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REVIEW PAPER

Artificial neural networks in medicine

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Abstract
In the past several decades, the intricate neural networks of the human brain have inspired the further development of intelligent systems. Many disciplines, including the complex field of medicine, have taken advantage of the useful applications of artificial neural networks (ANNs). To review and provide a comprehensive introduction to artificial neural networks, as well as a general discussion of its recent applications in the medical field. A search of the PsycINFO, Google Scholar, PubMed, and University of Rhode Island Library databases from 1943 to 2017 was conducted for articles on artificial neural networks to describe (1) general introduction, (2) historical overview, (3) modern innovations, (4) current clinical applications, and (5) future applications of the field. The relevance of artificial neural networks has increased significantly over the past few decades as technology advances. Evidence from several studies demonstrates that artificial neural networks can be used to not only aid in the diagnosis, prognosis and treatment of major diseases, but can also aid in the advancement of the environment and community.

Keywords Artificial neural networks · Medicine · Disease · Diagnosis

1 Introduction

Neural networks have presented the most influential basis for studying, and comprehending, how the brain is able to solve fundamental problems that, until recently, seemed uniquely human. When it comes to intelligent systems, researchers have been working diligently on solving the challenges presented by computer technology. Some of these challenges include: generalization and learning facility, flexibility and adaptability of new information, and simultaneous processing of information. When comparing artificial intelligence (AI) with human intelligence, it is apparent that human brain ability far exceeds that of any current computational system regarding abstract concepts such as pattern recognition and creative thinking. Researchers aim to solve this AI shortcoming via artificial neural networks, which are based upon the growing study of existing complex biological neural networks [1, 2].

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1.1 Function and organization of biological neural networks

The brain is composed of billions of specialized nerve cells called neurons. These nerve cells are responsible for acquiring, processing, and transmitting information throughout the brain and nervous system of an organism. Each neuron is organized into three major components: the soma (cell body), the axon, and the dendrites (Fig. 1). The soma contains the nucleus and cell plasma. The nucleus stores hereditary information within the cell while the plasma contains the molecular machinery necessary for generating materials required by the cell [1, 3, 4].

Towards both extremities of the neuron reside the dendrites. These are responsible for receiving signals from adjacent neurons, and transmitting these signals along the axon to the dendrites at the opposite side of the cell. Small gaps, or synapses, separate networking neurons. Once the signal reaches the synapse, specific neurotransmitters cross the synapse and are received by receptor neurons [1].

1.2 What are artificial neural networks?

Artificial neural networks (ANNs) are data-processing systems based on and inspired by the neurological networks found in brains. Systems are mainly used for pattern

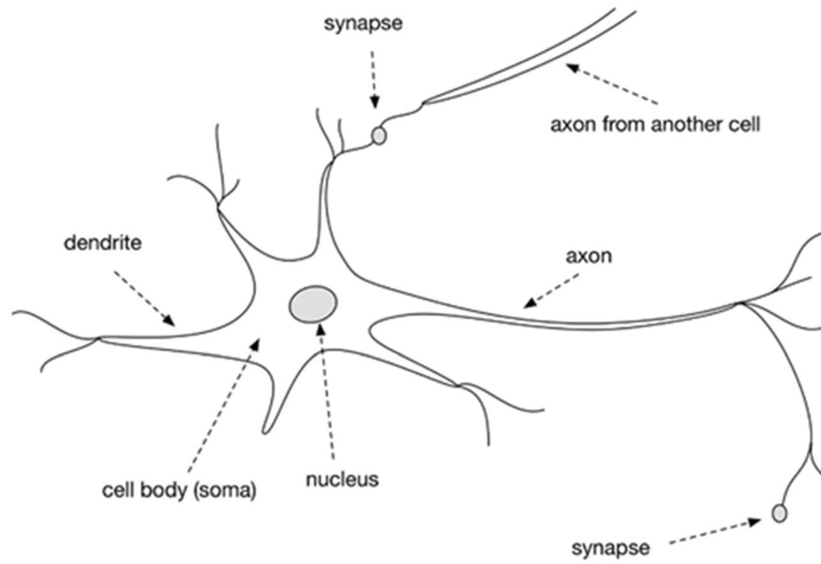

Fig. 1 Neural Anatomy

identification and processing, and are able to progressively improve performance based on analytic results from previous tasks [5–7].

