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Artificial Neural Networks in Medico-Diagnostics †

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Abstract: Artificial Neural Networks (ANNs) have emerged as one of the leading algorithmic approaches to solve healthcare challenges including biomarker detection, disease diagnosis, medical imaging, identification, and classification of chemical compounds. In this paper, we aim to provide insight into the fundamentals and topologies of ANNs, such as Deep Neural Networks (DNNs) and Convolutional Neural Networks (CNNs), while also familiarizing the reader with the applications of ANNs within cancer identification, diabetes diagnosis and Covid-19 detection.

Keywords: Artificial Neural Networks; Medico-Diagnostics; Healthcare Applications; Neural Network Topologies; Cancer Identification; Diabetes Diagnosis; Covid-19 Detection; Deep Learning; Biosensors and Biomarkers; Convolutional Neural Networks

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1. Introduction

The healthcare sector generates large amounts of data each year and traditional methods of data analysis within this field are both time-consuming and require large amounts of domain expertise [1,2]. The ability of Artificial Neural Networks (ANNs) to automatically analyze and identify underlying patterns within the input data (through a process called Representational Learning) without a need for the resource-intensive process of manual feature selection by domain experts has considerably accelerated the process of neural network generation and lowered the cost involved in utilizing ANNs [2,3]. Recognizing the potential of such technologies, the global "AI in healthcare" sector is expected to grow at a rate of 43.6% annually reaching a staggering total of $61.59 Billion in 2027 [4]. Figure 1a below displays how ANNs fit within the healthcare sector.

In this paper, we aim to provide insight into the fundamentals and topologies of ANNs, such as Deep Neural Networks (DNNs) and Convolutional Neural Networks (CNNs), while also familiarizing the reader with the applications of ANNs within cancer identification, diabetes diagnosis and Covid-19 detection.

2. Methods

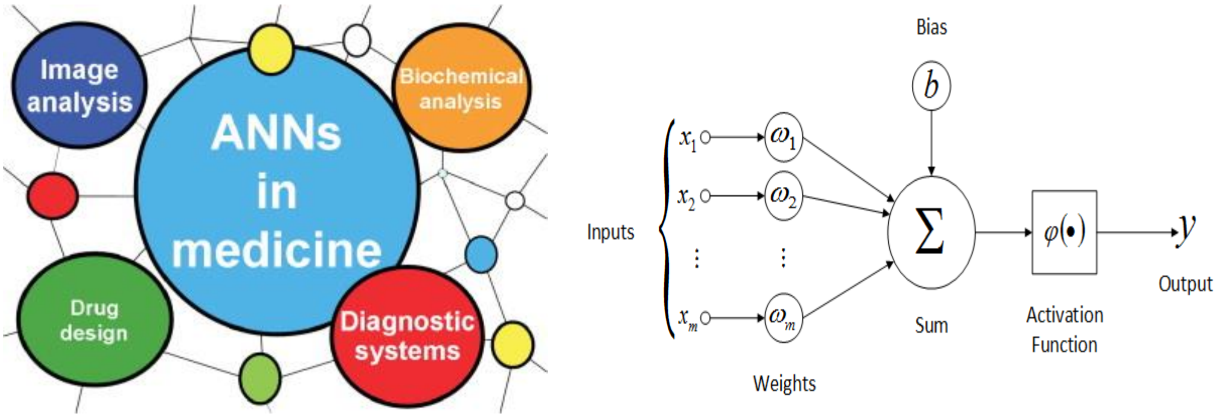
Artificial Neurons:

Artificial neurons mimic a biological neurons approach of problem solving and input analysis by using mathematical models [6]. The components of artificial neurons are as follows (see Figure 1b):

1) **Input and Weights**:

Artificial neurons generally receive inputs from either the external environment or from other artificial neurons, these inputs serve as a representation of external information as processed by the network [6,8].

Weights are adaptive coefficients associated with each input and they determine the intensity of the relationship between an input signal and the output. The greater the magnitude of weight, the larger the impact a particular input has on the outcome and vice-versa [6,8].



(**a**) (**b**)

Figure 1. (**a**) Displays the relation of ANNs to various medical applications. Image taken from [5]; (**b**) Model of an artificial neuron. Image taken from [7].

