But feature building is a challenging, error-prone endeavor. Even though there are many examples, certain minor exceptions might be overlooked or inadequately illustrated. The correct management of aberrant events might therefore be exceedingly challenging.

Artificial neural networks: A specific technique for empirical learning is called an artificial neural network (ANN). When compared in terms of their generalization capacity, ANNs have consistently shown themselves to be on par with or even better than other empirical learning systems in a variety of fields. Their method of experiential learning presents particular challenges, though. These issues include: It takes a while to train. How well concepts are learned can be considerably influenced by the network's initial parameters. Neural networks are notoriously challenging to interpret after training.

Hybrid learning systems: The practical knowledge-free technique of experiential learning differs significantly from the knowledge-intensive, learning-by-learning approach of hand-built classifiers. "Hybrid" learning techniques, which employ both manually crafted rules and categorized examples during learning, help to bridge some of this gap. The creation of such systems has become a crucial component of machine learning due to several factors. The awareness that knowledge-intensive and knowledge-free learning are merely two endpoints of a spectrum on which an intelligent system can function is foremost among these trends.

Copyright@ 2022 REST Publisher

3. Optical Neural Networks

The fundamentals of optical computing are modeled by optical neural networks (ONNs), which are briefly discussed in this section. Electronics-based light beam processing is used in optical technologies. For creating interconnects, optical technology has various benefits, especially in terms of density, efficiency, and 2D programmability. An optical vector-matrix product processor or crossbar connector architecture was employed in one of the earliest ONN designs. A learning neural network system is constructed from 2D data. The development of ONNs has been hampered by the absence of effective optical switches and large-capacity erasable optical memory. Typically, a deformable mirror device (TMD), also known as an optical switch or spatial light modulator, is used to create such devices. TMDs are challenging to create on a wide scale by nature. The "holographic associative memory" developed at Caltech is an illustration of an optical neurocomputer. The computer's objective is to determine which holographic images from its memory most closely resemble an input image. As the brightness of the light beam varies, linear optical switching devices (also known as optical transistors) can alter their transmission properties. Holograms used in the construction of weighted patches allow for the recording and reconstruction of light intensity.

4. EDAS Method

The EDAS score is primarily based on the space from the suggested agreement machine is the installed energy for a manufacturing plant. Experts' critiques and derived numbers do not trust each different concerning solar energy and geothermal electricity. Although solar strength is a renewable power source, its miles the desired electricity supply by professionals due to Access and giant availability characterization (2d in Fuzzy AHP space) however numeric Physically damaging electricity due to the high setup cost (4th area in EDAS). And low performance. EDAS is a powerful approach for multi-standards stock type and dealer choice, and it can be effectively carried out to a few conflicting standards. EDAS is subtle, from average response Amazing distance, every from the alternative recommendation solution Terrible distance too Calculates based on the criteria type. (advantage vs. Price). Third, the proposed method of Evaluation of each opportunity calculates the score and uses the CVPFRS model to assess every opportunity through the Usual Appraisal Value. Later on, A full assessment of alternatives We get the EDAS approach a rating for everything calculates the estimated options, and ranks the options in step with decreasing values of the evaluation score. Hydrogen mobility roll-up alternatives EDAS methods for assessment are used This MCDM method helps calculate a smoothness rating and rank every opportunity The ideal is contradictory in nature Hydrogen Mobility Roll-up to choose an alternative. Every method is its strength and obstacles. EDAS approach is proposed for their stock category. The top-notch benefit of EDAS Compared to other methods for class, it has greater correct performance and Fewer math calculations. EDAS in, each of the evaluation of alternatives Appreciate the scale as well a form standard solution Depends on the location of the character replacement, introducing a prolonged EDAS technique for figuring out providers. strong waste for removal in determining the site, EDAS-based totally instinct counseled a fuzzy model. In this study, EDAS was incorporated to analyze boundaries for RE improvement. Application of EDAS technique in MAGDM. Firstly, the Basic definition of projects and distance method is Briefly advocated. Next, amplified EDAS The approach is classical underneath real context Inspired using the EDAS method. EDAS method Solving the MCDM hassle with inverse houses an original and green device to resolve. AVS to prioritize choices uses and strong waste disposal website PDA and NDA EDAS technique for evaluation used prolonged the EDAS version. EDAS technique for MCGDM. Also, EDAS compiles a few algorithms for neutrosophic easy selection making. It is clear that EDAS has obtained a whole lot of attention from pupils, however, given those arguments and motivations, no work extends EDAS to q- Rung. To solve problems related to MCDM EDAS is a brand new system that Can be used as a framework This is a review of the literature that revealed prime time use of a prolonged EDAS model based totally on the proposed intuitive parametric difference measures. Furthermore, it is an empirical Sanitary disposal approach It helps to fix the selection problem for evaluating opportunity sanitary First-time waste disposal techniques to ensure the stability of results for the proposed approach Evaluation is done between some current techniques to demonstrate the validity of the consequences done. The EDAS method has been extended to the DHHFL framework for 0 carbon operations to allow Indian Smart Cities' carbon footprint to be significantly reduced in size via the manner of 2050. EDAS Completely distance based The ranking technique is the average using parameters Sweet and nadir statistics factors. EDAS is developed among the best and most popular MCDM methods, however, the EDAS method is the best alternative. EDAS Methodology for Supplier Selection. However, to the satisfaction of our expertise, no take look at the MADM problem primarily based on the EDAS approach has been reported within the current academic literature. Therefore, the usage of EDAS in MADM is a thrilling research subject matter to rank and determine the pleasant opportunity below an unmarried-valued neutrosophic clean environment. EDAS (Estimation distance from the mean solution-based) method A new and It is efficient technique is proposed and carried out to solve the stock type problem. Validated the effectiveness of the EDAS method by comparing it with some different MCDM techniques. A fuzzy extension of EDAS is proposed) and applied to the provider selection trouble. Also, developed an intuitive EDAS method and carried out it to stable waste disposal website selection. Proposed a few algorithms for gentle selection-making with neutrosophic units based on the EDAS approach. An EDAS approach is proposed for order allocation thinking about dealer evaluation and context. Some steps of the EDAS technique and mathematics functions of IT2FS are used to assess providers with recognition of environmental standards. The result of this evaluation method is two parameters for every supplier: effective ratings and negative scores. Purchase expenses and glued parameters are used to develop multi-goal linear programming to determine the order amount from each supplier. We use a fuzzy programming method to resolve this multi-objective model.