Neural organization and networking can be explained, at the basic level, by the multilayer perceptron model. This model describes neural networking as taking place in the form of layers that make connections in one direction, otherwise known as a feedforward neural network (Fig. 2). Figure 2 demonstrates several layers of nodes: input, hidden, and output. The connections between the different nodes alter the behaviors of the networks. The input layers receive information as connections are made between the input and the hidden layers. Hidden layers subsequently process the information, which in turn is released into the output layers. Lastly, the output layers become an input for the next layer and the sequence continues [6, 8].

2 Historical overview

From the early 1940's researchers have become increasingly interested in the workings of the brain. In 1943, neuroscientist Warren McCullochand logistic Walter Pittspublished a their groundbreaking paper, first comprehensively describing how neurons in the brain communicate [9]. Their goal was to understand how the brain is able to calculate, create complex patterns, perceive, and do many other intricate operations by only using the connections between nerve cells. After analyzing the neural operations, they combined logic and computation to develop the McCulloch-Pitt Model (MCP). This model became a basic model of a neuron, and eventuallybecame an important foundation for the development of artificial neural networks. [10–12].

Early versions of MCP neurons were not without limitations. One such limitation was that the MCP neurons were unable to "learn" from or adapt to the input that they were receiving. Researchers later provided additional features which would enable the MCP neurons to accomplish this goal. One such feature was the concept of a perceptron, introduced by psychologist Frank Rosenblatt [10–12].

2.1 Rosenblatt's perceptron convergence theorem, 1958

While attempting to develop a machine which could reproduce the abilities of the brain, Frank Rosenblattdeveloped the perceptron [13].

The importance of Rosenblatt's invention becomes evident when taking into consideration the algorithms involved in the perceptron (see Fig. 3) . Rosenblatt's concept of the perceptron inspired researchers from other disciplines, and garnered further investigation into a variety of different properties of ANNs. M Gardnera and S Dorlinga provide a thorough description of the algorithmic workings of the perceptron in their article "Artificial neural networks (the

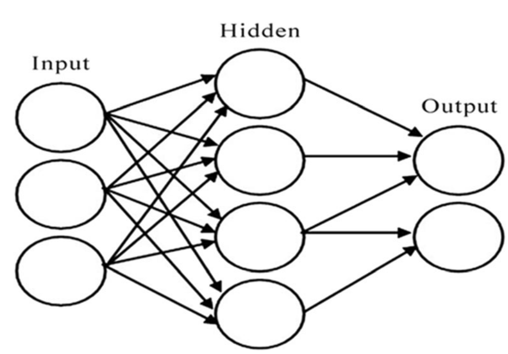

Fig. 2 Basic Neural Organization

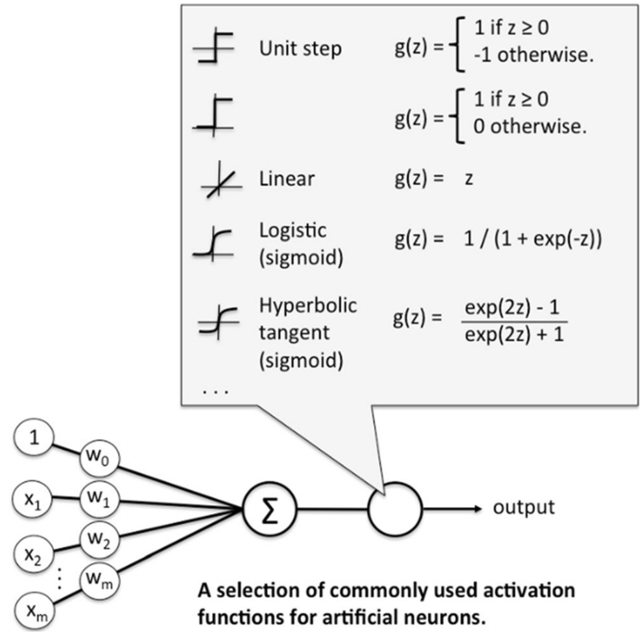

Fig. 3 Functions of the Perceptron

multilayer perceptron)—a review of applications in the atmospheric sciences" [14].

