

A REVIEW OF ARTIFICIAL NEURAL NETWORKS FOR BIOMEDICAL APPLICATIONS: TRENDS AND PROSPECTS

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Abstract: *The use of Artificial Neural Network (ANN) as a technology is prevalent in recent times in many facets of life owing to its ability to be applied in decision making, pattern recognition, face detection, prediction and so on. Lately in the field of medicine, it has been used for various purposes such as pre-clinical and post-clinical diagnosis and treatment of diseases like sleep apnea-hypopnea syndrome, for therapeutic purposes as in esophageal cancer and for decision making supports for physicians such as Computer Aided Diagnosis. This present work reviews the various biomedical applications of the technology and its prospective capabilities in the medical field. The first section gives the introduction into the review, the next section discusses the Artificial Neural Network, the subsequent section contains the various biomedical applications in which the technology has been applied for medical purposes in recent times as well as the ANN futurists' prospects of its applications and the last section gives the conclusion of the review.*

Keywords: *Artificial Neural Network, Artificial Intelligence, Medical Decision making, classification, fuzzy logic.*

1. INTRODUCTION

Artificial Neural Network (ANN) is a branch of Artificial intelligence which has been accepted as a new technology in computer science [1]. It is a mathematical model that tries to simulate the structure and functionalities of biological neural networks. ANNs design and functionalities are derived from observation of a biological neuron that is basic building block of biological neural networks which includes the brain, spinal cord and peripheral ganglia [2].

Artificial Neural Networks (ANN) have been widely employed in a large variety of applications in various fields in the last two decades owing to their remarkable capabilities such as; recognition of patterns in complex biological data sets that cannot be detected with conventional linear statistical analysis [3], modeling non-linear systems and learning to make generalization from data similarly to a human reaction. For example, in biological applications; plant biology [4], [5], gene [6] and stem cell [7], in pharmaceutical applications [8], and in medical applications; diagnosis [9], skin diseases, sclerosis, anesthesia and cardiovascular, in clinical and other applications such as remote tele-care [10] and medical image processing [11]. The technology has rapidly evolved in recent times [1]. This development has led to an entirely new approach for the solution of many data processing-based problems usually encountered in real applications [12].

In this paper, an attempt has been made to review the use of artificial neural networks in the medical field.

2. ARTIFICIAL NEURAL NETWORK

An Artificial Neural Network is a group of nodes interconnected together in a similar manner to the network of neurons in an animal brain. ANNs are characterized in principle by a network topology, a connection pattern, neural activation properties and a training strategy to process data [13]. Every Artificial Neural Network has a basic building block called artificial neuron organized in layers, which is a simple mathematical model composed of three simple sets of rules namely; multiplication in which every individual input is multiplied with individual weight at the entrance, summation of all weighted

inputs and bias in the middle section and lastly, activation where the result obtained from the middle section is taken through a process called transfer function as illustrated in the Figure (1) below.

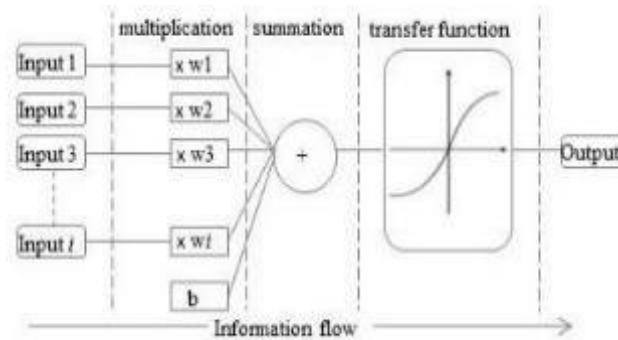


Fig.1. Working Principle of an artificial neuron

In biological systems, a neuron is composed of branched structures known as dendrites, a processing unit called cell body and a long axon through which the impulses are transmitted as an output to the peripheral. Thus, the dendrites receive impulses from neighboring dendrites, transmit the impulses to the processing unit and pass the processed impulses via the long axon to give an output as shown in figure (2) below.

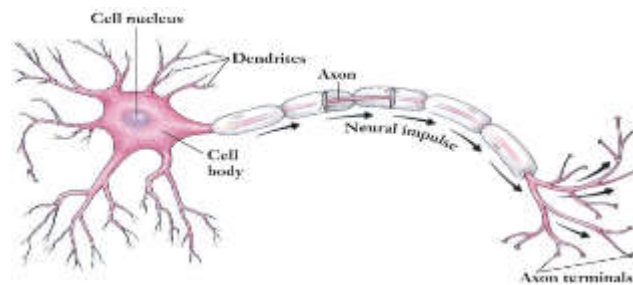


Fig. 2. A Biological Neuron Model [14]

In a similar manner, an artificial neuron receives information via weighted inputs which is then transmitted to the body where the weighted inputs and bias are summed up. The information is then processed with what is known as transfer function after which it is passed via the output(s) shown in figure (3) below.

