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A Study of Neural Networks

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Abstract

The purpose of the Artificial Neural Network is to build useful computers for targeted real-world issues. It is a functional replication of a simplified model of biological neurons. It re-creates sophisticated data analysis. It employs several approaches like as pattern recognition, classification, and generalisation by utilising artificial neurons, which are simple, distributed, and resilient processing units. A vast fine-grained parallel distributed structure of neurons makes up the Artificial Neural Network. An appropriate algorithm for a given application must also be used to train these neurons in ANN. These networks function well with both linear and nonlinear systems, as well as static and dynamic systems. The great degree of connection of the vast and parallel-distributed neurons gives ANN its intelligence and its capacity to tackle difficult tasks. The tremendous processing capacity of ANN architecture and methods can benefit real-time applications in VLSI technology, which is driving the current resurgence of interest in ANN. The number of ANN applications has exploded in recent years, fueled by successful practical uses of gained theoretical knowledge across a wide range of fields. The overview and advances of ANN-related applications are presented in this research study. The theory, models, and applications of artificial neural networks are briefly discussed.

Keywords *— Neural Network models, Biological neural network, Supervised and Unsupervised learning, Reinforcement learning, Neural Network Learning, Neural Network applications.*

1 INTRODUCTION

Neural networks are those information processing systems. These are constructed and implemented to model the human brain. The main objective of the neural network research is to develop a computational device for modelling the brain to perform the various computational tasks at a faster rate than the traditional systems. Artificial neural networks perform various tasks such as pattern-matching and classification, developing optimisation functions, approximation, vector quantization and data clustering.

Biological Neural Network

Human brains consist of a huge number of neurons, approximately 10^{11} with numerous interconnections. The Cell Nucleus is located in the Cell body, which can get connected to the nerves through Dendrites, which are tree-like networks made of nerve fibre as shown in Fig.1. An axon is a single, long interconnection extending from the cell body and carrying signals from the neuron i.e the impulse of the neuron. The end of the axon splits into fine strands. Each strand is discovered to terminate in a tiny bulb-like organ known as a synapse. This synapse is where the neuron sends its signal to other adjacent neurons. On adjacent neurons, the receiving end of these synapses can be located on both the dendrites and the cell body. In the human brain, there are roughly 104104 synapses per neuron [1].

Between the synapses and the dendrites, electric impulses are transferred. Specific transmitting molecules are released from the sending side of the junction, resulting in a rise or reduction in the electric potential inside the receiving cell's body.

Artificial neural network

An ANN is a man-made information processing system that has features that are identical to those of a biological neural network, as shown in Fig. 2. It is made up of a huge number of highly linked processing components known as nodes, units, or neurons, which are arranged in regular patterns to function in parallel. The connecting link receives the input signal in the form of weights. The information utilised by the neuron network can be used to tackle a specific problem. The capacity of ANN to learn, record, and generalise training patterns is a defining feature of their collective behaviour. Additionally, the data is comparable to that of a human brain. ANNs have the potential to model original neuron networks present in the brain. Artificial neurons are the processing components of ANNs.

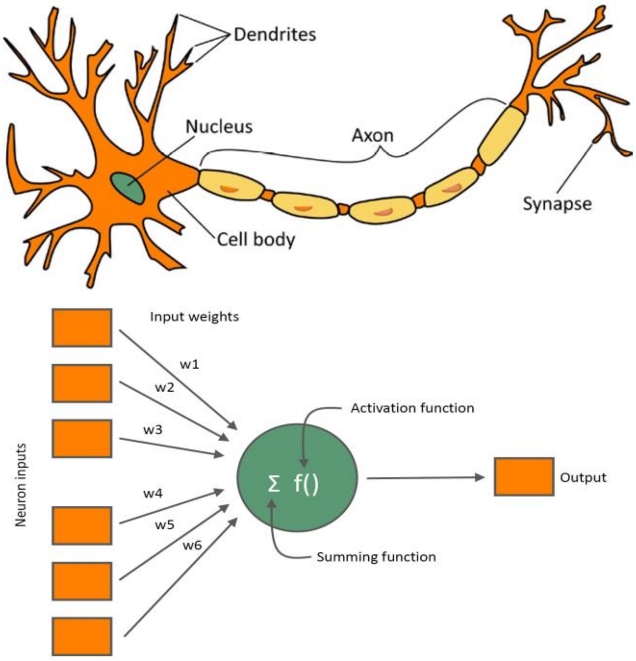

Fig.1. An artificial neuron as used in an artificial neuron network and a biological neuron on which the artificial neuron is modelled.

We can see from Fig.1, Each "neuron" is a relatively simple element --- for example, summing its inputs and applying a threshold to the result, to determine the output of that "neuron"[2].

2. BASIC MODEL OF ARTIFICIAL NEURAL NETWORK

There are some basic entities of ANN model. The model is made up of different synaptic interconnection, the training rules which is adopted for updating, adjusting the connection weights and their activation functions as well [3].