Until the late 1960s, most researchers accepted the concept of Rosenblatt's perceptron. The most influential critique of the perceptron was introduced in 1969 by Minsky and Papert in their book titled "Perceptrons". This book analyzes in great mathematical detail the computational flaws found in Rosenblatt's invention. Following the popularization of the book, uncertainty arose, and individuals no longer had confidence in the perceptron or neural networks [15, 16].

2.2 Minsky and Papert, 1969

Marvin Minsky, a cognitive scientist, and Seymour Papert, a mathematician, were interested in the workings of artificial intelligence. After analysis, they indentified several shortcomings in relation to neural networks and computational machines. One such shortcoming involved the inability of the perceptron to process information coming from one of two circuits. Another was that computational systems couldn't retain the processing capacity required to operate heavy neural networks. These issues became critical and as a result, research pertaining computational systems and neural networks stagnated until the 1980s [15, 16].

2.3 Hopfield's energy approach, 1982

At the beginning of the 1980s, a scientist named John Hopfield revitalized research in the area of ANNs. He proposed an associative model for neural networks that described the storage of information as taking place between the linkage of neurons. Hopfield suggested that data processing is accomplished by turning some neurons "on" or "off" depending on outside stimuli [17]. This concept helped to solve the issues originally described by Minsky and Papert. The model did this by proposing that individual neurons work in association with those around them. In other words, what happens to an individual neuron typically happens to surrounding neurons. Theseneural associations provide the bases for pattern recognition, associative memory, and error correction, while also providing enough processing capacity to store information from large neural networks [18, 19].

3 Modern innovations with ANNs

After the publication of Hopfield's network model, research in artificial neural networks greatly increased [18]. This provided advances in computational systems, and state of the art technology [20].

3.1 Recognizing Bharatanatyam gestures

One such advancement from C. V Soumya and Muzameel Ahmed, was to use mathematical algorithms to identify human gestures. In their article "Artificial neural network based identification and classification of images of Bharatanatyam gestures" they investigate an innovative method used to recognize and describe expressive body gestures. These body gestures were mainly observed in Mudra, a classical dance practiced by Indian culture. Their purpose was to build a system using pattern recognition and image processing that could readily identify specific human gestures which would in turn provide a description and health benefits of those body movements [21].

3.2 Community structure and microbial fuel cells

ANNs have also become an essential aid at predicting and identifying microbial accumulation in various environments. Keaton Larson Lesnik described in his article "Consider the Community: Developing Predictive Linkages between Community Structure and Performance in Microbial Fuel Cells" several methods used to obtain data from microorganisms. His purpose was to use the information gathered to increase knowledge in order to facilitate the performance of microbial fuel cells in the process of converting chemical potential energy from waste streams into electrical energy [22, 23].

3.3 Predicting stock market performance

ANNs have recently been implemented in the prediction of stock market performance [24]. Kamran Raza developed several techniques based on four different versions of ANNs which are described in the article "Prediction of Stock Market performance by using machine learning techniques". The purpose of developing these techniques was mainly to design a prediction model which would facilitate the jobs of investors involved in the stock market. In order to find the best prediction model, several techniques were individually compared. The results demonstrated that the behavior of the stock market could be predicted with up to 77% accuracy [25, 26].

4 Current clinical applications

ANNs have been a great advantage for the development of medicine. Many areas have been integrating the use of artificial neural networks to facilitate diagnosis, prognosis, and treatment of many diseases [27–29]. Examples of ANNs implementation in several medical fields are described below.

4.1 Oncology

ANNs have been proven to detect breast cancer [30], hepatocellular carcinoma [31] and other malignancies in humans [32]. Ritchings, McGillion and Moore developed a prototype system using ANNs to evaluate the voice performance and quality of individuals recovering from laryngeal cancer. The voices of male subjects were evaluated by a speech and language therapist according to a ranking system which judged voice quality. Information from the ranking system was later used to train and test artificial neural networks to assess the influence of using ANNs as a tool for clinical evaluation [33]. ANNs have also been utilized to predict the presence of metastases in common primary cancers.[51] A recent study from Nowikiewicz et al. validated a predictive test to detect the presence of lymph-node metastases in breast cancer patients using ANNs. The ANN nomogram was demonstrated to achieve better predictive ability than comparable non-ANN predictive assessments [34].