2) **Summation Junction**:

Within the summation junction, the input signals (x_1, x_2, …, x_i) and their associated weights (w_1, w_2, …, w_i) are combined to generate a single scalar value. This combination is usually done by performing a summation operation on the dot product of each input signal and their associated weights to generate what is known as the weighted sum of the input vectors, this weighted sum serves as a representation of each input-weight combination [6]. It can be represented mathematically as [6]:

$$\text{weighted sum } 'u' = \sum_{1}^{i} w_i x_i$$

3) **Bias Factor**:

The bias is a constant term added within the summation junction to increase the flexibility of a neural network as it searches for the optimal path through a given solution space [8]. Like the weights, the bias is an adaptive parameter as its optimal value is unknown before performing the experiment [8]. Thus, the new equation for the weighted sum within the summation junction would be of the form [8]:

$$\text{weighted sum } 'u' = \sum_{1}^{i} w_i x_i + b$$

4) **Activation Function**:

The activation function is perhaps the most important component of an artificial neuron. The activation function controls whether an input combination would succeed or fail in triggering a neuron i.e., generating an output [6,8,9].

Since the range of y in the formula for the weighted sum $y = \sum_1^i w_i x_i + b$ is $(-\infty, \infty)$, we use the activation function to transform this y value into another value (usually within a smaller range) that can be analyzed more easily [6,8,9]. Table 1 below lists several types of activation functions in use and their respective formulas.

Table 1. This table outlines information about several activation functions [8,9].

Activation Function	Formula	Advantages	Disadvantages
Step function	$f(y) = \begin{cases} 0 \ if \ y < Z \\ 1 \ if \ y \geq Z \end{cases}$ where Z is the threshold value	• Can be used within binary classification problems since there are two possible states that the neuron can output (0 and 1).	• Difficult to use in classification problems involving more than two states.
Linear function	$f(y) = cy$ where c is a constant	• Can generate multiple values unlike the step function above.	• Any combination of neural networks we create using this activation function can be condensed to a single activation function.
Sigmoid function	$f(y) = \frac{1}{1 + e^{-y}}$	• Commonly used activation function. • As it is non-linear, we can stack multiple artificial neurons together.	• It suffers from the vanishing gradient problem i.e., it is hard to differentiate values occurring at the extremities of the graph.[1]
Tanh function	$f(y) = \frac{e^{y} - e^{-y}}{e^{y} + e^{-y}}$	• Commonly used activation function. • It has a gradient of descent steeper than the sigmoid function. • As it is non-linear, we can stack multiple artificial neurons together.	• It suffers from the vanishing gradient problem i.e., it is hard to differentiate values occurring at the extremities of the graph.[1]
Rectified Linear Unit (ReLU) function	$f(y) = \max(0, y)$ where max is a function that returns the greater term	• Commonly used activation function. • As it is non-linear, we can stack multiple artificial neurons together. • It is computationally less expensive than the sigmoid or Tanh function since it involves simpler mathematical operations.	• It suffers from the dying ReLU problem i.e., when the input becomes 0 or negative, the gradient of descent of the function becomes 0.[1]

[1] Backpropagation (a technique of error minimization) relies upon the gradient of descent [3].

Artificial Neural Network Topologies:

Researchers often combine several artificial neurons in varying topologies to create what is known as artificial neural networks [6]. In this paper, we will look at two such popular topologies (namely Deep Neural Networks and Convolutional Neural Networks) and within the next section we will highlight their usage in cancer identification, diabetes diagnosis and Covid-19 detection.

1) **Deep Neural Network (DNN)**:

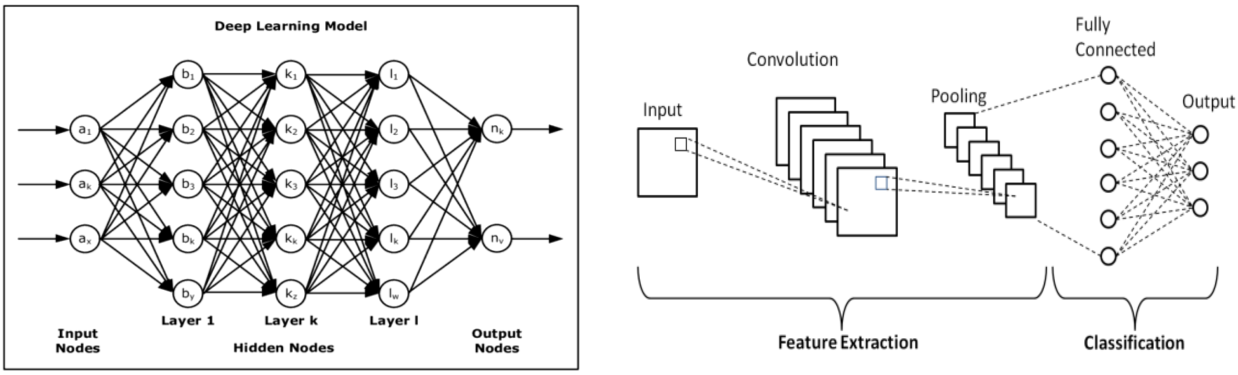
ANNs with a large number of hidden layers are known as Deep Neural Networks (see Figure 2a below) [1,10]. DNNs can analyze and interpret complex data, the presence of a deep architecture (having several hidden layers) allows the given network to make better abstractions from non-linear datasets in comparison to shallow ANNs (having a limited number of hidden layers) [1,3,12].

