Data Analytics and Artificial Intelligence
Vol: 2(5), 2022
REST Publisher; ISBN: 978-81-948459-4-2
Website: http://restpublisher.com/book-series/data-analytics-and-artificial-intelligence/

Artificial Neural Network – An Important Asset for Future Computing

*** ABHISHEK V, CHETHAN PRAKASH P**
MGR COLLEGE Hosur, Krishnagiri, Tamil Nadu, India.
*Corresponding author Email: abhiabhi9566@gmail.com

Abstract. Artificial Neural Network (ANN) is an information-processing paradigm that is inspired by the way biological nervous systems, such as the brain, processes information. "Artificial Neural Network" can be used for many different purposes. The key element of this paradigm is the novel structure of the information processing system. It is composed of a large number of highly interconnected processing elements (neurons) working in unison to solve specific problems. ANNs, like people, learn by example. An ANN is configured for a specific application, such as pattern recognition or data classification, through a learning process.

Artificial Neural Networks single-handedly can be regarded as the ultimate irony of man searching for better intelligence and coming up with it, on his own. Today for the layman on the street "ANN" might be a vague technical abbreviation, another term that bounced off the walls of science, but believe it or not, we are fast headed there, where ANN enhances and aids our very existence. Not only was neuroscience, but psychologists and engineers also contributed to the progress of neural network simulations

Keywords: ANN, Back Propagation Algorithm, Biological Neurons, Artificial Neuron, Threshold, Transition Function.

1. Introduction

Neural network simulations appear to be a recent development. However, this field was established before the arrival of computers, and has survived several eras. Many important advances have been boosted by the use of inexpensive computer emulations. The first artificial neuron was produced in 1943 by the neurophysiologist Warren McCulloch and the logician Walter Pitts[5]. The networks were based on simple neurons, which were considered to be binary devices with fixed threshold. Not only was neuroscience, but psychologists and engineers also contributed to the progress of neural network simulations. Significant progress has been made in the field of neural networks-enough to attract a great deal of attention and fund further research. Neurally based chips are emerging and applications to complex problems developing. Clearly, today is a period of transition for neural network technology. Neural networks, with their remarkable ability to derive meaning from complicated or imprecise data, can be used to extract patterns and detect trends that are too complex to be noticed by either humans or other computer techniques Neural network theory revolves around the idea that certain key properties of biological neurons can be extracted and applied to simulations, thus creating a simulated (and very much simplified) brain. The first important thing to understand them is that the components of an artificial neural network are an attempt to recreate the computing potential of the brain. The second important thing to understand, however, is that no one has ever claimed to simulate anything as complex as an actual brain. Whereas the human brain is estimated to have something on the order of ten to a hundred billion neurons, a typical artificial neural network (ANN) is not likely to have more than 1,000 artificial neurons.

2. Historical Background

Neural network simulations appear to be a recent development. However, this field was established before the advent of computers, and has survived at least one major setback and several eras. Many important advances have been boosted by the use of inexpensive computer emulations. Following an initial period of enthusiasm, the field survived a period of frustration and disrepute. During this period when funding and professional support was minimal, important advances were made by relatively few researchers. These pioneers were able to develop convincing technology which surpassed the limitations identified by Minsky and Papert. Minsky and Papert,[6] published a book (in 1969) in which they summed up a general feeling of frustration (against neural networks) among researchers, and was thus accepted by most without further analysis. Currently, the neural network field enjoys a resurgence of interest and a corresponding increase in funding. The first artificial neuron was produced in 1943 by the neurophysiologist Warren McCulloch and the logician Walter Pits. But the technology available at that time did not allow them to do too much. [5].

3. Need of ANN

Modern digital computers have outperformed humans in the domain of numeric computation and related symbol manipulation. However, humans can effortlessly solve complex perceptual problems at such a fast speed and extent as to dwarf the world's fastest computer. Why does there exist such a remarkable difference in their performance? The biological computer employs a completely different architecture than other computers like Van Neumann architecture. Numerous efforts have been made on developing “intelligent” programs. Neural networks, with their remarkable ability to derive meaning from complicated or imprecise data, can be used to extract patterns and detect trends that are too complex to be noticed by either humans or other computer techniques. [1] A trained neural network can be thought of as an "expert" in the category of information it has been given to analyze.

