Perspective
Volume 15:2, 2022

Journal of Computer Science & Systems Biology

ISSN: 0974-7230

Open Access

Short Notes on Neural Networks

Elisha Stewart*

Department of Information Science, University of Bergen, Norway

Introduction

Neural networks, also known as artificial neural networks or simulated neural networks, are a subset of machine learning that form the foundation of deep learning algorithms. Their name and structure are inspired by the human brain, and they mimic the way biological neurons communicate with one another. Artificial Neural Networks (ANNs) are made up of node layers, each of which has an input layer, one or more hidden layers, and an output layer. Each node, or artificial neuron, is linked to another and has its own weight and threshold [1].

If the output of any individual node exceeds the specified threshold value, that node is activated and begins sending data to the network's next layer. Otherwise, no data is passed to the next network layer. Training data is used by neural networks to learn and improve their accuracy over time. However, once these learning algorithms have been fine-tuned for accuracy, they become powerful tools in computer science and artificial intelligence, allowing us to classify and cluster data at high speeds [2].

When compared to manual identification by human experts, tasks in speech recognition or image recognition can be completed in minutes rather than hours. Google's search algorithm is one of the most well-known neural networks. There are several types of neural networks, each of which serves a different purpose. While this is not an exhaustive list, the types listed below are representative of the most common types of neural networks encountered in common use cases [3].

Description

Deep Learning and neural networks are terms that are frequently used interchangeably in conversation, which can be perplexing. As a result, it's important to note that the "deep" in deep learning simply refers to the number of layers in a neural network. A deep learning algorithm can be defined as a neural network with more than three layers, which includes the inputs and outputs. A neural network with only two or three layers is referred to as a basic neural network [4].

This article has primarily focused on feedforward neural networks, also known as Multi-layer Perceptrons (MLPs). They are made up of three layers: an input layer, a hidden layer or layers, and an output layer. While these neural networks are also known as MLPs, it is important to note that they are made up of sigmoid neurons rather than perceptrons, as most real-world problems are nonlinear. These models are typically fed data to train them, and they serve as the foundation for computer vision, natural language processing, and other neural networks [5].

Conclusion

Convolutional Neural Networks (CNNs) are similar to feedforward networks in that they are used to recognise images, patterns, and/or perform computer vision. These networks use linear algebra principles, specifically matrix multiplication, to identify patterns in images. The feedback loops of Recurrent Neural Networks (RNNs) distinguish them. These learning algorithms are primarily used when making predictions about future outcomes using time-series data, such as stock market predictions or sales forecasting. Convolutional Neural Networks (CNNs) are made up of five layers: input, convolution, pooling, fully connected, and output. Each layer serves a specific function, such as summarising, connecting, or activating. Convolutional neural networks have made image classification and object detection more popular. CNNs, on the other hand, have been used in other fields such as natural language processing and forecasting.

Recurrent Neural Networks (RNNs) make use of sequential information, such as time-stamped data from a sensor device or a spoken sentence made up of a series of terms. Unlike traditional neural networks, the inputs to a recurrent neural network are not independent of one another, and the output for each element is dependent on the computations of the elements before it. RNNs are used in applications such as forecasting and time series analysis, sentiment analysis, and other text applications.

References

1. Gorman, Paul R. and Terrence J. Sejnowski. "Analysis of hidden units in a layered network trained to classify sonar targets." *Neural Netw* 1 (1988): 75-89.
2. Lesaffre, Emmanuel and Adelin Albert. "Partial separation in logistic discrimination." *J R Stat Soc Series B Stat Methodol* 51 (1989): 109-116.
3. Cohn, David and Gerald Tesauro. "How tight are the Vapnik-Chervonenkis bounds?." *Neural Comput* 4 (1992): 249-269.
4. Hornik, Kurt, Maxwell Stinchcombe and Halbert White. "Multilayer feedforward networks are universal approximators." *Neural Netw* 2 (1989): 359-366.
5. Gelfand, Saul B. and Sanjoy K. Mitter. "Recursive stochastic algorithms for global optimization in R^d." *SIAM J Control Optim* 29 (1991): 999-1018.

How to cite this article: Stewart, Elisha. “Short Notes on Neural Networks.” J Comput Sci Syst Biol 15 (2022): 397.

***Address for Correspondence:** Elisha Stewart, Department of Information Science, University of Bergen, Norway, E-mail: ElishaStewart50@gmail.com*

Received 07-Feb-2022, Manuscript No.Jcsb-22-58214; **Editor assigned:** 09-Feb-2022, Pre QC No. P-58214; **Reviewed:** 23-Feb-2022, QC No. 58214; **Revised:** 28-Feb-2022, Manuscript No. R-58214; **Published:** 07-Mar-2022, DOI: 10.37421/jcsb.2022.15. 397