However, it should be noted that the presence of a large number of hidden layers also increases the training time of a given dataset [1], thus DNNs have a high degree of hardware dependency and it was only after the introduction of advances in hardware technologies such as multicore processing and GPUs that DNNs became commercially viable [1,12].

2) **Convolutional Neural Network (CNN)**:

The architecture of Convolutional Neural Networks takes inspiration from the human visual cortex and subsequently this neural network is commonly used when dealing with images [1,3,12]. As seen in Figure 2b below, CNNs can be divided into two parts, one is responsible for feature extraction and another is responsible for classification [13]. As the input image passes through the network, it gets repeatedly passed through filters (within convolution layer) such that the network can identify regions containing information and those regions that do not [3,13]. Within the pooling layer, the image size is reduced while maintaining regions containing information (i.e., features), these features are finally combined and connected within the classification section and subsequently outputted [3,13].

However, it should be noted that CNNs require a large amount of labeled training data to function, thus the usage of CNNs is restricted by the availability of large datasets for training [1].



(**a**) (**b**)

Figure 2. (**a**) Displays the basic structure of an DNN. Image taken from [11]; (**b**) Displays the basic structure of a CNN. Image taken from [13].

3. Results and Discussion

In this section, we focus upon ANN-based applications within the fields of Cancer identification, Diabetes diagnosis and Covid-19 detection.

Cancer Identification (See Table 2 below):

Cancer is a disease in which some of the cells within the body start growing uncontrollably [20]. These cells can occur almost anywhere within the body and could potentially lead to life-threatening tumors [20]. It is estimated that by 2040 cancer will affect 29.5 million people and kill 16.4 million every year [20,21], thus early detection of cancer to administer proper treatment is a must.

ANN-based technologies have been relatively successful in being able to detect cancerous specimens, some ANNs such as those in [14] and [15] have achieved accuracies exceeding 98% when trained and tested on breast cancer datasets. CNNs like those in [16] and [17] have also shown positive results by achieving accuracies of 93.64% and 81% respectively when used to detect the presence of skin cancer. Several DNNs (such as [18] and [19]) have also been largely successful in identifying kidney cancers from a given specimen. Considering the success of ANN-based technologies within this domain, it seems likely that they will continue to play a larger role in future breakthroughs.

Table 2. This table outlines several applications of ANN-based technologies for cancer identification.

Detection Application	Network Structure	Approx. Performance			Reference
		Accuracy	Specificity	Sensitivity	
Breast cancer	ANN	98.1%	-	-	[14]
	ANN	98.05%	-	-	[15]
Skin cancer	CNN	93.64%	95.18%	92.1%	[16]
	CNN	81%	80%	81%	[17]
Kidney cancer	DNN	AUC*: 98%	-	-	[18]
	DNN	AUC*: 90%	-	-	[19]

*AUC: Area under the receiver operating characteristic curve.

Diabetes Diagnosis (See Table 3 below):

Diabetes is a chronic disease caused by the body's inability to either produce enough insulin or efficiently use the insulin it produces [25]. As diabetes is a major cause of blindness, heart attacks and kidney failure [25], efficient mechanisms of early detection and prediction are necessary.

ANN-based technologies such as [22], [23] and [24] have been able to successfully diagnose diabetes with accuracies above 85% on publicly available datasets, the relatively high accuracy rates obtained from using ANNs serve as a good indicator on the potential these technologies possess.

Table 3. This table outlines several applications of ANN-based technologies for diabetes diagnosis.

Detection Application	Network Structure	Approx. Performance			Reference
		Accuracy	Specificity	Sensitivity	
Diabetes diagnosis	DNN	97.11%	98.80%	96.25%	[22]
	ANN	92%	-	-	[23]
	ANN	87.3%	-	-	[24]

Covid-19 Detection (See Table 4 below):

Covid-19 is an infectious respiratory disease caused by a coronavirus [27,29,30]. It has been responsible for a global pandemic and the death of more than 3 million people worldwide [29]. CNNs such as [26] and [28] have been able to make use of X-ray images to identify those patients affected by Covid-19 with an extremely high accuracy rate of above 97%. The ability of ANN-based technologies to make use of transfer learning as was done in [27] to identify new datasets provides an additional layer of flexibility within these technologies, making them applicable for unseen datasets.