A set of highly interconnected processing elements is ANN. The output of each processing unit is discovered to be related to the other processing components or to itself via weights. Delay leads and lag-free connections are permitted here. As a result, for an ANN, the geometry of their interconnections and the organisation of these processing parts are critical. The purpose of each processing element in an ANN should be stated, as well as the point at which the connection begins and ends. The network architecture is made up of layers of neurons and the patterns of connections that form within and between them.There are different basic types of neuron connection architectures. We will see these architectures in this section.

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Single layer feed forward network

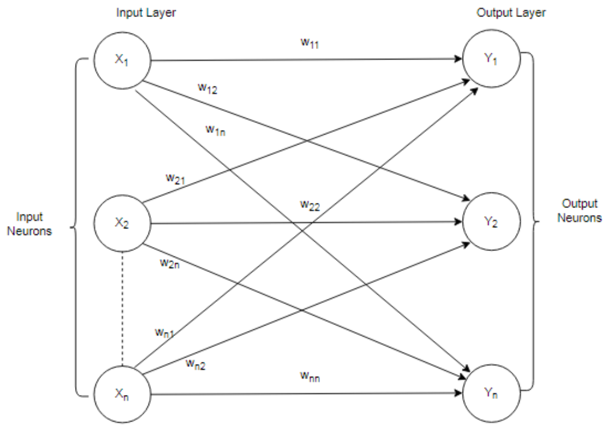

Fig.2. Single Layer feedforward Network

A single layer feedforward network is formed by taking a processing element. Also combining the processing elements with other processing elements. The inputs can be connected to these nodes with various weights, when a layer of the processing nodes is formed which is then resulting in a series of outputs, one per node [4].

Multilayer feedforward network

The interconnection of several layers is a formation of multilayer feedforward network. The input layer is receives the input. The input layer has function of buffering the input signal. The output of the network is generated by output layer. Any layer that is formed between the input layer and the output layer is called the hidden layer [5].

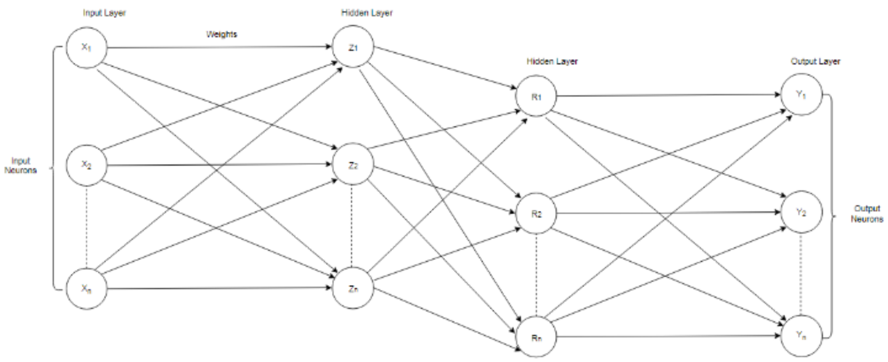

Fig.3. Multilayer feedforward Network

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Single node with its own feedback

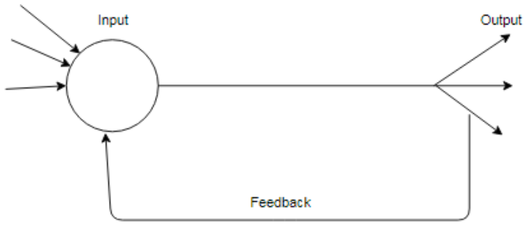

Fig.4. Single Node with its own feedback

The lateral feedback is the network where the feedback of the output is directed back as an input. The input to the processing elements in the same layer [6].

Competitive network

The competitive interconnections have fixed weight-εε. I.e. Maxnet[7].

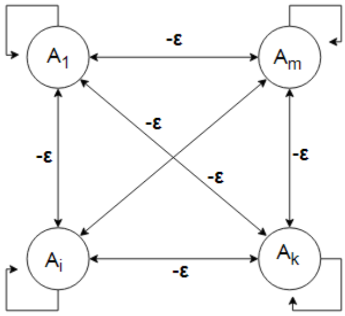

Fig.5. Competitive Network

Single layer recurrent network

Recurrent networks are the feedback networks with a closed loop.

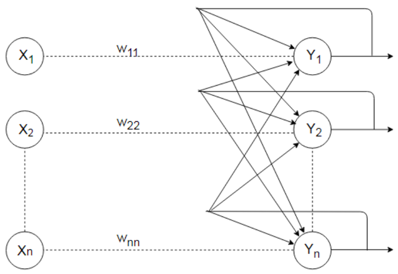

Fig.6. Single Layer Recurrent Network

Multilayer recurrent network

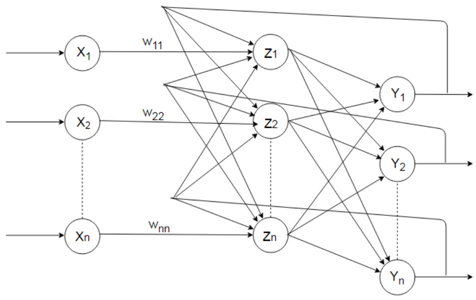

Fig.7. Multilayer recurrent Network

Lateral inhibition structure

This structure works on the phenomenon where neuron's response to a stimulus is inhibited by the excitation of a neighboring neuron [8].

