

Introduction to Neural Networks Design Architecture

Md. Adam Baba, Mohd Gouse Pasha, Shaik Althaf Ahammed, S. Nasira Tabassum

Abstract— This paper is an introduction to Artificial Neural Networks. The various types of neural networks are explained and demonstrated, applications of neural networks are described, and a detailed historical background is provided. The connection between the artificial and the real thing is also investigated and explained. Finally, the mathematical models involved are presented and demonstrated. During the last ten years neural networks have shown their worth. The success of a neural network approach is deeply dependent on the right network architecture. The architecture of a neural network determines the number of neurons in the network and the topology of the connections within the network. The emphasis of this paper is on automatic generation of network architecture.

Index Terms— Artificial Neural Networks, neural networks, Neural Network mathematical models, Neural network architecture.

1 INTRODUCTION

Neural networks have been used in connection with many different applications. The tasks for which they are used are generally problems of pattern recognition or function approximation. Typically, a network will be asked to classify an input pattern as belonging to one of a number of different possible classes, or to produce an output value as a (previously) unknown function of one or more input values. The crucial feature of neural networks is their ability to learn how to make the desired mapping from inputs to outputs without explicitly having to be told the rules for doing so. Instead, they adjust their internal connections based on a number of examples of the required mapping, and are then used to generalise from the given examples to others that they have not previously seen. Thus they are used for capturing patterns in sets of data, and use these captured patterns to perform the required computations.

1.1 WHAT IS A NEURAL NETWORK?

An Artificial Neural Network (ANN) is an information processing paradigm that is inspired by the way biological nervous systems, such as the brain, process information. 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 pat-

tern recognition or data classification, through a learning process. Learning in biological systems involves adjustments to the synaptic connections that exist between the neurons. This is true of ANNs as well.

1.2 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, 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 Pitts. But the technology available at that time did not allow them to do too much

1.3 WHY USE NEURAL NETWORKS?

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. A trained neural network can be thought of as an "expert" in the category of information it has been given to analyse. This expert can then be used to provide projections given new situations of interest and answer "what if" questions.

- Md Adam Baba holds a masters degree in technology from Holy Mary Instituter of technology and science, JNTU, A.P, India, E-mail: md.adam4011@gmail.com
- Mohd Gouse Pasha holds a masters degree in technology from Holy Mary Instituter of technology and science, JNTU, A.P, India, E-mail: Mohammed.unique@gmail.com
- Shaik Althaf Ahammed holds a masters degree in computer applications from Madurai Kamaraj University, T.N, India, E-mail: shaik_althaf123@yahoo.com
- S.Nasira Tabassum holds a masters degree in technology and computer applications from JNTU and Osmania University, A.P, India, E-mail: nasira.tabassum@gmail.com

Other advantages include:

- Adaptive learning: An ability to learn how to do tasks based on the data given for training or initial experience.
- Self-Organisation: An ANN can create its own organisation 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

1.4 NEURAL NETWORKS VERSUS CONVENTIONAL COMPUTERS

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 be 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.

Neural networks and conventional algorithmic computers are not in competition but complement each other. There are tasks 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.