The factors which make ANN successful are; Power: Neural Networks are very sophisticated modeling techniques capable of modeling extremely complex functions. In particular, neural networks are nonlinear. For many years linear modeling has been the commonly used technique in most modeling domains since linear models have well-known optimization strategies. Where the linear approximation was not valid-which was frequently the case-the models suffered accordingly. Neural networks also keep in check the curse of dimensionality problem that bedevils attempts to model nonlinear functions with large numbers of variables. Ease of Use: Neural networks learn by example. The neural network user gathers representative data, and then invokes training algorithms to automatically learn the structure of the data. Although the user does need to have some heuristic knowledge of how to select and prepare data, how to select an appropriate neural network, and how to interpret the results, the level of user knowledge needed to successfully apply neural networks is much lower than would be the case using.

.

Table 1 Modern Computer and Biological Computer

	Modern Computer	Biological Computer
Processor	Complex	Simple
	High Speed	Low Speed
	One or Few	Large Number
Memory	Separate from	Integrate into

4. Human and Artificial Neurons – Investigating The Similarities

How the Human Brain Learns: Much is still unknown about how the brain trains itself to process information, for that so many theories are derived. In the human brain, a typical neuron collects signals from others through a host of fine structures called *dendrites*. The neuron sends out spikes of electrical activity through a long, thin stand known as an *axon,* which splits into thousands of branches. At the end of each branch, a structure called a *synapse* converts the activity from the axon into electrical effects that inhibit or excite activity from the axon into electrical effects that inhibit or excite activity in the connected neurons. When a neuron receives excitatory input that is sufficiently large compared with its inhibitory input, it sends a spike of electrical activity down its axon. Learning occurs by changing the effectiveness of the synapses so that the influence of one neuron on another changes. Then the activation signal is passed through an activation function (also known as a transfer function) to produce the output of the neuron. If the step activation function is used (i.e., the neuron's output is 0 if the input is less than zero, and 1 if the input is greater than or equal to 0) then the neuron acts just like the biological neuron (subtracting the threshold from the weighted sum and comparing with zero is equivalent to comparing the weighted sum to the threshold). Actually, the step function is rarely used in artificial neural networks. Also weights can be negative, which implies that the synapse has an inhibitory rather than excitatory effect on the neuron: inhibitory neurons are found in the brain. Below are the figures for neurons.

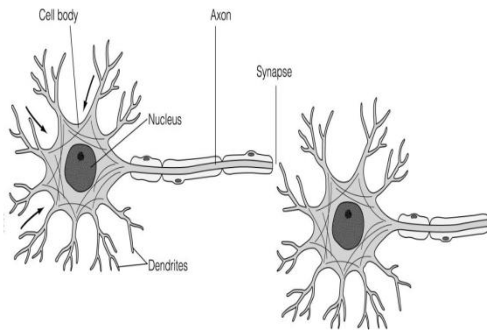

Fig.1 Components of a Neuron

From Human Neurons to Artificial Neurons: However because our knowledge of neurons is incomplete and our computing power is limited, our models are necessarily gross idealizations of real networks of neurons.[5] It receives a number of inputs (either from original data, or from the output of other neurons in the neural network). Each input comes via a connection that has a strength (or weight). Each neuron also has a single threshold value. The weighted sum of the inputs is formed, and the threshold subtracted, to compose the activation of the neuron.

