International Research Journal of Engineering and Technology (IRJET) e-ISSN: 2395-0056
Volume: 09 Issue: 12 | Dec 2022 www.irjet.net p-ISSN: 2395-0072

A Review of Neural Networks Architectures, Designs, and Applications

SHIVANI KAMBOJ, PADMAVATHI HG

---***---

Abstract: Artificial neural networks (ANNs) are cutting-edge computing techniques that have been widely applied to resolving a variety of challenging issues in the real world. The extraordinary data processing characteristics of ANNs, which are mostly connected to high parallelism, fault and noise tolerance, learning, and vast nonlinearity skills, are what make them so alluring. To serve as a toolkit and resource for ANNs modelers, this work offers an overview of a few ANN architectures in the areas of recognition, prediction, and control. The review mechanism depends on comparing the most recent research in these disciplines in terms of the field that was implemented, the tools that were used, the research methodology, and the key goals that were achieved.

Keywords *— Neural networks architectures, deep neural networks, graph neural networks and fully convolutional neural networks.*

I. INTRODUCTION

There are numerous factors driving the recent resurgence of interest in neural networks, including the emergence of training techniques for advanced network topologies that go beyond the constraints of early neural networks [1].

Modeling brain processes is made easier by fast digital computers [2]. It is now possible to produce specialized hardware for neural networks thanks to technology [3]. While advancements have been made, new directions in neural network research have emerged as a result of limitations in standard computer series that have sped up neural network analysis [4].

Artificial Neural Networks (ANNs) are recently developing machine modeling techniques that are widely used to solve challenging real-world issues across a variety of fields [5]. ANNs are defined as structures made up of interconnected, adaptable processing units (also known as artificial neurons or nodes) that have the ability to process and represent information in large-scale concurrent computations [6]. Even though ANNs are blatant abstractions of their biological counterparts, their purpose is to solve complicated issues by using the functionality data of physical networks rather than trying to mimic the structure of natural systems. The fascinating history of ANNs is what makes them so appealing [7]. Managing attributes include nonlinearity, high parallelism, solidity, tolerance for flaws and errors, intelligence, and the ability to manage fluid and inaccurate information [8].

Both in its creation and in its use, neural network research is a highly interdisciplinary field [9]. A brief overview of a few neural networks now in use demonstrates the breadth of their potential applications, from successful corporate applications to successful science that holds great promise for the future [10]:

1. Generating signals: Eventually, noise and non-seismic signals contaminate registered seismic signals from various sources, such as ocean waves, wind, traffic, noise, electric noise, etc. [11],[12]. In the general area of signal processing for neural networks, there is a tone of software. The telephone line noise reduction was one of the first commercial applications [13].

2. Monitor management: Everyone who has attempted or observed these maneuvers at first is aware of the difficulties of backing a trailer. A skilled driver, however, does the task with remarkable ease [14]. An effective vector control method called sliding mode control (SMC) aims to have the managed system's direction always point to a certain multiplicity and finally border within a specific tiny area surrounding the specific area manifold [15], [16].

3. Understanding Pattern: The broad area of pattern recognition encompasses a number of key issues [17]. Numerous neural network applications have been developed for the automatic recognition of handwritten characters, whether they are numbers or letters [18],[19]. Both an essential area of machine learning research and a crucial aspect of our daily lives is audio pattern recognition [20].

4. Therapeutic: The idea behind the programmer is to teach an artificial neural memory network to retain a lot of medical records, each of which contains details on a given case's symptoms, diagnosis, and course of treatment [21],[22]. One of the safest methods to lower breast cancer mortality was early detection and treatment. For the purpose of finding breast cancer, mammography and ultrasound are also employed. The bioelectric signal produced by the human heartbeat serves as a reflection of knowledge about many physiological characteristics. A biological event in the human body causes pulse manifestation [23].

5. Speech development and voice recognition: One of the most distinctive features of humans is their ability to speak society and creation. Speech represents a great deal of individualized knowledge [24]. There were several technologies built utilizing the latest development technologies a speech signal's generated information [25]. The Learning to read English literature aloud is a difficult endeavor because how a letter is phonetically pronounced depends on the context in which the message is used [26]. It is normal to create a table of exceptions to a set of rules dictating how specific groups of letters are typically pronounced when tackling this issue [27]. Additionally, progress is being made in the challenging, speaker-neutral field of voice recognition. Many sound systems have limited vocabulary or grammar or need to be retrained for different speakers [28, 29].