5. Result and Discussion

TABLE 1. Artificial Neural Network

	Speed (MHz)	RAM (Mbytes)	Display (inches)	Price (Euro)
n1	1200.00	128.00	14.00	1119.00
n2	1200.00	256.00	14.00	1399.00
n3	1300.00	256.00	15.00	1449.00
n4	1200.00	256.00	12.00	1449.00
n5	1600.00	256.00	15.00	1949.00
AVj	1300.00000	230.40000	14.00000	1473.00000

Table 1 shows the data set using the Analysis method in EDAS. Notebook (n1), Notebook(n2), Notebook(n3), Notebook(n4), Notebook(n5), Speed (MHz), RAM (Mbytes), Display (inches), Price (Euro) is seen all Average in Value.

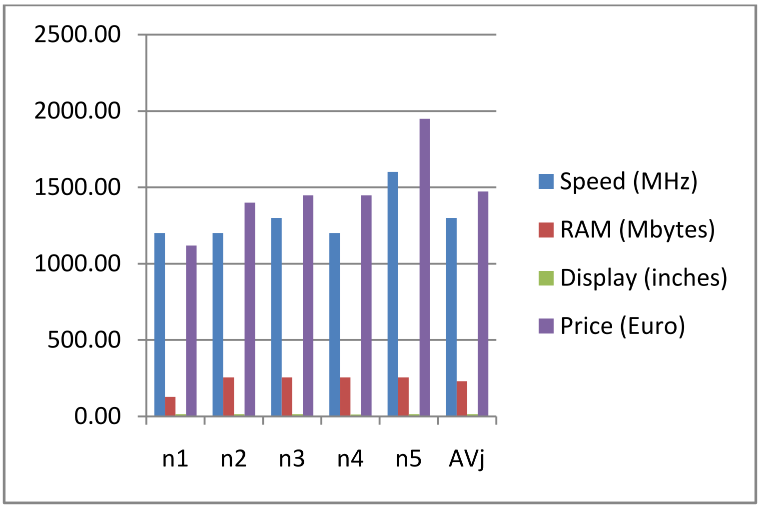

FIGURE 1. Artificial Neural Network

Figure 1 shows the shows the data set using the Analysis method in EDAS. Notebook (n1), Notebook(n2), Notebook(n3), Notebook(n4), Notebook(n5), Speed (MHz), RAM (Mbytes), Display (inches), Price (Euro)