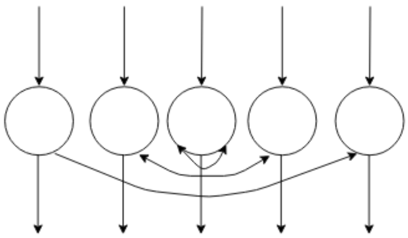

Fig.8. Lateral Inhibition Structure

3 NEURAL NETWORK LEARNING

Training neutral network is the process of learning where neural network adapts itself by making proper parameter adjustments and then it results in the desired response production.
Broadly, there are two kinds of learning in neutral network i.e. Parameter learning which up-dates the connecting weights in a neutral net.and Structured learning, it focuses on the change in network structure.These two types of learning can be performed simultaneously or sepa-rately[9].
These are two categories of learning. Further, the learning in a neutral network can be gener-ally classified into three categories as

i. Supervised learning

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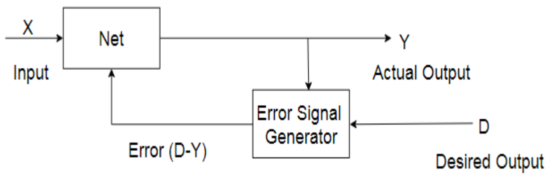

Fig.9. Supervised learning Network

ii. Unsupervised learning

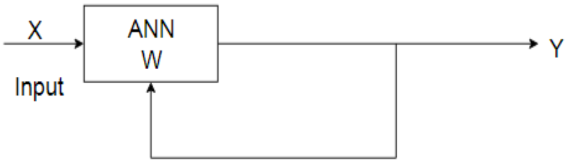

Fig.10. Unsupervised learning Network

iii. Reinforcement learning

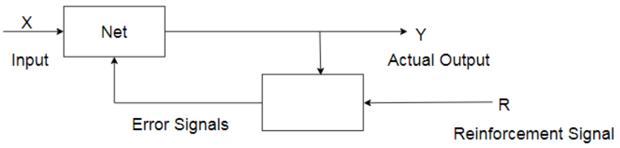

Fig.11. Reinforcement learning Network

4 BUILDING A PREDICTIVE MODEL FOR IMAGES WITH NEURAL NETWORKS

Once training images are prepared, we need a system that can process them and use them to make a prediction on new, unknown images. That system is an artificial neural network. The image recognition algorithms of neural network can work on text, images, audio files, and videos. Also it can helps to classify them. Neural networks are an interconnected collection of nodes called perceptrons[10].

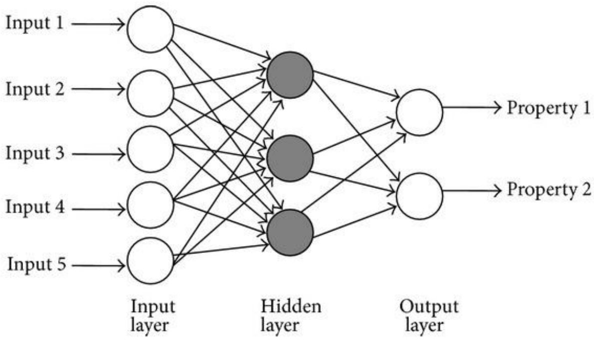

Fig.12. Perceptron Input and Output

To obtain a result, each neuron takes one piece of input data, generally one pixel of an image, and performs a basic computation called an activation function. Each neuron has a numerical weight that has an impact on the outcome. The output is fed into more neural layers until the neural network delivers a prediction for each input or pixel at the conclusion of the process. In a technique known as backpropagation, this method is repeated for a large number of pictures, and the network learns the best suitable weights for each neuron that offer correct predictions. Once a model has been trained, it is tested on a new collection of photos that did not participate in the training process. After some tuning, the model can be used to classify real-world images [11].

5 APPLICATIONS OF NEURAL NETWORKS

Neural networks have many applications text classification, information extraction, semantic parsing, question answering, paraphrase detection, language generation, multi-document summarization, machine translation, and speech and character recognition.

These applications of neural networks are essential, particularly in the high assurance engineering systems that have emerged in various fields, including flight control, automotive control, medical systems, chemical engineering, power plants and other systems that require autonomy [12].

It can be useful for speech recognition, face recognition, character recognition annnd signature recognition too. It has been useful for natural language processing for text classification, named entity recognition.

6 CONCLUSION

In the future, neural networks will be used in a variety of applications, depending on their kinds. Fuzzy logic neural networks are producing good outcomes. It is more beneficial to humans since it provides more effective and efficient answers to issues. The study into neural networks appears to be progressing in the correct direction toward the ultimate aim of all artificial intelligence, both now and in the future.

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