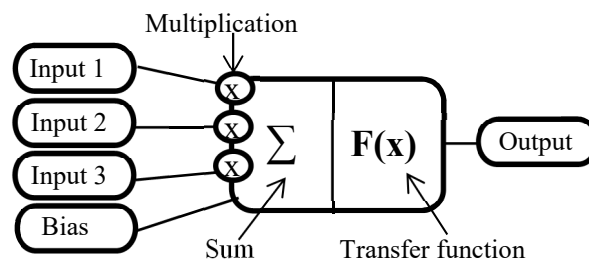


Fig. 3. An Artificial Neuron Model

The model above can be mathematically depicted as;

$$y(t) = F\left(\sum_{i=0}^k w_i(t) \cdot x_i(t) + b\right) \quad (1)$$

Where

$y(t)$ is the output value in discrete time t

F is a transfer function

$w_i(t)$ is the weight of the input in discrete time t

$x_i(t)$ is input value in discrete time t

b is the bias

$0 \geq i \leq k$

Artificial Neural Networks possess the ability of solving complex real-life problems by processing information in their basic building blocks (artificial neurons) in a non-linear, distributed, parallel and local way.

The manner in which individual artificial neurons are interconnected is called topology, architecture or graph of an artificial neural network [2]. Thus, scientists have come up with a variety of ANN topology which are suitable for various kinds of application selected based on the requirements of problem at hand [15]. For example, in Feed-Forward Neural Network FNN, the flow of information is in one direction from input nodes through the hidden nodes then, to output nodes without back loops [16]. On the other hand, Recurrent Neural Networks RNN permits back flow of information with back loops. As such, they are multidirectional and can use their internal state (memory) to process sequences of inputs. This makes them suitable for tasks such as unsegmented, connected handwriting [17] or speech recognition [18], [19]. The RNNs have been modified for better suitability in special cases of information backflow such as; Hopfield, Elman, Jordan, bi-directional and other networks.

A selected ANN topology is taken through a process called learning in which the ANN is taught how to perform the required task effectively [20]. Learning is done by updating the weights and bias levels at the input layer of the network as it is simulated in a given data environment and the actual result obtained is compared with the expected result [21], [22]. Supervised, unsupervised and reinforcement learning are the various ANN learning paradigms available [23] whose selection is dependent on the kind of problem. The supervised learning is also called learning with a teacher [21]. It involves modification of the synaptic weights of a neural network by applying a set of labeled training samples or task examples (input-output pairs) and learns a function that maps from input to output [21], [24]. It is used for pattern recognition (classification), Sequential data (hand writing, speech and gesture recognition), Regression (Function approximation). In unsupervised learning, also referred to as learning without a teacher, [25] the network learns patterns in the input even when no explicit feedback or label is supplied. Once the network has become tuned to the statistical regularities of the input data, the network develops the ability to form internal representations for encoding features of the input and thereby to create new classes automatically [26]. It is used for filtering, compression and commonly for clustering tasks. In reinforcement learning, the learning of an input–output mapping is performed through continued interaction with the environment in order to minimize a scalar index of performance [25].

3. ARTIFICIAL NEURAL NETWORKS IN BIOMEDICAL ENGINEERING

Biomedical engineering is a rapidly growing field which is an interdisciplinary domain that links many disciplines such as engineering, medicine, biology, physics, physiology etc [27] set up to meet various medical challenges and to make the practice of medicine more beneficial for man. Thus, a more efficient approach to diagnosis for early detection of diseases and treatment with reliable accuracies and convenience is crucial. In order to achieve this, ANN is a sophisticated tool suitable for a variety of biomedical applications. Currently, it has been applied in many regards such as for image analysis, drug development, Computer-Aided Diagnostic systems etc. This section gives a review of its capabilities and potential applications in different fields in healthcare.

3.1. Medical Imaging

Physicians, in time past used their discretion aided by experience to analyze medical images obtained from different imaging sources such as ultrasound, x-ray, CT scan and MRI to make diagnostic medical decisions. This method is not only time consuming but also inaccurate because the Physicians are limited to only the information within their visual and mental capability. Objects such as lesions and body organs may be represented in inaccurately for analysis [28]. However, nowadays, computer methods of image visualization and recognition have become a ‘hot cake’ in analyzing different types

of medical images. Thus, Artificial Neural Networks (ANNs) are essential tools used in the medical imaging field, including medical image exploration and Computer-Aided Diagnosis (CAD) [29], [30].

Several models of ANN topology have been used in medical imaging field. The choice of which is dependent on the condition and the required kind of analysis [15]. For example, Feed-Forward Neural Network FNN has been employed for tasks such as; diagnosis of breast cancer [31], early detection of Ovarian Cancer [32], interpretation of mammographic images [33] and lesion size quantification in SPECT images [34].