Table 4. This table outlines several applications of ANN-based technologies for Covid-19 detection.

Detection Application	Network Structure	Approx. Performance			Reference
		Accuracy	Specificity	Sensitivity	
Covid-19 detection	CNN	98.75%	98.75%	92.85%	[26,27]
	CNN	97.40%	97.09%	99.10%	[27,28]

4. Conclusion and Perspective

Within this paper, we provided a summary of the individual components of any artificial neuron and explained the fundamentals of popular ANN topologies like DNNs and CNNs. Finally, we highlighted the applications of various ANN-based technologies within the context of Cancer Identification, Diabetes Diagnosis and Covid-19 detection using specific examples to highlight the high accuracy rate ANN-based technologies possess and to display the potential these technologies offer.

In the future, real-time, personalized health monitoring devices and electrochemical biosensors would generate a tremendous amount of data for disease biomarkers [30–32]. We speculate researchers would perform feature selection on such datasets, perform training and validation tests on ANN models before finally passing the live data into the ANN for analysis and prediction.

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References

1. D. Ravi, C. Wong, F. Deligianni, M. Berthelot, J. Andreu-Perez, B. Lo, and G.-Z. Yang, “Deep Learning for Health Informatics,” *IEEE Journal of Biomedical and Health Informatics*, vol. 21, no. 1, pp. 4–21, 2017.
2. A. S. Lundervold and A. Lundervold, “An overview of deep learning in medical imaging focusing on MRI,” *Zeitschrift für Medizinische Physik*, vol. 29, no. 2, pp. 102–127, 2019.
3. Y. LeCun, Y. Bengio, and G. Hinton, “Deep learning,” *Nature*, vol. 521, no. 7553, pp. 436–444, 2015.
4. “Artificial Intelligence (AI) in Healthcare Market Size Worth $61.59 Billion By 2027: CAGR of 43.6% By Reports and Data,” GlobeNewswire News Room, 19-Jan-2021. [Online]. Available: https://www.globenewswire.com/news-release/2021/01/19/2160281/0/en/Artificial-Intelligence-AI-in-Healthcare-Market-Size-Worth-61-59-Billion-By-2027-CAGR-of-43-6-By-Reports-and-Data.html. [Accessed: 11-Jun-2021].
5. F. Amato, A. López, E.M. Peña-Méndez, P. Vaňhara, A. Hampl, and J. Havel, “Artificial neural networks in medical diagnosis,” Journal of Applied Biomedicine, vol. 11, no. 2, pp. 47–58, 2013.
6. Anderson D, McNeill G. Artificial neural networks technology. Kaman Sciences Corporation, No. 1992; F30602–889–0082.
7. R. M. Oliveira, R.C. Araújo, F.J. Barros, A.P. Segundo, R.F. Zampolo, W. Fonseca, V. Dmitriev, and F. S. Brasil, “A System Based on Artificial Neural Networks for Automatic Classification of Hydro-generator Stator Windings Partial Discharges,” *Journal of Microwaves, Optoelectronics and Electromagnetic Applications*, vol. 16, no. 3, pp. 628–645, 2017.
8. M. T. Hagan, H.B. Demuth, M.H. Beale, and Jesús Orlando De, *Neural network design*, 2nd ed. Martin Hagan, USA 2014.
9. Nwankpa C, Ijomah W, Gachagan A, Marshall S (2018) Activation functions: Comparison of trends in practice and research for deep learning. Preprint arXiv:1811.03378.
10. G. Hinton, L. Deng, D. Yu, G. Dahl, A.-Rahman Mohamed, N. Jaitly, A. Senior, V. Vanhoucke, P. Nguyen, T. Sainath, and B. Kingsbury, “Deep Neural Networks for Acoustic Modeling in Speech Recognition: The Shared Views of Four Research Groups,” *IEEE Signal Processing Magazine*, vol. 29, no. 6, pp. 82–97, 2012.
11. W. Serrano, “Smart Internet Search with Random Neural Networks,” *European Review*, vol. 25, no. 2, pp. 260–272, 2017.
12. B. Sahiner, A. Pezeshk, L.M. Hadjiiski, X. Wang, K. Drukker, K.H. Cha, R.M. Summers, and M. L. Giger, “Deep learning in medical imaging and radiation therapy,” *Medical Physics*, vol. 46, no. 1, 2018.