4.2 Neurology

ANNs are often incorporated into machinery such as magnetic resonance imaging systems which are useful for studying segments of the brain [35] One way in which ANNs are used in neurology was demonstrated by Andre Gabor and Masud Seyal. They conducted a study that showed the effectiveness of using artificial neural networks in the identification of electroencephalographic (EEG) patterns. By recording epileptiform transients in individuals, they measured two different levels of certainty of recognition to detect spikes and sharp waves. These spikes and waves are essential in recording EEG activities. The results of this study showed that using ANNs is an effective way of recording brain activity with precision and accuracy [36, 37]. Another study that looked at the workings of ANNs in detecting EEG spikes was conducted by Robert Webber and peers. In their article "Automatic EEG spike detection: what should the computer imitate?" they proposed using several EEG tracing methods using ANNS in order to have more reliable EEG readings [38].

4.3 Radiology

ANNs may be used in radiology to identify different brain structures. Vincent Magnotta and peers used ANNs to identify various structures of the brain. They described in their article "Measurement of Brain Structures with Artificial Neural Networks: Two- and Three-dimensional Applications" the potential of artificial neural networks to identify those structures when applied to magnetic resonance images. They found that ANNs are able to identify brain structures as accurately as human technicians could, however quicker [39].

4.4 Orthopedics

ANNs have also contributed to several recent diagnostic measures and tools in orthopedics. Shioji et al. utilized ANNs to predict bone loss rate and future bone mineral density in postmenopausal women [40]. This predictive tool was demonstrated to achieve superior predictive ability when compared to current non-ANN models, and will provide a useful tool for the early diagnosis and treatment of osteoporosis.

Another recent study from Arbabi et al. utilizes trained ANNs to robustly determine mechanical and physical properties of cartilage. This could prove to be an important tool in cartilage repair, grafting or regeneration [41]. A third application of ANNs in orthopedics was demonstrated in a study from Lin et al., where they utilized ANN models to predict mortality in elderly hip fracture patients. This predictive tool outperformed current logistic regression-based models, and provides a high-value mechanism for assisting in the complex clinical decision making that accompanies elderly hip fracture [42].

4.5 Cardiology

ANNs have proven to be a key component in the diagnostics of cardiac diseases [43]. Javad Kojuri and peers studied the effectiveness of using ANNs to predict the development of myocardial infarction. Their article "Prediction of acute myocardial infarction with artificial neural networks in patients with nondiagnostic electrocardiogram" describes how they tested individuals with varying degrees of chest pains using ANNs. Their aim was to study how early ANNs are able to predict and detect myocardial infarctions. They found that ANNs were able to make such predictions up to 2 weeks in advance, which proves to be a great advantage for the early treatment of the disease [44, 45].

4.6 Pulmonology

ANNs have become essential in the diagnosis of important chest diseases, including acute pulmonary embolism [46]. Orhan Er, Nejat Yumusak, and Feyzullah Temurtas created a comparative diagnosis of chest diseases in their article “Chest diseases diagnosis using artificial neural networks”. In their study, they used a variety of methods such as learning vector quantization, and generalized regression neural networks, to prepare a dataset from a hospital’s chest diseases database [47]. Kazuto Ashizawa and peers used a similar method to test the effectiveness of using ANNs to diagnose lung disease [48]. Both studies provided evidence in favor of using ANNs to diagnose chest diseases.

Another study, conducted by Sanjay Patil, tested the accuracy of computerized pattern recognition in the diagnosis of pulmonary embolism (PE). They hypothesized that ANNs would be able to predict the likelihood of a person developing acute PE based on clinical characteristics. Their results demonstrated that ANNs could predict PE as accurately as experienced clinicians [49].

5 Future applications

Research in the field of artificial neural networks continues to increase at a rapid rate. Many advantages have been found in ANNs for medical usage and the development of modern innovations [27, 50]. In the clinical realm, ANNs especially hold diagnostic and predictive value, and will likely assist in early prediction, detection, and treatment of many diseases and conditions moving forward [52]. A promising application for the future is a possible incorporation of ANNs in salinity forecast of rivers. McCullough and Harry James proposed a model in their article “An investigation of the predictive accuracy of salinity forecast using the source IMS for the Murray-Darling river” to analyze the prediction accuracy of salinity levels using ANNs [51, 53, 54].

Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

Ethical approval This article does not contain any studies with human participants or animals performed by any of the authors.

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