TABLE 2. Positive Distance from Average (PDA)

	Positive Distance from Average (PDA)			
n1	0.00	0.00	0.00	0.00
n2	0.00	0.11	0.00	0.00
n3	0.00	0.11	0.07	0.00
n4	0.00	0.11	0.00	0.00
n5	0.23	0.11	0.07	0.32

Table 2 shows the Positive Distance from Average (PDA) in data set using the Analysis method in EDAS. Notebook (n1), Notebook(n2), Notebook(n3), Notebook(n4), Notebook(n5), Speed (MHz), RAM (Mbytes), Display (inches), Price (Euro) is seen all Maximum Value.

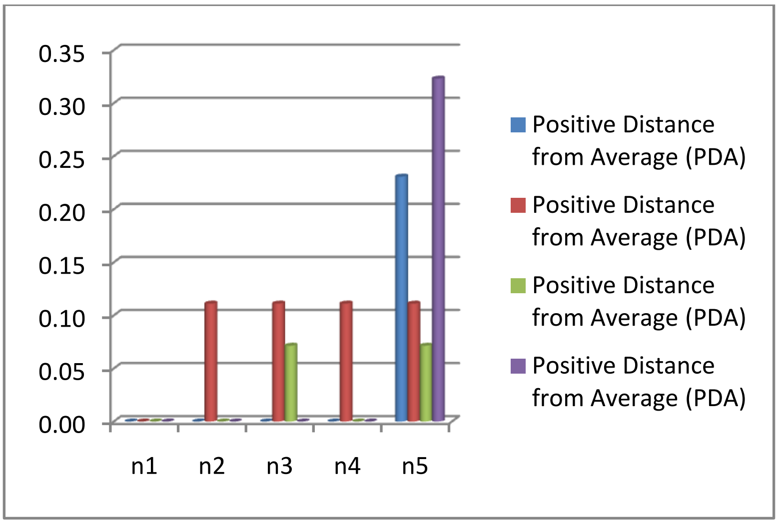

FIGURE 2. Positive distance from average (PDA)

Figure 2 shows the Positive Distance from Average (PDA) in data set using the Analysis method in EDAS. Notebook (n1), Notebook(n2), Notebook(n3), Notebook(n4), Notebook(n5), Speed (MHz), RAM (Mbytes), Display (inches), Price (Euro) is seen all Maximum Value.

TABLE 3. Negative Distance from Average (NDA)

	Negative Distance from Average (NDA)			
n1	0.07692	0.44444	0.00000	0.24033
n2	0.07692	0.00000	0.00000	0.05024
n3	0.00000	0.00000	0.00000	0.01629
n4	0.07692	0.00000	0.14286	0.01629
n5	0.00000	0.00000	0.00000	0.00000

Table 3 shows the Negative Distance from Average (NDA) in data set using the Analysis method in EDAS. Notebook (n1), Notebook(n2), Notebook(n3), Notebook(n4), Notebook(n5), Speed (MHz), RAM (Mbytes), Display (inches), Price (Euro) is seen all Maximum Value.

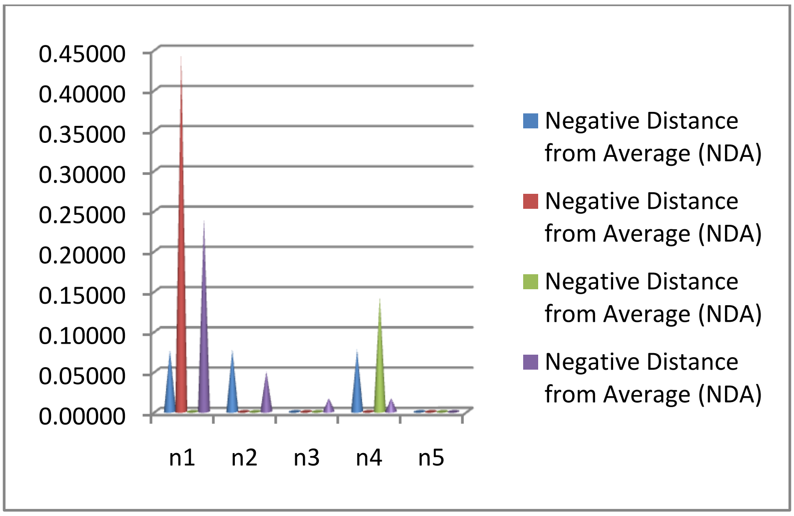

FIGURE 3. Negative distance from average (NDA)

Figure 3 shows the Negative Distance from Average (NDA) in data set using the Analysis method in EDAS. Notebook (n1), Notebook(n2), Notebook(n3), Notebook(n4), Notebook(n5), Speed (MHz), RAM (Mbytes), Display (inches), Price (Euro) is seen all Maximum Value.