6. Business and Company: Neural networks are employed in a range of business settings [30]. Although the laws that form the fundamentals of mortgage subscription are easily comprehended, it is difficult to adequately describe the procedure by which experts make choices in marginal circumstances [31]. Artificial or computer intelligence can perceive sensory information in a variety of ways, one of which is through neural networks. The first neural networks were modeled after neuronal biological networks [32].

The primary difficulty with all of these activities is predicting the upcoming events. So-called case logs are where data is normally kept after prior processes have been completed [33]. These logs are a trustworthy source for predictive training models, which implies that historical occurrences are an important indicator of how a mechanism will develop in the future [31]. There is a weight layer in a neural network with one layer. Separation is also possible between input units that receive signals from the outside environment and output units from which the net response can be gleaned [34]. An interconnection between the input and output units of one or more node layers (or levels) is known as a multilayer network [8]. The weight for two neighboring unit levels is typically present (input, hidden, or output) [35]. More complex issues can be handled by multilayer networks than by single-layer ones. A layer that competes has lots of neural networks in it. In architectural diagrams, such networks are typically not connected to neurons in the competitive layer [36]. In order for some applications to be successfully completed with decent results, certain ANNs techniques are essential. This study intends to give a preliminary grasp of these techniques. Therefore, the goal is to produce a thorough explanation of the most well-known and significant ANN strategies, together with information on the implementation domains, tools, and platforms that are appropriate for each methodology. As a result, the researchers are assisting in the quick advancement of these key procedures. The remainder of this work is structured as follows. In section II, a survey of neural networks. All referenced and reviewed studies are contrasted and discussed in section III. The conclusion of this work is stated in section IV.

II. NEURAL NETWORKS SURVEY

In the past few years, a lot of academics have discussed neural networks and the frameworks used to construct them. The key findings of various recent studies are discussed in this section.

TD Gebhard and colleagues [37] outlined in detail the challenges that machine learning can attempt to address in the context of looking for compact binary coalescences (CBC) gravity waves, and addressed their shortcomings when taking the place of matched or Bayesian parameter evaluation methods. Then use evolutionary neural networks (CNNs) to extend the present binary classification-based strategy to account for the varying input lengths. Additionally, upcoming challenges and subtle occurrences in the data generation process are emphasized, which could result in inaccurate comparisons. Finally, our architecture's empirical results demonstrate that deep neural networks are a potent addition to the current pipeline for quick and effective trigger creation.

J. Zhou, H. Liu, and others [38] proposed a novel method for fault detection employing recurrent neural networks in the form of an auto encoder (RNN). The Gated Recurrent Unit (GRU)-based denoising auto-encoder used in this method predicts numerous vibration values for rolling bearings in the future. These GRU-NP-DAEs, which are nonlinear auto encoders, are well-suited for generalizing each fault pattern. Then, reconstruction errors between the following cycle and output data produced by various GRU-NP-DAEs are used as input data to diagnose unstable conditions and identify fault type. The effectiveness and dominance of the suggested diagnostic approach over alternative state-of-the-art procedures are attested by historical data sets for spinning machines.

N. Choma and others [39] used GNN networks to improve signal identification in the Ice cube neutrino observation. The Ice-Cube detector array is represented as a table, with the sensors serving as the vertices and the edges serving as a learned attribute of the sensors' spatial coordinates. The author claims that our GNN is adaptive and that measurement is limited to the input signal support since only a portion of the Ice-sensor Cubes are used during a given observation. The author shows how our GNN design is useful for describing ice cube events since it outperforms both the conventional physics-based approach and the traditional 3D convergence of neural networks.

V.-A. Le and others [40] a novel 3D overhead crane system with an adaptable sliding hierarchical mode control system has been developed. The process of building a controller begins with the hierarchical configuration of two sliding surfaces of the first order, which are represented by two actuated and unsaturated bridge crane subsystems. As a result of disturbances in the 3D overhead crane dynamic model, unknown parameters are provided to characterize radial base function networks whose weights are retrieved from a Lyapunov function in this situation. As a result, the controller parameters are intelligently generated. The suggested remedy renders the crane system stable under unforeseen circumstances, when it is challenging to construct such ambiguous and ill-defined characteristics [55–56].