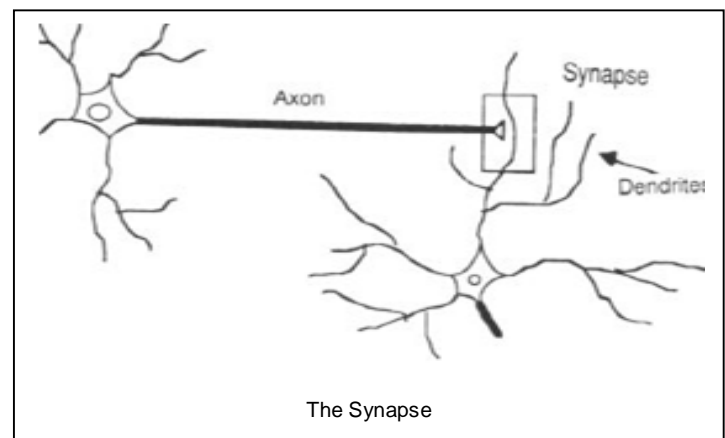
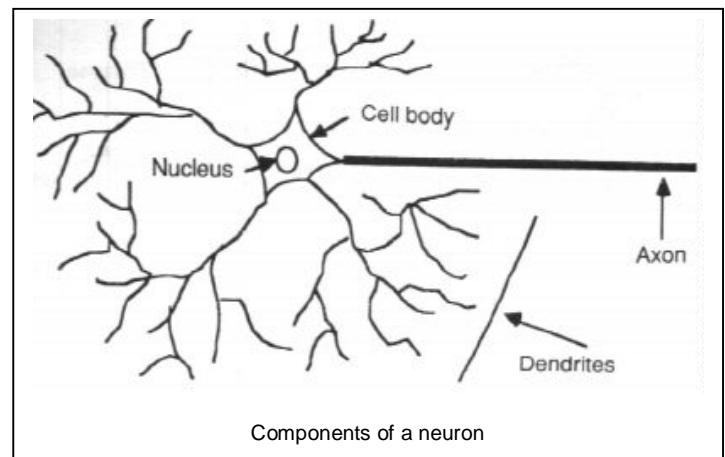
2 HUMAN AND ARTIFICIAL NEURONS - INVESTIGATING THE SIMILARITIES

2.1 How the Human Brain Learns?

Much is still unknown about how the brain trains itself to process information, so theories abound. In the human brain, a typical neuron collects signals from others through a host of fine structures called dendrites.

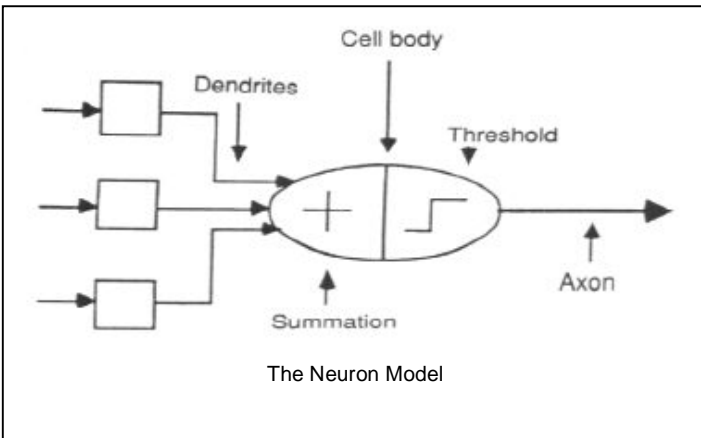
The neuron sends out spikes of electrical activity through a long, thin strand known as an axon, which splits into thousands of branches. At the end of each branch, a structure called a synapse converts the activity from the axon into electrical effects that inhibit or excite activity from the axon into 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.



2.2 From Human Neurons to Artificial Neurons

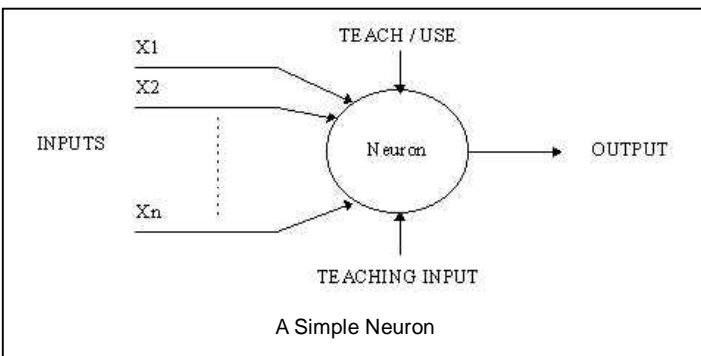
We conduct these neural networks by first trying to deduce the essential features of neurons and their interconnections. We then typically program a computer to simulate these features. However because our knowledge of neurons is incomplete and our computing power is limited, our models are necessarily gross idealisations of real networks of neurons.



3 AN ENGINEERING APPROACH

3.1 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.



3.2 Firing rules

The firing rule is an important concept in neural networks and accounts for their high flexibility. A firing rule determines how one calculates whether a neuron should fire for any input pattern. It relates to all the input patterns, not only the ones on which the node was trained.

A simple firing rule can be implemented by using Hamming distance technique.

