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Deep Learning Algorithms – A Case Study

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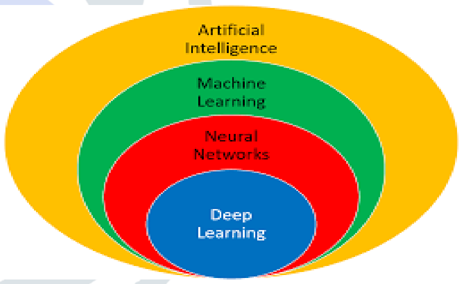
Abstract : Deep learning has grown significantly in scientific computing over the past few years, and businesses that handle complicated problems frequently use its techniques. Different kinds of neural networks are used by all deep learning algorithms to carry out particular tasks. Deep learning techniques, a subtype of machine learning[2], are becoming more important for precise outcomes in speech recognition, object recognition, and image segmentation. Deep learning offers adaptable techniques for handling and evaluating large amounts of data. The goal of the work is to compare approaches, research issues, and trends while surveying a variety of deep learning algorithms[4][2] employed in evolving research. The purpose is to clarify these algorithms' application in Big Data is necessary.

Keywords: Deep Learning, Machine Learning, Neural Network, Convolution Neural Network, NLP.

I. INTRODUCTION

A subset of machine learning that is entirely based on artificial neural networks is deep learning. The idea of deep learning is not new; it has been around for a while. Deep learning uses neural networks to encourage decision-making that is similar to that of a human. Deep learning is learning based on neural networks. The feature extraction method is one of the difficulties with machine learning. . Deep learning modes are capable of selecting the proper features on their own.

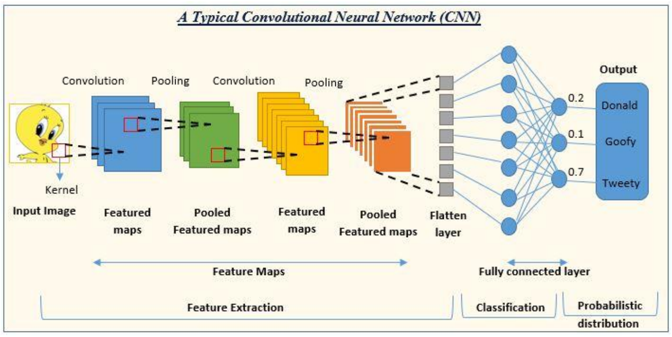


Building learning algorithms that resemble the brain is the goal of deep learning.

A. *Convolutional Neural Network*

A feed-forward neural network called convolutional network analysis visual images by processing data in a grid-like architecture. ConvNet is another name for it. To find and categorize items in an image, a convolutional neural network[8] is employed. Every image on CNN is represented as an array of pixel values. In terms of successful object recognition and handwritten optical character recognition (OCR), CNN is a high-performance classifier that is multi-class, hard to learn, and quick to classify.

The tiers of CNN are as follows: 1. Convolution 2. Pooling Third, flattening These components enable CNN to perform better than ANN. Convolution will do the necessary operations for a specific input and re-estimate it as the weighted average of all the inputs nearby. While the Pooling layers offer a method for down-sampling feature maps by enumerating the existence of features in different feature map patches. Average pooling and max pooling, which respectively summarize a feature's average presence and its maximum activated presence, are two popular pooling techniques. Flattening is the process of combining all of the 2-Dimensional arrays from the pooled feature maps into a single, long, continuous linear vector.



To categorize the image, the flattened matrix is provided as input to the fully linked layer.

B. RADIAL BASIS FUNCTION NETWORK(RBFNs)

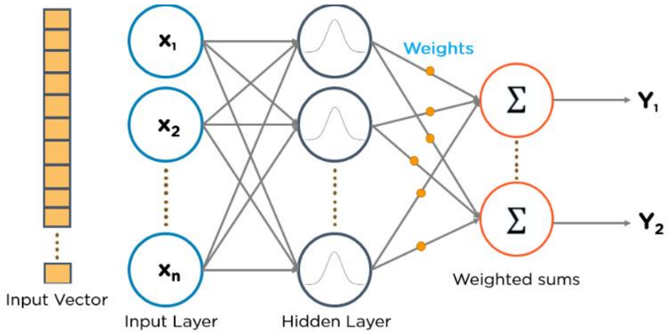
Radial basis functions are a unique class of feedforward neural networks (RBFNs)[5][6] that are used as activation functions. They are typically used for classification, regression, and time-series prediction and have an input layer, a hidden layer, and an output layer.

1. 1.RBFNs classify data by evaluating how closely the input resembles samples from the training set.
2. 2. The input layer of RBFNs is fed by an input vector. They contain an RBF neuron layer.

3. Each category or class of data has its own node in the output layer, and the function computes the inputs' weighted sum.

4. The Gaussian transfer functions, which have outputs that are inversely proportional to the distance from the neuron's centre, are present in the neurons in the hidden layer.

5. The output of the network is a linear combination of the parameters of the neuron and the radial-basis functions of the input.



Architecture of RBFNs

C.DEEP BELIEF NEURAL NETWORK(DBNs)

To solve the problems with traditional neural networks in deep layered networks, deep belief networks (DBNs) were developed. Such as requiring a large amount of training datasets, slow learning, and becoming stuck in local minima as a result of bad parameter selection.

DBNs are generative models made up of a number of layers of latent, stochastic variables. Latent variables, often known as hidden units, have binary values.

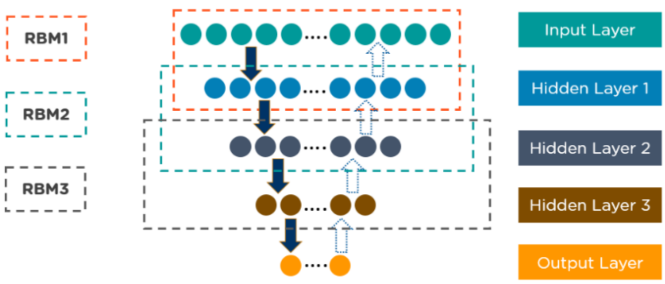
Each RBM layer in a DBN can communicate with both the layer above it and the layer below it because there are connections between the layers of a stack of Boltzmann machines. For image identification, video recognition, and motion capture, Deep Belief Networks (DBNs)[7] are employed.

1. DBNs are trained via greedy learning algorithms. The top-down, generative weights are learned via the greedy learning method layer by layer.

2. On the top two hidden layers, DBNs do the Gibbs sampling steps. In this step, a sample is taken from the RBM that the top two hidden layers have defined.

3.DBNs use a single ancestral sampling run through the rest of the model to select a sample from the visible units.

4.DBNs discover that a single, bottom-up pass may infer the values of the latent variables in every layer.



Architecture of DBN

IV. CONCLUSION

We can refer to the enormous number of parameters in deep learning models like the Convolutional Neural Network (CNN) as hyper-parameters because the model itself does not optimize them. Grid searching for the best values for these hyper-parameters is possible, but it takes a lot of hardware and effort.

Building on the design and architecture of the specialists who have conducted in-depth research in the field, frequently with powerful hardware at their disposal, is one of the finest methods to improve the models. They graciously open-source the resulting modeling architectures and reasoning rather frequently.

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