A new neural network identification and evaluation method developed by H. Niu et al. [41] is centered on an attack that detects abnormal traffic flow caused by a class of attacks on contact links in a networked control system feedback loop (NCS). The network attack identification residual is created by modeling the present network flow in the bottleneck node as a nonlinear function and employing an N.N. Observer. The residual is then used to determine whether it exceeds a set threshold when the contact network assault occurs begins—after the finding, another N.N. The attack's flow injection is employed to approximation. The author develops an attack detection strategy for the physical system using optimal event-led adaptive dynamic programming. The network processor pauses and receives insufficient packets.

The suggested approach will detect and assess network threats as well as the physical device's sensors.

The Incident Cause (EABSET) exponential mitigation approach was created by Y. Fan et al. [42] to achieve the worldwide stabilization of delayed nerve networks (MNNs). The issue is raised for two reasons: first, the methods for maintaining the weights of state-dependent links may be difficult to use, and second, the current event trigger's procedures may be conservative in decreasing trigger times. The stabilization conundrum is initially developed in a networked control system to address these problems. Then, an exponential attenuation term is needed for the given threshold function. It will decrease the frequency of data packet transmission and lengthen the time between two consecutively triggered events. Some appropriate requirements are obtained utilizing the input delay approach, temporal and component-based Lyapunov functionality, and matrix norm inequalities.

S. Xie et al. [43] investigated a larger range of communication patterns using neural network lenses that were randomly linked. The concept of a stochastic network generator, which encompasses the entire process of network development, is introduced by the author first. Encapsulation provides a unified perspective on the random wiring networks and the search for neural architecture (NAS). The author then uses three traditional random graph models to generate randomly wired network graphs. The results are unexpected: several iterations of these random generators produce network instances with computable compared to the ImageNet benchmark, precision.

D. K. Jain and others, [44] suggested a system for categorizing each image into one of six categories of facial expression. The Deep Neural Networks (DNNs) model is made up of deep residual blocks and single layers of convolution. In the suggested model, an image mark was first made on each face as a prelude.

Second, the suggested DNN model incorporates the images. Dataset Expanded Cohn- Kanade (C.K.+) and Female Japanese Facial Expression were used to train this model (JAFFE). Overall findings indicate that the present DNN model will perform better than the new emotion detection methods. Even the proposed model improves on our previous model's precision.

R. Ptucha and others [45] presented a wholly convolutional network architecture that generates text symbols of any length. A canonical display of the input blocks is a preprocessing phase norm, negating the need for an expensive, repeating symbol rectification. The author frequently includes a probabilistic error rate to rectify wrong blocks of terms if a lexicon is known. Our multi-State convolution method is the first method to demonstrate cutting-edge results on both lexicon-based and subjective handwriting recognition benchmarks.

M. S. Ayhan et aldescription .'s of an intuitive technique for measuring the state-of-the-art diagnostic instability in Deep Neural Networks (DNNs) for the diagnosis of diabetes [46] was centred on test time data growth. The author claims that the computation of confusion derived is fair and that even experienced doctors frequently struggle to identify cases of uncertain diagnosis. This opens the door for an adaptive ambiguity treatment for DNN-based diagnostic systems.

K. Akyol employed the clinical dataset provided by the University of Bonn to evaluate the suggested model, which was provided with an ensemble stacking technique. The proposed seizure detection model's viability was demonstrated using both the proposed model and a deep neural network model. The proposed model is competitive with the Deep Neural Networks (DNNs) base model, according to experiments. A Nonlinear Predictive Model Technique (NMPC) for Atmospheric

Pressure Plasma Jets (APPJs) was presented by A. D. Bonzanini et al. [48] with examples of implementations in plasma medicine. The goal of NMPC is to maintain patient comfort and safety standards while controlling the cumulative thermal impacts of plasma in a substratum. With a simple, explicit control law, deep neural networks are employed to approximate the NMPC implicit law. By projecting the neural network output onto a set that ensures that the state stays within a properly defined invariant group, the maximum possible constraint fulfillment is made possible.

Closed-loop simulations and in-the-moment control tests show how nonlinear control costs can be successfully managed in a fast sampling cycle while maintaining the indicated estimates.