The rule goes as follows:

Take a collection of training patterns for a node, some of which cause it to fire (the 1-taught set of patterns) and others which prevent it from doing so (the 0-taught set). Then the patterns not in the collection cause the node to fire if, on comparison, they have more input elements in common with the 'nearest' pattern in the 1-taught set than with the 'nearest' pattern in the 0-taught set. If there is a tie, then the pattern remains in the undefined state.

For example, a 3-input neuron is taught to output 1 when the input (X1,X2 and X3) is 111 or 101 and to output 0 when the input is 000 or 001. Then, before applying the firing rule, the truth table is;

X1:		0	0	0	0	1	1	1	1
X2:		0	0	1	1	0	0	1	1
X3:		0	1	0	1	0	1	0	1
OUT:		0	0	0/1	0/1	0/1	1	0/1	1

As an example of the way the firing rule is applied, take the pattern 010. It differs from 000 in 1 element, from 001 in 2 elements, from 101 in 3 elements and from 111 in 2 elements. Therefore, the 'nearest' pattern is 000 which belongs in the 0-taught set. Thus the firing rule requires that the neuron should not fire when the input is 001. On the other hand, 011 is equally distant from two taught patterns that have different outputs and thus the output stays undefined (0/1).

By applying the firing in every column the following truth table is obtained;

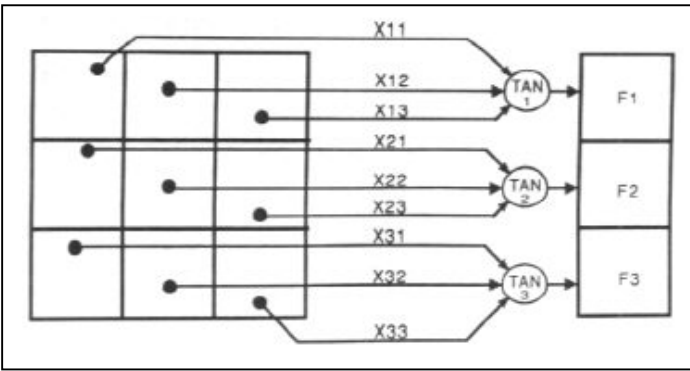
X1:		0	0	0	0	1	1	1	1
X2:		0	0	1	1	0	0	1	1
X3:		0	1	0	1	0	1	0	1
OUT:		0	0	0	0/1	0/1	1	1	1

The difference between the two truth tables is called the generalisation of the neuron. Therefore the firing rule gives the neuron a sense of similarity and enables it to respond 'sensibly' to patterns not seen during training.

3.3 Pattern Recognition - an example

An important application of neural networks is pattern recognition. Pattern recognition can be implemented by using a feed-forward (figure 1) neural network that has been trained accordingly. During training, the network is trained to associate outputs with input patterns. When the network is used, it identifies the input pattern and tries to output the associated output pattern. The power of neural networks comes to life when a pattern that

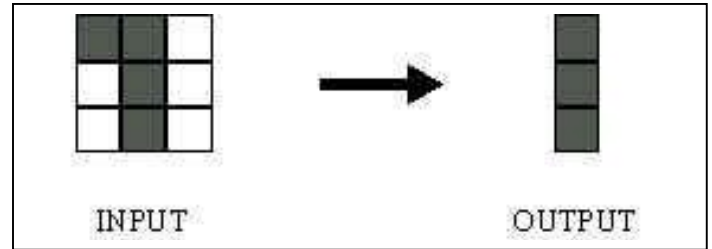
has no output associated with it, is given as an input. In this case, the network gives the output that corresponds to a taught input pattern that is least different from the given pattern.