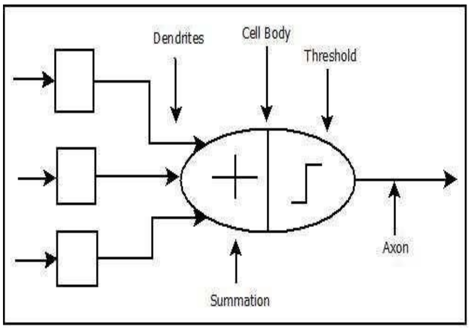

Fig. 2 The neuron model

5. An Engineering Approach- Analogy

A Simple Neuron: An artificial neuron is a device with many inputs and one output. The neuron has two modes of operation; the training mode and the using mode. In the training mode, the neuron can be trained to fire (or not), for particular input patterns. In the using mode, when a taught input pattern is detected at the input, its associated output becomes the current output. If the input pattern does not belong in the taught list of input patterns, the firing rule is used to determine whether to fire or not. [7] The Mathematical Model: When creating a functional model of the biological neuron, there are three basic components of importance. First, the synapses of the neuron are modeled as weights. The strength of the connection between an input and a neuron is noted by the value of the weight. Negative weight values reflect inhibitory connections, while positive values designate excitatory connections [7]. The next two components model the actual activity within the neuron cell. An adder sums up all the inputs modified by their respective weights. This activity is referred to as linear combination. Finally, an activation function controls the amplitude of the output of the neuron. An acceptable range of output is usually between 0 and 1, or -1 and 1. An artificial neural network consists of a pool of simple processing units which communicate by sending signals to each other over a large number of weighted connections.

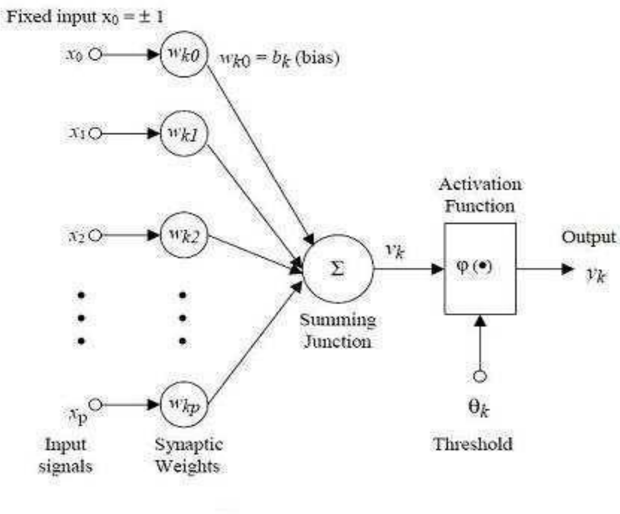

Fig-3. Mathematical Processing

6. Architecture of Artificial Neural Networks

Armed with these three concepts: Connection Strength, Inhibition/Excitation, and the Transfer Function, we can now look at how artificial neural nets are constructed. In theory, an artificial neuron (often called a 'node') captures all the important elements of a biological one. Nodes are connected to each other and the strength of that connection is normally given a numeric value between -1.0 for maximum inhibition, to +1.0 for maximum excitation. All values between the two are acceptable, with higher magnitude values indicating stronger connection strength. The transfer function in artificial neurons whether in a computer simulation, or actual microchips wired together is typically built right into the nodes design.[1]

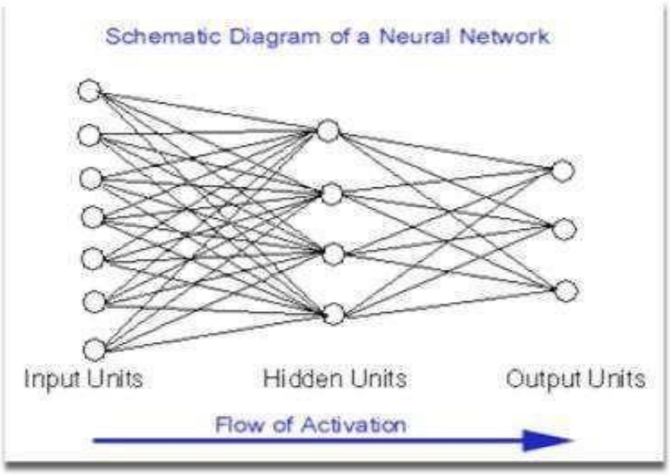

Fig-4. Architecture of ANN

Perhaps the most significant difference between artificial and biological neural nets is their organization. While many types of artificial neural nets exist, most are organized according to the same basic structure. There are three components to this organization: a set of input nodes, one or more layers of 'hidden' nodes, and a set of output nodes. The input nodes take in information, and are akin to sensory organs. Whether the information is in the form of a digitized picture, or a series of stock values, or just about any other form that can be numerically expressed, this is where the net gets its initial data. The information is supplied as activation values, that is, each node is given a number, higher numbers representing greater activation. Network layers: The common type of artificial neural network consists of three groups, or layers, or units: a layer of "input" units is connected to a layer of "hidden" units, which is connected to a layer of "output" units. The activity of the input units represents the raw information that is fed into the network. The activity of each hidden unit is determined by the activities of the input units and the weights on the connections between the input and the hidden units. The behaviour of the output units depends on the activity of the hidden units and the weights between the hidden and output units. This simple type of network is interesting because the hidden units are free to construct their own representations of the input. The weights between the input and hidden units determine when each hidden unit is active, and so by modifying these weights, a hidden unit can choose what it represents.