Batur Dinler et al. [49] attempted to form a sizable Kurdish vocabulary dataset and determine the model's ideal parameters for the identification of speech segments based on consonant, vowel, and silence (C/V/S) discrimination. To achieve this, the phoneme borders were portrayed using three hybrid function vector techniques, three window types, and four window sizes. A recurrent Gated Recurrent Unit (GRU) network with six different C/V/S discriminatory classification algorithms was used to determine phoneme boundaries. In Kurdish acoustic signals, the author demonstrated that the GRU model had high speech segmentation performance. By utilizing hybrid characteristics, window widths, window forms, and classification models for Kurdish speakers virtually, the experimental results of this study show the importance of segment-detection.

R.J. Wesley and others [50] after being combined in a process known as "reconstructed space," segmented speech phonemes are examined using cutting-edge filters (RPS). Since they were created from start with embedded voice data, these characteristics for extracting Convolutional filters are ideal for various data networks. A geometric explanation of the dynamics of the observable structure can be found in the reconstruction of phase space. then provide a study demonstrating the use of a convolutional neural network to distinguish between attributes arising from the texture and shape of this geometric representation (CNN). CNNs are widely employed in picture tasks, although they were not used in step space portraiture, likely due to the integration's higher dimensionality.

Anjos and others [51] designed a serious game controlled in real-time by children's voices to aid kids in controlling the development of European Portuguese sibilant sounds (E.P.). By utilizing a sibilant classifier for a consonant Kid can practice creating these sounds more frequently because the game doesn't require adult supervision, which may speed up voice improvement. The author suggests that E.P. sibilant phonemes should be recognized by deep convolutional neural networks and incorporated into our challenging speech and language therapy games. Utilizing the Mel frequency cepstral coefficients or Mel log filter banks to compare the effectiveness of various artificial neural networks.

By showing how the many behaviors included in a phase influenced the forecast, M. Harl et al. [53] contributed a methodology that further exemplifies a forecast. This thesis is the first to employ GGNN PBPM and the first to describe decisions using GNN networks. It uses a data set of process events to demonstrate our approach.

III. COMPARISON AND DISCUSSION

It is clear from the previous section that researchers have used a variety of approaches and strategies across a range of disciplines. Researchers have underlined key elements that are relevant to comparing their proposals. A comparison of the queries described in Section II is shown in Table 1. In order to validate the objectives outlined in their technique in the field of the neural network, the comparison contains four crucial qualities that match their patterns. The comparison of implemented field, tools used, research methodology, and significant goals achieved the chart makes it clear that the sources [37], [39] directly depend on the signal processing field. References [40, 42] job as controllers, but instead of staying researchers, they worked in the fields of speech production, speech recognition, business, and pattern recognition. The researcher employs a crucial technique depending on the field of study—Neural Networks, Deep Neural Networks, and Deep Convolutional Neural Networks. Recurrent neural networks, convolutional neural networks, gated graph neural networks, and other techniques are also employed. Both researchers have strong structures, frames, and functions as a result of applying these methodologies and strategies. However, the trend among researchers has been toward contemporary commercial and medical domains.

IV. CONCLUSION

In this research, active methods for constructed neural network architectures were discussed. Various active mechanisms play a crucial part in the sectors where neural networks are implemented, one can infer from the examined studies. These industries include speech production and recognition, pattern recognition, medical, business, and signal processing. Powerful technologies are also employed in this field, including Sibilant Consonant Classifier, Control Problem Formulation, Phoneme Set and its Properties, and Bayesian Deep Neural Networks. The methods used are Deep Neural Networks, Deep Convolutional Neural Networks, Fully Convolutional Neural Networks, Recurrent Neural Networks, Graph Neural Networks, and Gated Graph Neural Networks. Today's academics are focusing more on business, speech recognition, and medical applications. Frames for effective neural networks consequently, several systems have been created, including those that make prediction more understandable, speech segment detection for the Kurdish language, a framework based on an increase in test-time data, a novel technique of output prediction, and a multi-stage in-depth learning approach. Additionally, it may be concluded that the best method for signal processing is Convolutional Neural Networks. Additionally, both fully convolutional neural networks and deep neural networks are appropriate for use in both commercial and medical applications. While Deep Convolutional Neural Networks are effective for implementations of Speech Production and Recognition.

V. REFERENCES

1. R. W. P. D. S. Levine and D. L. Long, Fundamentals of neural network modeling: Neuropsychology and cognitive neuroscience: Mit Press, 1998

2. L. da Fontoura Costa and G. Travieso, "Fundamentals of neural networks: By Laurene Fausett. Prentice-Hall, 1994, pp. 461, ISBN 0-13-334186-0," ed: Elsevier, 1996.