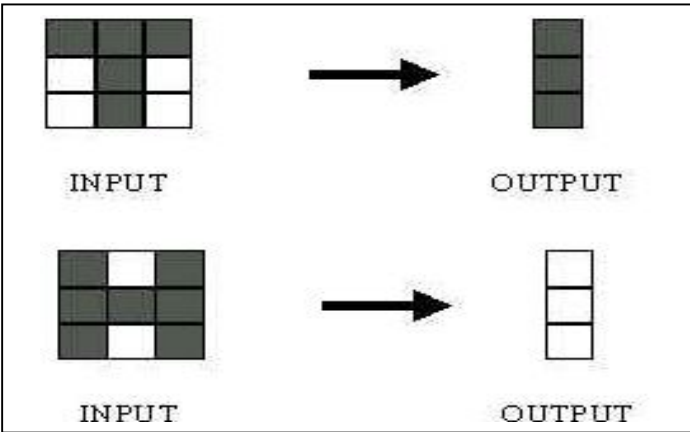
X21:		0	0	0	0	1	1	1	1
X22:		0	0	1	1	0	0	1	1
X23:		0	1	0	1	0	1	0	1
OUT:		1	0	1	1	0	0	1	0

Bottom neuron

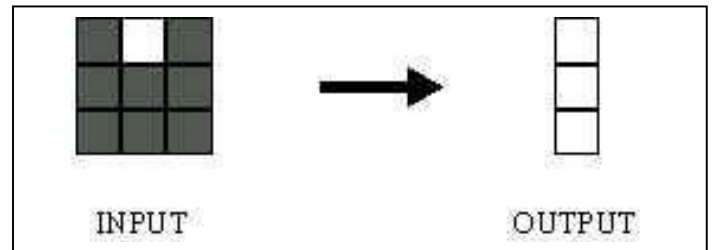
From the tables, the following associations can be extracted:



For example; the network of figure above is trained to recognise the patterns T and H. The associated patterns are all black and all white respectively as shown below



In this case, it is obvious that the output should be all blacks since the input pattern is almost the same as the 'T' pattern.

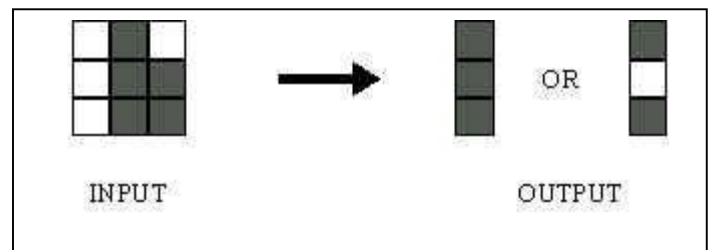


Here also, it is obvious that the output should be all whites since the input pattern is almost the same as the 'H' pattern.

If we represent black squares with 0 and white squares with 1 then the truth tables for the 3 neurones after generalisation are;

X11:		0	0	0	0	1	1	1	1
X12:		0	0	1	1	0	0	1	1
X13:		0	1	0	1	0	1	0	1
OUT:		0	0	1	1	0	0	1	1

Top neuron



Here, the top row is 2 errors away from the a T and 3 from an H. So the top output is black. The middle row is 1 error away from both T and H so the output is random. The bottom row is 1 error away from T and 2 away from H. Therefore the output is black. The total output of the network is still in favour of the T shape.

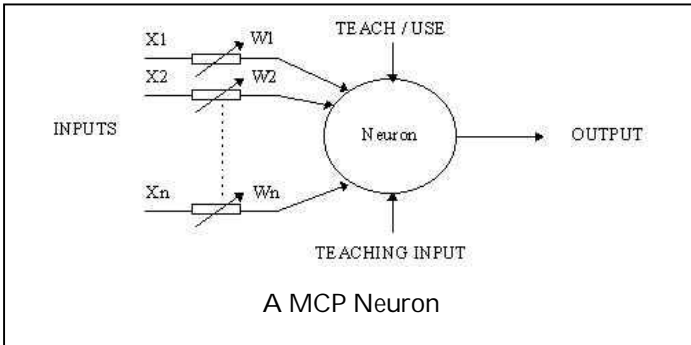
3.4 A more complicated neuron

The previous neuron doesn't do anything that conventional computers don't do already. A more sophisticated neuron (figure 2) is the McCulloch and Pitts model (MCP). The difference from the

X21:		0	0	0	0	1	1	1	1
X22:		0	0	1	1	0	0	1	1
X23:		0	1	0	1	0	1	0	1
OUT:		1	0/1	1	0/1	0/1	0	0/1	0

Middle neuron

previous model is that the inputs are 'weighted'; the effect that each input has at decision making is dependent on the weight of the particular input. The weight of an input is a number which when multiplied with the input gives the weighted input. These weighted inputs are then added together and if they exceed a pre-set threshold value, the neuron fires. In any other case the neuron does not fire.