7. Versatibility of ANN

Neural networks take a different approach to problem solving than that of conventional computers. Conventional computers use an algorithmic approach i.e. the computer follows a set of instructions in order to solve a problem. Unless the specific steps that the computer needs to follow are known the computer cannot solve the problem. That restricts the problem solving capability of conventional computers to problems that we already understand and know how to solve. But computers would be so much more useful if they could do things that we don't exactly know how to do. Neural networks process information in a similar way the human brain does. The network is composed of a large number of highly interconnected processing elements (neurons) working in parallel to solve a specific problem. Neural networks learn by example. They cannot be programmed to perform a specific task. The examples must be selected carefully otherwise useful time is wasted or even worse the network might be functioning incorrectly. The disadvantage is that because the network finds out how to solve the problem by itself, its operation can be unpredictable. On the other hand, conventional computers use a cognitive approach to problem solving; the way the problem is to solved must be known and stated in small unambiguous instructions. These instructions are then converted to a high level language program and then into machine code that the computer can understand. These machines are totally predictable; if anything goes wrong is due to a software or hardware fault.

Table 2 Biological Neurons and Artificial Neurons

Biological neurons	Artificial neurons
Synapses	Connection weights
Axons	Output wires
Dendrites	Input wires
Soma	Activation function

Neural networks and conventional algorithmic computers are not in competition but complement each other. There are tasks are more suited to an algorithmic approach like arithmetic operations and tasks that are more suited to neural networks. Even more, a large number of tasks, require systems that use a combination of the two approaches (normally a conventional computer is used to supervise the neural network) in order to perform at maximum efficiency. Functions: They are nonlinear**:** A neuron itself is not necessarily non-linear, but putted together with other neurons in a network, they enter a complexity that is able to calculate non-linear processes, this unlinearity is obviously the most important ability the neural network has. They can relate input with output: Another of the best qualities of neural networks is the ability to train. With a set of input-output examples and a training algorithm, we can train our neural network. They are error-tolerant: Neural networks have an amazing ability to recognize patterns (e.g. letters or speech) even if they are very blurred or distorted. The brain is also known to be able to function properly, even though several of the synaptic connections have been broken, or in other ways disabled. In a conventional computer today, a breach in one of the connections could be catastrophic, but the neural network would be tied together so well, that even though a couple of synapses where disabled, the network would still be able to work. And the ANN idea sizzles and being excited because, Adaptive learning: An ability to learn how to do tasks based on the data given for training or initial experience. Self-Organization: An ANN can create its own organization or representation of the information it receives during learning time. Real Time Operation: ANN computations may be carried out in parallel, and special hardware devices are being designed and manufactured which take advantage of this capability. Fault Tolerance via Redundant Information Coding Partial destruction of a network leads to the corresponding degradation of performance. However, some network capabilities may be retained even with major network damage.