3. I. A. Basheer and M. Hajmeer, "Artificial neural networks: fundamentals, computing, design, and application," Journal of microbiological methods, vol. 43, pp. 3-31, 2000.

4. A. S. Eesa, Z. Orman, and A. M. A. Brifcani, "A novel featureselection approach based on the cuttlefish optimization algorithm for intrusion detection systems," Expert systems with applications, vol. 42, pp. 2670-2679, 2015.

5. Y. Chen, L. Shen, R. Li, X. Xu, H. Hong, H. Lin, et al., "Quantification of interfacial energies associated with membrane fouling in a membrane bioreactor by using BP and GRNN artificial neural networks," Journal of Colloid and Interface Science, vol. 565, pp. 1-10, 2020.

6. G. Lan, Y. Wang, G. Zeng, and J. Zhang, "Compressive strength of earth block masonry: Estimation based on neural networks and adaptive network-based fuzzy inference system," Composite Structures, vol. 235, p. 111731, 2020.

7. M. R. Mahmood and A. M. Abdulazeez, "Different Model for Hand Gesture Recognition with a Novel Line Feature Extraction," in 2019 International Conference on Advanced Science and Engineering (ICOASE), 2019, pp. 52-57.

8. F. H. Guenther, "Neural networks: Biological models and applications," Oxford: International Encyclopedia of the Social & Behavioral Sciences, pp. 10534-7, 2001.

9. J. A. Ahmed and A. M. A. Brifcani, "A new internal architecture based on feature selection for holonic manufacturing system," International Journal of Mechanical, Aerospace, Industrial, Mechatronic and Manufacturing Engineering, vol. 2, p. 1431, 2015.

10. S. Russel and P. Norvig, Artificial intelligence: a modern approach: Pearson Education Limited, 2013.

11. W. Zhu, S. M. Mousavi, and G. C. Beroza, "Seismic signal denoising and decomposition using deep neural networks," IEEE Transactions on Geoscience and Remote Sensing, vol. 57, pp. 9476-9488, 2019.

12. A. K. Mukhopadhyay and S. Samui, "An experimental study on upper limb position invariant EMG signal classification based on deep neural network," Biomedical Signal Processing and Control, vol. 55, p. 101669, 2020.

13. N. K. N. Aznan, A. Atapour-Abarghouei, S. Bonner, J. D. Connolly, N. Al Moubayed, and T. P. Breckon, "Simulating brain signals: Creating synthetic eeg data via neural-based generative models for improved ssvep classification," in 2019 International Joint Conference on Neural Networks (IJCNN), 2019, pp. 1-8.

14. Y. Zhou and Z. Zeng, "Event-triggered impulsive control on quasisynchronization of memristive neural networks with time-varying delays," Neural Networks, vol. 110, pp. 55-65, 2019.

15. S. Wang, Y. Cao, T. Huang, Y. Chen, P. Li, and S. Wen, "Sliding mode control of neural networks via continuous or periodic sampling event-triggering algorithm," Neural Networks, vol. 121, pp. 140-147, 2020.

16. J. Ni and P. Shi, "Global predefined time and accuracy adaptive neural network control for uncertain strict-feedback systems with output constraint and dead zone," IEEE Transactions on Systems, Man, and Cybernetics: Systems, 2020.

17. A. Raphael, Z. Dubinsky, D. Iluz, and N. S. Netanyahu, "Neural Network Recognition of Marine Benthos and Corals," Diversity, vol. 12, p. 29, 2020.

18. S. Zhang, W. Huang, and C. Zhang, "Three-channel convolutional neural networks for vegetable leaf disease recognition," Cognitive Systems Research, vol. 53, pp. 31-41, 2019.

19. D. A. Zebari, D. Q. Zeebaree, A. M. Abdulazeez, H. Haron, and H. N. A. Hamed, "Improved Threshold Based and Trainable Fully Automated Segmentation for Breast Cancer Boundary and Pectoral Muscle in Mammogram Images," IEEE Access, 2020.

20. Q. Kong, Y. Cao, T. Iqbal, Y. Wang, W. Wang, and M. D. Plumbley, "Panns: Large-scale pretrained audio neural networks for audio pattern recognition," IEEE/ACM Transactions on Audio, Speech, and Language Processing, vol. 28, pp. 2880-2894, 2020.