13. Phung and Rhee, “A High-Accuracy Model Average Ensemble of Convolutional Neural Networks for Classification of Cloud Image Patches on Small Datasets,” *Applied Sciences*, vol. 9, no. 21, p. 4500, 2019.
14. H. A. Abbass, “An evolutionary artificial neural networks approach for breast cancer diagnosis,” *Artificial Intelligence in Medicine*, vol. 25, no. 3, pp. 265–281, 2002.
15. D. B. Fogel, E.C. Wasson, and E. M. Boughton, “Evolving neural networks for detecting breast cancer,” *Cancer Letters*, vol. 96, no. 1, pp. 49–53, 1995.
16. V. Pomponiu, H. Nejati, and N.-M. Cheung, “Deepmole: Deep neural networks for skin mole lesion classification,” *2016 IEEE International Conference on Image Processing (ICIP), 2016*.
17. E. Nasr-Esfahani, S. Samavi, N. Karimi, S.M.R. Soroushmehr, M.H. Jafari, K. Ward, and K. Najarian, “Melanoma detection by analysis of clinical images using convolutional neural network,” *2016 38th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), 2016.*
18. M. Zhu, B. Ren, R. Richards, M. Suriawinata, N. Tomita; et al., “Development and evaluation of a deep neural network for histologic classification of renal cell carcinoma on biopsy and surgical resection slides,” *Scientific Reports*, vol. 11, no. 1, 2021.
19. N. Hadjiyski, “Kidney Cancer Staging: Deep Learning Neural Network Based Approach,” *2020 International Conference on e-Health and Bioengineering (EHB), 2020.*
20. “Comprehensive Cancer Information,” National Cancer Institute. [Online]. https://www.cancer.gov/. [Accessed: 12-Jun-2021].
21. Global Cancer Observatory. [Online]. https://gco.iarc.fr/. [Accessed: 12-Jun-2021].
22. S. Islam Ayon and M. Milon Islam, “Diabetes Prediction: A Deep Learning Approach,” *International Journal of Information Engineering and Electronic Business*, vol. 11, no. 2, pp. 21–27, 2019.
23. S. Srivastava, L. Sharma, V. Sharma, A. Kumar, and H. Darbari, “Prediction of Diabetes Using Artificial Neural Network Approach,” *Engineering Vibration, Communication and Information Processing*, pp. 679–687, 2018.
24. El Jerjawi, Nesreen Samer & Abu-Naser, Samy S. (2018). Diabetes Prediction Using Artificial Neural Network. *International Journal of Advanced Science and Technology* 121:54-64.
25. “Diabetes,” World Health Organization. https://www.who.int/en/news-room/fact-sheets/detail/diabetes. [Access: 12-Jun-2021].
26. Simonyan K Zisserman A (2015) Very deep convolutional networks for large-scale image recognition. arXiv preprint arXiv:14091556.
27. I. D. Apostolopoulos and T. A. Mpesiana, “Covid-19: Automatic detection from X-ray images utilizing transfer learning with convolutional neural networks,” *Physical and Engineering Sciences in Medicine*, vol. 43, no. 2, pp. 635–640, 2020.
28. Howard AG Zhu M Chen B et al. (2017) MobileNets: Efficient convolutional neural networks for mobile vision applications. arXiv preprint arXiv:170404861.
29. “WHO Coronavirus (COVID-19) Dashboard,” World Health Organization. [Online]. Available: https://covid19.who.int/. [Accessed: 13-Jun-2021].
30. S. Kotru, M. Klimuntowski, H. Ridha, Z. Uddin, A.A. Askhar, G. Singh, and M. M. R. Howlader, “Electrochemical sensing: A prognostic tool in the fight against COVID-19,” *TrAC Trends in Analytical Chemis*try, vol. 136, p. 116198, 2021.
31. J. Schultz, Z. Uddin, G. Singh, and M. M. R. Howlader, “Glutamate sensing in biofluids: Recent advances and research challenges of electrochemical sensors,” *The Analyst*, vol. 145, no. 2, pp. 321–347, 2020.

32. M. Klimuntowski, M.M. Alam, G. Singh, and M. M. R. Howlader, "Electrochemical Sensing of Cannabinoids in Biofluids: A Noninvasive Tool for Drug Detection," *ACS Sensors*, vol. 5, no. 3, pp. 620–636, 2020.