In mathematical terms, the neuron fires if and only if;
 $X1W1 + X2W2 + X3W3 + \dots > T$

The addition of input weights and of the threshold makes this neuron a very flexible and powerful one. The MCP neuron has the ability to adapt to a particular situation by changing its weights and/or threshold. Various algorithms exist that cause the neuron to 'adapt'; the most used ones are the Delta rule and the back error propagation. The former is used in feed-forward networks and the latter in feedback networks.

4 ARCHITECTURE OF NEURAL NETWORKS

4.1 Feed-forward networks

Feed-forward ANNs allow signals to travel one way only; from input to output. There is no feedback (loops) i.e. the output of any layer does not affect that same layer. Feed-forward ANNs tend to be straight forward networks that associate inputs with outputs. They are extensively used in pattern recognition. This type of organisation is also referred to as bottom-up or top-down.

4.2 Feedback networks

Feedback networks can have signals travelling in both directions by introducing loops in the network. Feedback networks are very powerful and can get extremely complicated. Feedback networks are dynamic; their 'state' is changing continuously until they reach an equilibrium point. They remain at the equilibrium point until the input changes and a new equilibrium needs to be found. Feedback architectures are also referred to as interactive or recurrent, although the latter term is often used to denote feedback connections in single-layer organizations.

4.3 Network layers

The commonest type of artificial neural network consists of three groups, or layers, of 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.

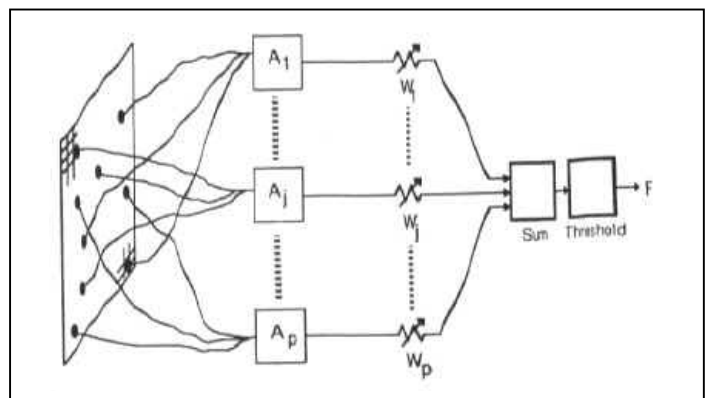
This simple type of network is interesting because the hidden units are free to construct their own representations of the input. The weights between the input and hidden units determine when each hidden unit is active, and so by modifying these weights, a hidden unit can choose what it represents.

We also distinguish single-layer and multi-layer architectures. The single-layer organization, in which all units are connected to one another, constitutes the most general case and is of more potential computational power than hierarchically structured multi-layer organizations. In multi-layer networks, units are often numbered by layer, instead of following a global numbering.

4.4 Perceptrons

The most influential work on neural nets in the 60's went under the heading of 'perceptrons' a term coined by Frank Rosenblatt. The perceptron turns out to be an MCP model (neuron with weighted inputs) with some additional, fixed, pre-processing. Units labelled A_1, A_2, A_j, A_p are called association units and their task is to extract specific, localised features from the input images.

Perceptrons mimic the basic idea behind the mammalian visual system. They were mainly used in pattern recognition even though their capabilities extended a lot more.



In 1969 Minsky and Papert wrote a book in which they described the limitations of single layer Perceptrons. The impact that the book had was tremendous and caused a lot of neural network researchers to lose their interest. The book was very well written and showed mathematically that single layer perceptrons could not do some basic pattern recognition operations like determining the parity of a shape or determining whether a shape is con-

nected or not. What they did not realise, until the 80's, is that given the appropriate training, multilevel perceptrons can do these operations.

4.5 Neural Networks in Practice

Neural networks have broad applicability to real world business problems. In fact, they have already been successfully applied in many industries.

