A Study On Neural Networks

Anirban Chakraborty[1]

[1] MTECH, Artificial Intelligence, Lovely Professional University, Punjab, India

ABSTRACT

This paper deals with Literature Review on some papers based on Neural Networks and also provides Hypothesis on the types of Neural Networks. Neural Networks is now used in almost every field. It is very advanced and can work like Human Brain. It has different layers through which it can work and solve problems. Many weights are used to solve problems. Brief description of various uses of Neural Networks are stated in this paper.

Keyword:- *CNN, RNN, Neural Networks, Computer, AI, Deep Learning*

1. INTRODUCTION

Computer systems loosely influenced by biological neural networks which shape animal's brains, or connection systems are neural networks (ANN).[1] This machine "learns," for example, to do tasks, usually without being programmed with task-specific laws. By analyzing examples of images that are manually laid down as "cat" or "no cat," you may learn how to identify images that contain cats by using the results to identify cats in other images. For example they do so without knowing beforehand that cats have fur, tails, whiskers and. The characteristics of identifying examples are generated instead automatically.

An ANN is focused on an artificial neuron-like set of linked units or nodes that model neurons loosely in the biological brain. An interaction will send a signal to other neurons, like the synapses in a biological brain. An artificial neuron receiving a signal then processes and can signal connected neurons.

The "signal" on a link is a real number for ANN implementations and the value of each neuron is calculated with the non-linear total of its inputs. The ties are named boundaries. Neurons and borders usually weigh on a learning basis. The strength of the signal in a link increases or decreases. Neurons will only produce a signal once the combined signal reaches the threshold. Neurons are typically combined in layers. Various layers can turn their inputs in various ways. The first layer of signals (input layer), the last layer (output layer) may travel from the first layer to the last layer after crossing several layers.

The ANN approach's original aim was to solve problems just as a human brain might do. With time, however, attention has been paid to specific tasks, leading to biological deviations. ANNs were used in other functions, such as computer vision , speech recognition, data communication, social network scanning, play board and video games, medical diagnoses, and even things traditionally regarded as human-reserved, such as drawing.

2. OBJECTIVES

- Reduce complexity.
- Increase accuracy.
- Shorter results.
- Work like human brain.

3. LITERATURE RIVIEW

1. Mitali Kapoor provides a short overview of the Artificial Neural Network (ANN) prediction methodology. It is used to increase model predictability, where experimental information is less dependent. In addition to numerous ANN instruction, the specific steps used in MATLAB are recorded. The training aims to

minimize a significant mistake. For process preparation and optimization of process parameters, an ANN model can be used easily for the estimation of output parameters that aid in the optimal selection of machining parameters.

2. Raj Singla stated that Recent theoretical and empirical studies demonstrate that the generalization capability of artificial neural networks can be enhanced by the combination in redundant ensembles of multiple artificial neural networks. A summary of common ensemble methods is provided in this paper. For the estimation of index flood and the 10-year flood quantize, six approaches are employed to create artificial neural network assemblies.
3. Ravi Roy proposed that CNN indicate that assemblies of the artificial neural networks create improved flood estimates and are less sensitive than a single artificial neural network to the choice of initial parameters. Factors that can affect artificial neural network ensemble generalization and are analyzed. In terms of how the ensemble members are made, the result are discussed.
4. Raman Singh said that The diversity of models, introduced to reduce prediction errors by changing the original conditions of artificial neural base networks is comparable to more sophisticated methods such as bagging and boosting. If the same method is used to create ensemble members, it generally is better than a simple averaging to combine Member Networks using stacking. An ensemble scale of 10 or more artificial neural networks is suggested to generalize enough. The proper design of artificial neural network assemblies will significantly reduce the prediction error in contrast to parametric regression methods.
5. Sheetal Rani said that A theoretical approach for the safety of digital photographs and videos was suggested by the Yen and Guo chaotic neural network (CNN) in the area of signal encryption. This article tests the reliability of this cryptographic CNN framework and suggests it is not cryptographically secure: 1) known / choiced-plaintext attacks might easily crack it; 2) its defence against the assault was overestimated. Any studies demonstrate that the conclusions of this paper are endorsed. It also discusses how the encryption system can be improved.

4. HYPOTHESIS

A) **CNN:** In deep learning, the neural network convolution (CNN or ConvNet) is a class of deep neural networks, which is most frequently used for vision analysis[1] and are known as artificial neural networks (SIANN) that are invariant shift and invariant space, based on their shared weight and in-variance of the characteristics of translation[2][3].Multi-layer perceptrons are regularized copies of CNNs. Usually, multi layer perceptrons mean fully linked networks, meaning that every neuron in one layer has a connection with the next layer of neurons. Such networks are "completely integrated" and can be over-fitted with info. Typical regularization methods include adding to the loss function some type of weight measurement. CNNs have a particular path to regularization: they use the linear data patterns and use smaller and simpler patterns to create more complicated patterns. CNNs are therefore at the lower extreme at the level of connectivity and complexity.

B) **RNN:** A recurrent neural network (RNC) is a class of artificial neural networks that link the nodes in a temporal sequence in a directed graph. This allows it to display dynamic temporal behavior. Able to manage the variable length of inputs from feed-forward neural networks, RNN can use their own internal state (memory)[1] to manage tasks such as unsegmented, connected handwriting[2] or speech recognition[3][4].In indiscriminate terms, the term "recurring neural network" refers to two broad classes of networks with similar general structures, one being of finite and one of infinite impulses. Both groups of the networks demonstrate temporal dynamic behavior.[5] A persistent finite impulses network is a directed acyclic graph that can be rolled out and substituted with a robust neural network, while an eternal cyclical impulse network can not be rolled out. The recurring networks can both have endless impulse and the storage can be controlled by the neural network directly. Stock may also be substituted by a particular network or graph if time delays or feedback loops are implemented. Such controlled states are known as gated state or gated memory and belong to long-term recurring memory networks (LSMs). Feedback Neural Network is also known.

5. CONCLUSION

Neural networks are computing systems that work like neurons in the human brain with interconnected nodes. Using algorithms, you can detect and distinguish secret trends and associations in raw data and, over time, develop and grow continuously. It can be used like human brain and it is being used in every intelligent agencies. It is an amazing development in the history of Artificial Intelligence.

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BIOGRAPHY:

Mr. Anirban Chakraborty
MTECH, Artificial Intelligence
Lovely Professsional University
Punjab, India