TABLE 4. Weight

Weight			
0.25	0.25	0.25	0.25
0.25	0.25	0.25	0.25
0.25	0.25	0.25	0.25
0.25	0.25	0.25	0.25
0.25	0.25	0.25	0.25

Table 4 shows the Weight used for the analysis. We took same weights for all the parameters for the analysis.

TABLE 5. Weighted PDA SPI

Weighted PDA				SPi
0.00000	0.00000	0.00000	0.00000	0.00000
0.00000	0.02778	0.00000	0.00000	0.02778
0.00000	0.02778	0.01786	0.00000	0.04563
0.00000	0.02778	0.00000	0.00000	0.02778
0.05769	0.02778	0.01786	0.08079	0.18411

Table 5 shows the Weighted PDA SPi in data set using the Analysis method in EDAS Analysis is shown the Table 2 and Table 4 in Multiple Value. Notebook (n1), Notebook(n2), Notebook(n3), Notebook(n4), Notebook(n5), Speed (MHz), RAM (Mbytes), Display (inches), Price (Euro) is seen all Multiple Value.

TABLE 6. Weighted NDA SNI

Weighted NDA				SNi
0.01923	0.11111	0.00000	0.06008	0.19042
0.01923	0.00000	0.00000	0.01256	0.03179
0.00000	0.00000	0.00000	0.00407	0.00407
0.01923	0.00000	0.03571	0.00407	0.05902
0.00000	0.00000	0.00000	0.00000	0.00000

Table 6 shows the Weighted PDA SPi in Evaluation of E-learning using the Analysis method in EDAS Analysis is shown the Table 3 and Table 4 in Multiple Value. Notebook (n1), Notebook(n2), Notebook(n3), Notebook(n4), Notebook(n5), Speed (MHz), RAM (Mbytes), Display (inches), Price (Euro) is seen all Multiple Value.

TABLE 7. Final Result

	NSPi	NSPi	ASi	Rank
n1	0.00000	0.00000	0.00000	5
n2	0.15087	0.83306	0.49196	3
n3	0.24786	0.97861	0.61324	2
n4	0.15087	0.69007	0.42047	4
n5	1.00000	1.00000	1.00000	1

Table 7 shows the Final Result of data set using the Analysis for EDAS Method. Notebook (n5) has the highest rank whereas Notebook (n1) has the lowest rank.

Copyright@ 2022 REST Publisher

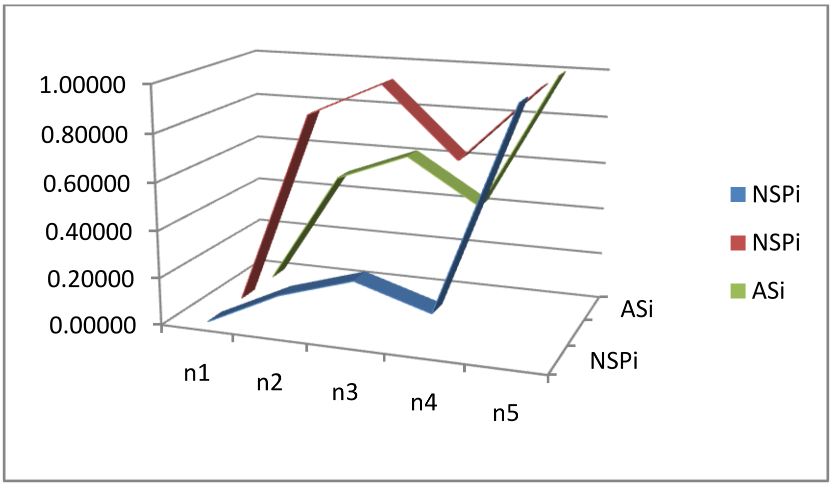

FIGURE 4 Final Results

Figure 4 shows the Final Result of data set using the Analysis for EDAS Method. Notebook (n5) has the highest rank whereas Notebook (n1) has the lowest rank.