Since neural networks are best at identifying patterns or trends in data, they are well suited for prediction or forecasting needs including:

- sales forecasting
- industrial process control
- customer research
- data validation
- risk management
- target marketing

But to give you some more specific examples; ANN are also used in the following specific paradigms: recognition of speakers in communications; diagnosis of hepatitis; recovery of telecommunications from faulty software; interpretation of multimeaning Chinese words; undersea mine detection; texture analysis; three-dimensional object recognition; hand-written word recognition; and facial recognition

4.6 Neural Networks in Medicine

Artificial Neural Networks (ANN) are currently a 'hot' research area in medicine and it is believed that they will receive extensive application to biomedical systems in the next few years. At the moment, the research is mostly on modelling parts of the human body and recognising diseases from various scans (e.g. cardiograms, CAT scans, ultrasonic scans, etc.).

Neural networks are ideal in recognising diseases using scans since there is no need to provide a specific algorithm on how to identify the disease. Neural networks learn by example so the details of how to recognise the disease are not needed. What is needed is a set of examples that are representative of all the variations of the disease. The quantity of examples is not as important as the 'quantity'. The examples need to be selected very carefully if the system is to perform reliably and efficiently

Modelling and Diagnosing the Cardiovascular System: Neural Networks are used experimentally to model the human cardiovascular system. Diagnosis can be achieved by building a model of the cardiovascular system of an individual and comparing it with the real time physiological measurements taken from the patient. If this routine is carried out regularly, potential harmful medical conditions can be detected at an early stage and thus make the process of combating the disease much easier.

A model of an individual's cardiovascular system must mimic the

relationship among physiological variables (i.e., heart rate, systolic and diastolic blood pressures, and breathing rate) at different physical activity levels. If a model is adapted to an individual, then it becomes a model of the physical condition of that individual. The simulator will have to be able to adapt to the features of any individual without the supervision of an expert. This calls for a neural network.

Another reason that justifies the use of ANN technology, is the ability of ANNs to provide sensor fusion which is the combining of values from several different sensors. Sensor fusion enables the ANNs to learn complex relationships among the individual sensor values, which would otherwise be lost if the values were individually analysed. In medical modelling and diagnosis, this implies that even though each sensor in a set may be sensitive only to a specific physiological variable, ANNs are capable of detecting complex medical conditions by fusing the data from the individual biomedical sensors.

Electronic noses: ANNs are used experimentally to implement electronic noses. Electronic noses have several potential applications in telemedicine. Telemedicine is the practice of medicine over long distances via a communication link. The electronic nose would identify odours in the remote surgical environment. These identified odours would then be electronically transmitted to another site where an odor generation system would recreate them. Because the sense of smell can be an important sense to the surgeon, tele-smell would enhance tele-present surgery.

Instant Physician: An application developed in the mid-1980s called the "instant physician" trained an autoassociative memory neural network to store a large number of medical records, each of which includes information on symptoms, diagnosis, and treatment for a particular case. After training, the net can be presented with input consisting of a set of symptoms; it will then find the full stored pattern that represents the "best" diagnosis and treatment.

4.7 Neural Networks in Business

Business is a diverted field with several general areas of specialisation such as accounting or financial analysis. Almost any neural network application would fit into one business area or financial analysis.

There is some potential for using neural networks for business purposes, including resource allocation and scheduling. There is also a strong potential for using neural networks for database mining that is, searching for patterns implicit within the explicitly stored information in databases. Most of the funded work in this area is classified as proprietary. Thus, it is not possible to report on the full extent of the work going on. Most work is applying neural networks, such as the Hopfield-Tank network for optimization and scheduling.

Marketing: There is a marketing application which has been integrated with a neural network system. The Airline Marketing Tactician (a trademark abbreviated as AMT) is a computer sys-

tem made of various intelligent technologies including expert systems. A feedforward neural network is integrated with the AMT and was trained using back-propagation to assist the marketing control of airline seat allocations. The adaptive neural approach was amenable to rule expression. Additionally, the application's environment changed rapidly and constantly, which required a continuously adaptive solution. The system is used to monitor and recommend booking advice for each departure. Such information has a direct impact on the profitability of an airline and can provide a technological advantage for users of the system.