Hopfield NN was applied for the detection of brain tumor boundaries in medical images obtained from Magnetic Resonance Imaging [35]. With this, a surgeon has an accurate knowledge of the exact location of a tumor prior to a surgical procedure and can dissect with precision during the surgical procedure to separate the tumor from the normal brain tissues.

The class of neural filters used for detection of edges from noisy images such as in radiographs and other digital pictures [36], [37] was developed by Suzuki *et al.* [38] who also suggested the first neural edge enhancer (NEE) [38] and reported that the NEE can correctly reproduce the subjective edges traced by cardiologists in left ventriculograms [39].

Massive Training Artificial Neural Network (MTANN) was developed by extension of the neural filters to accommodate many pattern recognition tasks [40]. It has been employed for enhancement and suppression of pattern. For example, separation of bone from soft tissue in chest x-ray [41], [42], and lung nodules enhancement in CT [28]. MTANN has capabilities for classification tasks. For instance, it was used in reduction of False Positive (FP) in CAD systems for detection of lung nodules in chest x-ray [43] and computerized tomography CT [40], [44], [45], distinction between benign and malignant lung nodules in CT [46], and FP reduction in a CAD scheme for polyp detection in CT colonography [47-51].

The class of convolution NNs has been applied to classification tasks such as the rapid diagnosis of colorectal polyp [52], classification of Cervical Cancer [53], thoraco-abdominal lymph node (LN) detection and interstitial lung disease (ILD) classification in CAD schemes [54].

Although, speculations that AI systems may replace physicians in the future have been reported [55], CAD systems, for example, are not to replace physicians and medical image users but to aid them in decision making and better diagnosis [29], [56].

3.2. Prediction And Prescription

Machine-assisted treatment recommendations have a potential to reduce physician time and aid more accurate decision making alleviating errors [57]. In this regard, the use of ANN has been found effective and was constructed for prediction of response and survival in the patients treated with radiation therapy for esophageal cancer [58] and non-malenoma skin cancer [59]. Aneja *et al.* [60] reported the use of CNN for predicting local failure succeeding stereotactic body radiation therapy. Another interesting area is the prediction of influenza vaccination outcome [61].

3.3. IBM Watson System

IBM Watson is a question answering cognitive computing platform that applies artificial intelligence and deep learning to assist physicians in medical diagnosis. It is composed of a massive database of medical information sifted from different library [62]. It has a robust memory space of data [63] which is updated as fast as research on many diseases and other health conditions such as; immunotherapy, diabetes, cancer and so on are advanced. However, it would require at least 160 hours of study in a week for a human doctor to keep up with advances in medical knowledge as research findings are being published [64].

IBM Watson has the ability to think and reason at a very fast rate like the human brain using DeepQA to provide answers to questions [65] supplied at a higher success rate than physicians. For example, its accuracy in diagnosis of lung cancer was found to be greater than 90% compared to 50% for human doctors. Even when diagnosing and deciding on treatment plans for patients, only about 20% of the knowledge employed by physicians relies on trial-based evidence according to Memorial Sloan-Kittering Cancer Center [66], [67].

3.4. Medical Records

Traditional method of using paper-pencil case note folders for capturing patients' medical history is becoming uncommon in advanced countries of the world like the United States. This is because many healthcare providers are now opting for an Electronic Health Record system EHRs. This system generates a vast amount of data which are stored electronically and can be used for enhancing better healthcare in many ways by employing ANN.

For example, recurrent neural network models have been designed for early detection of heart failure onset [68]. Also, ANN has been combined with HER data for supporting clinical research [69], for predictive analysis aimed at reducing readmission of patients with cardiac issues, pneumonia or COPD [70] and various risks [71],[72] associated with future readmissions [73]. Choi et al [74] proposed Doctor AI system using RNN for diagnosing multiple disease conditions and prescribing appropriate medications based on historical EHR data. This system also attempts to predict the patient's next appointment. Other applications of ANN in EHR are assessed in [75-77].

3.5. Other Applications

Other instances in which Artificial Neural Networks have been used for Biomedical applications include, but not limited to, areas like; biomaterials, electrophysiology, biotechnology, modeling, instrumentation, rehabilitation engineering, biomechanics, prosthetics, medical analysis, biosensors, robot assisted surgery, clinical analysis, computers devices, bioinformatics.

The applications of Artificial Neural Networks for biomedical purposes are inexhaustible in this review, thus more information about its potentials, challenges and applicability can be obtained from [78], [79].

4. CONCLUSION

Owing to its many capabilities and biomedical applicability in many regards, it is obvious from the review of various literatures that Artificial Neural Network (ANN) as a technology is a powerful problem solving tool which has revolutionized the practice of medicine in recent times and it is a pivot on which the future of effective healthcare delivery swings.

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