Applications: Artificial neural networks are undergoing the change that occurs when a concept leaves the academic environment and is thrown into the harsher world of users who simply want to get a job done. Many of the networks now being designed are statistically quite accurate but they still leave a bad aftertaste with users who expect computers to solve their problems absolutely. These networks might be 85% to 90% accurate. Unfortunately, few applications tolerate that level of error. Language Processing: Language processing encompasses a wide variety of applications. These applications include text-to-speech conversion, auditory input for machines, automatic language translation. Many companies and universities are researching how a computer, via ANNs, could be programmed to respond to spoken commands. Character Recognition: Character recognition is another area in which neural networks are providing solutions. Some of these solutions are beyond simply academic curiosities. HNC Inc., according to a HNC spokesman, markets a neural network based product that can recognize hand printed characters through a scanner. This product can take cards, like a credit card application form, and put those recognized characters into a database. This product has been out for two and a half years. It is 98% to 99% accurate for numbers, a little less for alphabetical characters. Currently, the system is built to highlight characters below a certain percent probability of being right so that a user can manually fill in what the computer could not. This product is in use by banks, financial institutions, and credit card companies. [7] Image (data) Compression: A number of studies have been done proving that neural networks can do real-time compression and decompression of data. These networks are auto associative in that they can reduce eight bits of data to three and then reverse that process upon restructuring to eight bits again. However, they are not loss less. Because of this losing of bits they do not favorably compete with more traditional methods. Pattern Recognition: The Wall Street Journal has featured a system that can detect bombs in luggage at airports by identifying, from small variances, patterns from within specialized sensor's outputs [3]. Yet, by far the biggest use of neural networks as a recognizer of patterns is within the field known as quality control. A number of automated quality applications are now in use. These applications are designed to find that one in a hundred or one in a thousand part that is defective. Signal Processing: Neural networks promise for signal processing has resulted in a number of experiments in various university labs. Neural networks have proven capable of filtering out noise. Windrow’s MADALINE was the first network applied to a real-world problem. It eliminates noise from phone lines. Financial: Neural networks are making big inroads into the financial worlds. Banking, credit card companies, and lending institutions deal with decisions that are not clear cut. They involve learning and statistical trends. The loan approval process involves filling out forms, which hopefully can enable a loan officer to make a decision. The data from these forms is now being used by neural networks, which have been trained on the data from past decisions. [4]

8. Possible Futures of ANN's

In truth, the futures of ANN’s are shady. The secrets of the human mind still escapes us no matter how much we boost the processing speed and size. That said, these neural networks have given us incredible advancements in things such as Optical Character Recognition, financial forecasting and even in medical diagnosis. For any group in which a known interrelationship exists with an unknown outcome there is a great possibility that ANN's will be helpful. As long as computer-based training and e-learning courses increase in application, the desire to develop computer systems that can learn by themselves and improve decision-making will be an ongoing goal of Computer Science & information technology.

9. DEMERITS

The inner workings of neural networks are like “BLACK BOXES”. They learn and model based on experience, but they cannot explain and justify their decisions (not that we human can!). Neural networks might have high accuracy, but not 100%, as we would want. And unfortunately, not all applications can tolerate that level of error. But again, even if not exact, they still can be used in conjunction with traditional methods to, for example, cutting down on time in search. Neural networks require lot of (sample) data for training purpose. It may have been an obstacle few years ago, but as we move forward that wouldn't be a problem. We are moving to an age where many of

10. Conclusion

For learning anything we need to learn and understand it correctly, so that whatever knowledge we get from this can be use in future. For this we need study to “Fundamentals” of anything. Fundamentals of artificial neural network give the brief idea about ANN. The art of neural networking requires a lot of hard work as data is fed into the system, performances are monitored, processes tweaked, connections added, rules modified, and on and on until the network achieves the desired results. These desired results are statistical in nature. The network is not always right. It is for that reason that neural networks are finding themselves in applications where humans are also unable to always be right. Neural networks can now pick stocks, marketing prospects, approve loans, deny credit cards, tweak control systems, and inspect work. Yet, the future holds even more promises. Neural networks need faster hardware. They need to become part of hybrid systems which also utilize fuzzy logic and expert systems. It is then that these systems will be able to hear speech, read handwriting, and formulate actions. They will be able to become the intelligence behind robots who never tire nor become distracted. It is then that they will become the leading edge in an age of "intelligent" machines. our activities are digitally recorded. From bank transactions to phone conversations and from medical history to lab results. As popularly portrayed, design and modeling of Neural Network is an Art, rather than a science. But in contrast to other Arts, the outcome of this one can be measured! Neural Network is not the perfect solution for every problem, but also there are lot more applications that can benefit from ANN characteristics than we see today.

Reference

[1]. Fausett V Laurene, “Fundamentals of neural networks”.
[2]. Bishop, Christopher, “Neural networks for pattern recognition”
[3]. Trippi, Robert and Turban, Efraim (editors), “Neural networks in finance and investing”, McGraw Hill, 1996.
[4]. W.S.McCulloch and W.Pitts, “A logical calculus of ideas immanent in nervous activity bulletin of mathematical biophysics”.