While it is significant that neural networks have been applied to this problem, it is also important to see that this intelligent technology can be integrated with expert systems and other approaches to make a functional system. Neural networks were used to discover the influence of undefined interactions by the various variables. While these interactions were not defined, they were used by the neural system to develop useful conclusions. It is also noteworthy to see that neural networks can influence the bottom line.

Credit Evaluation: The HNC company, founded by Robert Hecht-Nielsen, has developed several neural network applications. One of them is the Credit Scoring system which increases the profitability of the existing model up to 27%. The HNC neural systems were also applied to mortgage screening. A neural network automated mortgage insurance underwriting system was developed by the Nestor Company. This system was trained with 5048 applications of which 2597 were certified.

The data related to property and borrower qualifications. In a conservative mode the system agreed on the underwriters on 97% of the cases. In the liberal model the system agreed 84% of the cases. This is system run on an Apollo DN3000 and used 250K memory while processing a case file in approximately 1 sec.

NEURAL NETWORK DESIGN: provides a clear and detailed survey of fundamental neural network architectures and learning rules. In it, the authors emphasize mathematical analysis of networks, methods for training networks, and application of networks to practical engineering problems in pattern recognition, signal processing, and control systems. The book incorporates necessary background material (such as linear algebra, optimization, and stability) to the extent it is needed. The book includes extensive coverage of performance learning, including the Widrow-Hoff rule and backpropagation.

The authors describe several enhancements of backpropagation, such as the conjugate gradient and Levenberg-Marquardt variations. These techniques are illustrated with applications in pattern recognition, adaptive filtering, and function approximation. The authors use simple building blocks to explain associative and competitive networks, including feature maps, learning vector quantization, and adaptive resonance theory.

Recurrent associative memory networks, such as the Hopfield network, are also discussed. All topics are systematically present-

ed in a unified framework with a consistent notation. Detailed examples and numerous solved problems are included.

Optional exercises incorporating the use of MATLAB are built into each chapter, and a set of Neural Network Design Demonstrations make use of MATLAB to illustrate important concepts. In addition, the book's straightforward organization -- with each chapter divided into the following sections: Objectives, Theory and Examples, Summary of Results, Solved Problems, Epilogue, Further Reading, and Exercises -- makes it an excellent tool for learning and continued reference.

5 CONCLUSION

The computing world has a lot to gain from neural networks. Their ability to learn by example makes them very flexible and powerful. Furthermore there is no need to devise an algorithm in order to perform a specific task; i.e. there is no need to understand the internal mechanisms of that task. They are also very well suited for real time systems because of their fast response and computational times which are due to their parallel architecture.

Neural networks also contribute to other areas of research such as neurology and psychology. They are regularly used to model parts of living organisms and to investigate the internal mechanisms of the brain.

Perhaps the most exciting aspect of neural networks is the possibility that some day 'conscious' networks might be produced. There is a number of scientists arguing that consciousness is a 'mechanical' property and that 'conscious' neural networks are a realistic possibility.

Finally, I would like to state that even though neural networks have a huge potential we will only get the best of them when they are intergrated with computing, AI, fuzzy logic and related subjects.

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Author Profile:

Md.Adam baba holds Master's degree in technology from Holy Mary Institute of Technology & Science, Affiliated to JNTU Hyderabad, AP .India. His areas of interest include web technologies, data warehousing techniques, Artificial Intelligence, (Email: md.adam4011@gmail.com).

Mohd.Gouse Pasha holds Master's degree in technology from

Holy Mary Institute of Technology & Science, Affiliated to JNTU, Hyderabad, AP India. His areas of interest include web technologies, data warehousing techniques, Artificial Intelligence, (Email: Mohammed.unique@gmail.com).

S.Nasira Tabassum holds Master's degree in technology and Master of computer applications from JNTUH and Osmania University, AP India. Her areas of interest include web technologies, data warehousing techniques, Artificial Intelligence, Image Processing and Data Mining. (Email: nasira.tabassum@gmail.com).

Shaik Althaf Ahammed holds Master's degree in computer applications from M K University, T.N, India. His areas of interest include data mining and data warehousing techniques, Neural Networks and Artificial Intelligence. (Email: shaik_althaf123@yahoo.com).