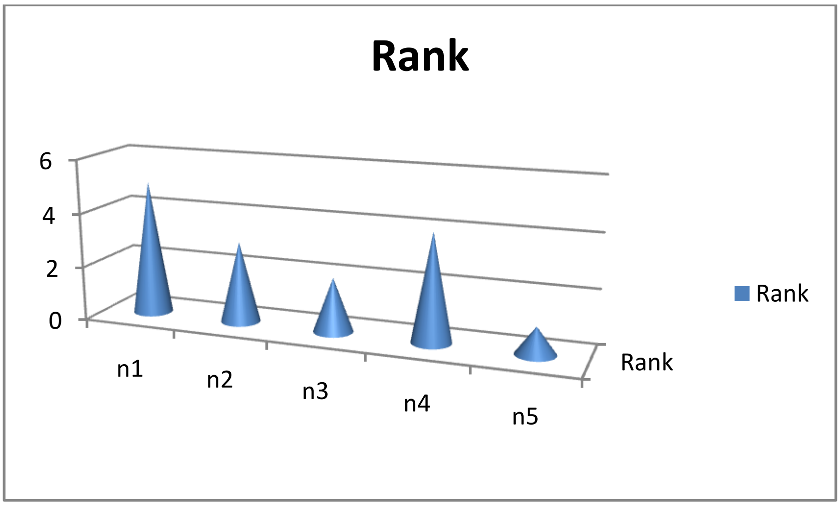

FIGURE 5 Shown the rank

Figure 5 Shows the Ranking for Notebook (n5) has the highest rank whereas Notebook (n1) has the lowest rank.

6. Conclusion

By analyzing artificial neural networks, we concluded that, due to parallel processing, as technology advances daily, artificial intelligence is becoming more and more in need. These days, parallel processing is necessary for any task involving computers or robotics since it allows for significant time and cost savings. In terms of future work, we can only state that more algorithms and alternative ways of solving puzzles must be created to get over the constraints of artificial neural networks. In particular, we intended to test the hypothesis that utilizing fewer first-layer units would promote networks to generalize better. This work explored approaches for creating artificial neural networks. Networks larger than the bare minimum needed to complete the task should be trained with noisy distorted inputs to produce neural networks with superior generalization. Removing pointless and repetitive units (level one pruning) will not have detrimental effects and will improve the network's capacity for generalization if a small network is needed. First-level pruning of clean trained networks dramatically increases noise immunity and yields a smaller network if the network cannot be trained with noise for any reason. Even though a small number of studies have been published in this field, the majority of study has been concentrated on different business sectors. In the article that was provided, 412 neural network applications from various fields were examined. Our findings suggest that the most commonly investigated issues in our study include financial crisis and bankruptcy analysis, stock price prediction, and credit scoring, although study authors have effectively used neural networks for a variety of tasks. It's interesting to note that the average volume of financial analysis and derivative articles stayed relatively constant throughout the investigation. On the other hand, compared to the early years of our study, research on equity,

Copyright@ 2022 REST Publisher

marketing, financial distress, and credit rating has expanded dramatically. Recent works have preferred high-frequency time series in particular, as well as perceived volatility. Although neural networks have helped to find solutions to some significant commercial issues, there are still many untapped potential applications. This is especially true for industries with accurate data, including expenses, bonds, and debt finance, as well as those where modelling is challenging due to the qualitative character of the problems. Two distinct neural network paradigms were also discussed, and their effectiveness was assessed. Chemo taxis was a more adaptable and simple-to-use algorithm than the well-known Baker propagation. The use of neural networks to address certain challenging process engineering issues is then investigated. NMS was initially employed as process estimators. The capability of neural assessors to make 'rapid' inferences of processing outputs from other, more easily measurable, significant, but 'hard to measure' factors is particularly intriguing. This is achievable because the introduction of secondary variables allows for feed forward anticipation of the consequences of load disruptions. In theory, a model-based control approach can directly use an NNM. Applications to a thermal reaction system that is extremely nonlinear produced very positive results.