21. A. J. Weisman, M. W. Kieler, S. B. Perlman, M. Hutchings, R. Jeraj, L. Kostakoglu, et al., "Convolutional Neural Networks for Automated PET/CT Detection of Diseased Lymph Node Burden in Patients with Lymphoma," Radiology: Artificial Intelligence, vol. 2, p. e200016, 2020.

22. D. Q. Zeebaree, H. Haron, A. M. Abdulazeez, and D. A. Zebari, "Machine learning and Region Growing for Breast Cancer Segmentation," in 2019 International Conference on Advanced Science and Engineering (ICOASE), 2019, pp. 88-93.

23. Z. Chen, A. Huang, and X. Qiang, "Improved neural networks based on genetic algorithm for pulse recognition," Computational Biology and Chemistry, vol. 88, p. 107315, 2020.

24. W. Zhang, Y. Liu, X. Wang, and X. Tian, "The dynamic and taskdependent representational transformation between the motor and sensory systems during speech production," Cognitive Neuroscience, pp. 1-11, 2020.

25. H. Abbasi, A. J. Gunn, L. Bennet, and C. P. Unsworth, "Deep convolutional neural network and reverse biorthogonal wavelet scalograms for automatic identification of high frequency microscale spike transients in the post-hypoxic-ischemic EEG," in 2020 42nd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC), 2020, pp. 1015-1018.

26. P. Nantasri, E. Phaisangittisagul, J. Karnjana, S. Boonkla, S. Keerativittayanun, A. Rugchatjaroen, et al., "A Light-Weight Artificial Neural Network for Speech Emotion Recognition using Average Values of MFCCs and Their Derivatives," in 2020 17th International Conference on Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology (ECTI-CON), 2020, pp. 41-44.

27. S. Parthasarathy and C. Busso, "Semi-supervised speech emotion recognition with ladder networks," IEEE/ACM transactions on audio, speech, and language processing, vol. 28, pp. 2697-2709, 2020.

28. M. Sajjad and S. Kwon, "Clustering-Based Speech Emotion Recognition by Incorporating Learned Features and Deep BiLSTM," IEEE Access, vol. 8, pp. 79861-79875, 2020.

29. T.-S. Nguyen, S. Stüker, J. Niehues, and A. Waibel, "Improving sequence-to-sequence speech recognition training with on-the-fly data augmentation," in ICASSP 2020-2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), 2020, pp. 7689-7693.

30. V. Vashisht, S. Kamya, and M. Vashisht, "Defect Prediction Framework using Neural Networks for Business Intelligence Technology Based Projects," in 2020 International Conference on Computer Science, Engineering and Applications (ICCSEA), 2020, pp. 1-5.

31. P. Philipp, R. Jacob, S. Robert, and J. Beyerer, "Predictive Analysis of Business Processes Using Neural Networks with Attention Mechanism," in 2020 International Conference on Artificial Intelligence in Information and Communication (ICAIIC), 2020, pp. 225-230.

32. S. Leoshchenko, A. Oliinyk, S. Subbotin, and T. Zaiko, "Using Recurrent Neural Networks for Data-Centric Business," in DataCentric Business and Applications, ed: Springer, 2020, pp. 73-91.

33. B. Singh, N. Kumar, and B. K. Panigrahi, "Steepest Descent Laplacian Regression Based Neural Network Approach for Optimal Operation of Grid Supportive Solar PV Generation," IEEE Transactions on Circuits and Systems II: Express Briefs, 2020.

34. Z. Guo, Y. Shen, A. K. Bashir, M. Imran, N. Kumar, D. Zhang, et al., "Robust spammer detection using collaborative neural network in internet of thing applications," IEEE Internet of Things Journal, 2020.

35. S. S. Basha, S. R. Dubey, V. Pulabaigari, and S. Mukherjee, "Impact of fully connected layers on performance of convolutional neural networks for image classification," Neurocomputing, vol. 378, pp. 112-119, 2020.

36. L. Nanni, A. Lumini, S. Ghidoni, and G. Maguolo, "Stochastic Selection of Activation Layers for Convolutional Neural Networks," Sensors, vol. 20, p. 1626, 2020.

37. T. D. Gebhard, N. Kilbertus, I. Harry, and B. Schölkopf, "Convolutional neural networks: A magic bullet for gravitationalwave detection?," Physical Review D, vol. 100, p. 063015, 2019.