References

1. Abiodun, Oludare Isaac, Aman Jantan, Abiodun Esther Omolara, Kemi Victoria Dada, Nachaat AbdElatif Mohamed, and Humaira Arshad. "State-of-the-art in artificial neural network applications: A survey." Heliyon 4, no. 11 (2018): e00938.
2. Krogh, Anders. "What are artificial neural networks?." Nature biotechnology 26, no. 2 (2008): 195-197.
3. Jain, Anil K., Jianchang Mao, and K. Moidin Mohiuddin. "Artificial neural networks: A tutorial." Computer 29, no. 3 (1996): 31-44.
4. Hopfield, John J. "Artificial neural networks." IEEE Circuits and Devices Magazine 4, no. 5 (1988): 3-10.
5. Dongare, A. D., R. R. Kharde, and Amit D. Kachare. "Introduction to artificial neural network." International Journal of Engineering and Innovative Technology (IJEIT) 2, no. 1 (2012): 189-194.
6. Mishra, Manish, and Monika Srivastava. "A view of artificial neural network." In 2014 international conference on advances in engineering & technology research (ICAETR-2014), pp. 1-3. IEEE, 2014.
7. Sietsma, Jocelyn, and Robert JF Dow. "Creating artificial neural networks that generalize." Neural networks 4, no. 1 (1991): 67-79.
8. Basheer, Imad A., and Maha Hajmeer. "Artificial neural networks: fundamentals, computing, design, and application." Journal of microbiological methods 43, no. 1 (2000): 3-31.
9. White, Halbert. "Learning in artificial neural networks: A statistical perspective." Neural computation 1, no. 4 (1989): 425-464.
10. Kuan, Chung-Ming, and Halbert White. "Artificial neural networks: An econometric perspective." Econometric reviews 13, no. 1 (1994): 1-91.
11. Towell, Geoffrey G., and Jude W. Shavlik. "Knowledge-based artificial neural networks." Artificial intelligence 70, no. 1-2 (1994): 119-165.
12. Lek, Sovan, and Jean-François Guégan. "Artificial neural networks as a tool in ecological modelling, an introduction." Ecological modelling 120, no. 2-3 (1999): 65-73.
13. Tkáč, Michal, and Robert Verner. "Artificial neural networks in business: Two decades of research." Applied Soft Computing 38 (2016): 788-804.
14. Yao, Xin. "Evolutionary artificial neural networks." International journal of neural systems 4, no. 03 (1993): 203-222.
15. Yao, Xin. "A review of evolutionary artificial neural networks." International journal of intelligent systems 8, no. 4 (1993): 539-567.
16. Willis, M. J., C. Di Massimo, G. A. Montague, M. T. Tham, and A. J. Morris. "Artificial neural networks in process engineering." In IEE Proceedings D (Control Theory and Applications), vol. 138, no. 3, pp. 256-266. IET Digital Library, 1991.
17. SHARKEY, AMANDA J. C. "On combining artificial neural nets." Connection science 8, no. 3-4 (1996): 299-314.
18. Huang, Yanbo. "Advances in artificial neural networks–methodological development and application." Algorithms 2, no. 3 (2009): 973-1007.
19. Misra, Janardan, and Indranil Saha. "Artificial neural networks in hardware: A survey of two decades of progress." Neurocomputing 74, no. 1-3 (2010): 239-255.
20. Zhang, Qiming, Haoyi Yu, Martina Barbiero, Baokai Wang, and Min Gu. "Artificial neural networks enabled by nanophotonics." Light: Science & Applications 8, no. 1 (2019): 1-14.

Copyright@ 2022 REST Publisher

21. Dawson, C. W., and R. L. Wilby. "Hydrological modelling using artificial neural networks." Progress in physical Geography 25, no. 1 (2001): 80-108.
22. Meireles, Magali RG, Paulo EM Almeida, and Marcelo Godoy Simões. "A comprehensive review for industrial applicability of artificial neural networks." IEEE transactions on industrial electronics 50, no. 3 (2003): 585-601.
23. Li, Eldon Y. "Artificial neural networks and their business applications." Information & Management 27, no. 5 (1994): 303-313.
24. Li, Eldon Y. "Artificial neural networks and their business applications." Information & Management 27, no. 5 (1994): 303-313.
25. Gal, Tomas, and Thomas Hanne. "Nonessential objectives within network approaches for MCDM." European Journal of Operational Research 168, no. 2 (2006): 584-592.

Copyright@ 2022 REST Publisher