38. H. Liu, J. Zhou, Y. Zheng, W. Jiang, and Y. Zhang, "Fault diagnosis of rolling bearings with recurrent neural network-based autoencoders," ISA transactions, vol. 77, pp. 167-178, 2018.

39. N. Choma, F. Monti, L. Gerhardt, T. Palczewski, Z. Ronaghi, P. Prabhat, et al., "Graph neural networks for icecube signal classification," in 2018 17th IEEE International Conference on Machine Learning and Applications (ICMLA), 2018, pp. 386-391.

40. V.-A. Le, H.-X. Le, L. Nguyen, and M.-X. Phan, "An efficient adaptive hierarchical sliding mode control strategy using neural networks for 3D overhead cranes," International Journal of Automation and Computing, vol. 16, pp. 614-627, 2019.

41. H. Niu, C. Bhowmick, and S. Jagannathan, "Attack detection and approximation in nonlinear networked control systems using neural networks," IEEE transactions on neural networks and learning systems, vol. 31, pp. 235-245, 2019.

42. Y. Fan, X. Huang, H. Shen, and J. Cao, "Switching event-triggered control for global stabilization of delayed memristive neural networks: an exponential attenuation scheme," Neural Networks, vol. 117, pp. 216-224, 2019.

43. S. Xie, A. Kirillov, R. Girshick, and K. He, "Exploring randomly wired neural networks for image recognition," in Proceedings of the IEEE International Conference on Computer Vision, 2019, pp. 1284-1293.

44. D. K. Jain, P. Shamsolmoali, and P. Sehdev, "Extended deep neural network for facial emotion recognition," Pattern Recognition Letters, vol. 120, pp. 69-74, 2019.

45. R. Ptucha, F. P. Such, S. Pillai, F. Brockler, V. Singh, and P. Hutkowski, "Intelligent character recognition using fully convolutional neural networks," Pattern recognition, vol. 88, pp. 604-613, 2019.

46. M. S. Ayhan, L. Kuehlewein, G. Aliyeva, W. Inhoffen, F. Ziemssen, and P. Berens, "Expert-validated estimation of diagnostic uncertainty for deep neural networks in diabetic retinopathy detection," Medical Image Analysis, p. 101724, 2020.

47. K. Akyol, "Stacking ensemble based deep neural networks modeling for effective epileptic seizure detection," Expert Systems with Applications, vol. 148, p. 113239, 2020.

48. A. D. Bonzanini, J. A. Paulson, D. B. Graves, and A. Mesbah, "Toward Safe Dose Delivery in Plasma Medicine using Projected Neural Network-based Fast Approximate NMPC⋆," in Proceedings of IFAC World Congress, 2020.

49. Ö. Batur Dinler and N. Aydin, "An Optimal Feature Parameter Set Based on Gated Recurrent Unit Recurrent Neural Networks for Speech Segment Detection," Applied Sciences, vol. 10, p. 1273, 2020.

50. R. J. Wesley, A. N. Khan, and A. Shahina, "Phoneme Classification in Reconstructed Phase Space with Convolutional Neural Networks," Pattern Recognition Letters, 2020.

51. I. Anjos, N. Cavalheiro Marques, M. Grilo, I. Guimarães, J. Magalhães, and S. Cavaco, "Sibilant consonants classification comparison with multi-and single-class neural networks," Expert Systems, p. e12620, 2020.

52. N. Mehdiyev, J. Evermann, and P. Fettke, "A novel business process prediction model using a deep learning method," Business & information systems engineering, vol. 62, pp. 143-157, 2020.

53. M. Harl, S. Weinzierl, M. Stierle, and M. Matzner, "Explainable predictive business process monitoring using gated graph neural networks," Journal of Decision Systems, pp. 1-16, 2020.

54. G. Park and M. Song, "Predicting performances in business processes using deep neural networks," Decision Support Systems, vol. 129, p. 113191, 2020.

55. S. B. Sadkhan, A. Q. Hameed, H. A. Hamed, " A proposed identification method for multi-user chirp spread spectrum signals based on adaptive Neural-Fuzzy Inference System (ANFIS)", 2016 Al-Sadeq International Conference on Multidisciplinary in IT and Communication Science and Applications (AIC-MITCSA.

56. S. B. Sadkhan., A. Q. Hameed, H. A. Hamed," Digitally modulated signals recognition based on adaptive neural-fuzzy inference system (ANFIS)", International Journal of Advancements in Computing Technology (IJACT)