Introduction To Deep Learning

13 July 2024 12:57 PM

Unit-1	**Basics of Artificial Neural Network**	Contact Hours:15 hours
	Basic of Neural Network: Computational models of neurons Structure of neural networks Functional units of ANN for pattern recognition tasks **Models of Neural Network:** Pattern classification using perceptron Multilayer feed forward neural networks (MLFFNNs) Backpropagation learning **DNN Training and optimization:** Empirical risk minimization Regularization Difficulty of training DNNs Greedy layer wise training Optimization for training DNNs Newer optimization methods for neural networks (AdaGrad, RMSProp, Adam)	
Unit-2	**Second Order Methods**	Contact Hours:15 hours
	Second order methods Introduction: Second order methods for training Regularization methods (dropout, drop connect, batch normalization) **Introduction to CNN**: Convolution Pooling Deep CNNs Different deep CNN architectures - LeNet, AlexNet, VGG **Training a CNN**: Weights initialization Batch normalization Hyper parameter optimization Understanding and visualizing CNNs	
Unit-3	**Sequence modelling**	Contact Hours:15 hours
	Sequence modelling: Sequence modelling using RNNs, Backpropagation through time **Time-Series Methods:** Long Short Term Memory (LSTM) Bidirectional LSTMs **Advance Sequence models:** Bidirectional RNNs Gated RNN Architecture Autoencoders (standard, denoising, contractive, etc) Variational Autoencoders Adversarial Generative Networks	

Labs:

Unit-1		Contact Hours:3 hours
	1. Implementing Multilayer feed forward neural networks 2. Implementing DNN 3. Greedy Layer wise training of DNN	
Unit-2		Contact Hours:4 hours
	4. AdaGrad optimization 5. Implementing CNN 6. Implementing Deep CNN 7. Sequence Modelling using RNN	
Unit-3		Contact Hours:3 hours
	8. Implementing LSTM 9. Implementing Autoencoder 10. Implementing Adversarial Generative Network	

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Introduction of Deep Learning

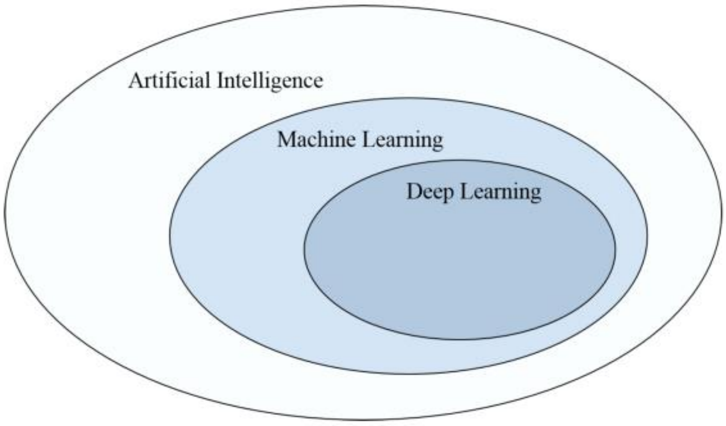
- The definition of Deep learning is that it is the branch of machine learning that is based on artificial neural network architecture. An artificial neural network or ANN uses layers of interconnected nodes called neurons that work together to process and learn from the input data.

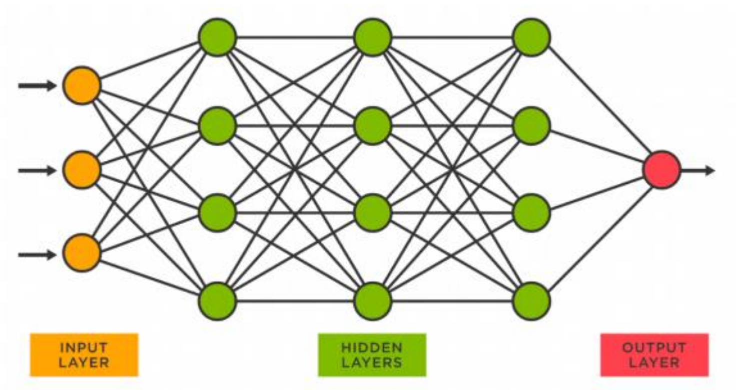
OR

- Deep Learning is a subfield of Artificial Intelligence and Machine Learning that is inspired by the structure of a human brain.

OR

- Deep learning algorithms attempt to draw similar conclusions as humans would by continually analysing data with a given logical structure called Neural Network.





Structure of Deep Neural Network (DNN)

Difference between Machine Learning and Deep Learning

- Machine learning and deep learning both are subsets of artificial intelligence but there are many similarities and differences between them.

Machine Learning	Deep Learning
Apply statistical algorithms to learn the hidden patterns and relationships in the dataset.	Uses artificial neural network architecture to learn the hidden patterns and relationships in the dataset.
Can work on the smaller amount of dataset	Requires the larger volume of dataset compared to machine learning
Better for the low-label task.	Better for complex task like image processing, natural language processing, etc.
Takes less time to train the model.	Takes more time to train the model.
A model is created by relevant features which are manually extracted from images to detect an object in the image.	Relevant features are automatically extracted from images. It is an end-to-end learning process.
Less complex and easy to interpret the result.	More complex, it works like the black box interpretations of the result are not easy.
It can work on the CPU or requires less computing power as compared to deep learning.	It requires a high-performance computer with GPU.

Deep Learning Applications

- The main applications of deep learning AI can be divided into computer vision, natural language processing (NLP), and reinforcement learning.
- **1. Computer vision**
- The first Deep Learning applications is Computer vision. In computer vision, Deep learning AI models can enable machines to identify and understand visual data. Some of the main applications of deep learning in computer vision include:
- **Object detection and recognition:** Deep learning model can be used to identify and locate objects within images and videos, making it

possible for machines to perform tasks such as self-driving cars, surveillance, and robotics.

- **Image classification:** Deep learning models can be used to classify images into categories such as animals, plants, and buildings. This is used in applications such as medical imaging, quality control, and image retrieval.
- **Image segmentation:** Deep learning models can be used for image segmentation into different regions, making it possible to identify specific features within images.
- **2. Natural language processing (NLP):**
- In Deep learning applications, second application is NLP. NLP, the Deep learning model can enable machines to understand and generate human language. Some of the main applications of deep learning in NLP include:
- **Automatic Text Generation:** Deep learning model can learn the corpus of text and new text like summaries, essays can be automatically generated using these trained models.
- **Language translation:** Deep learning models can translate text from one language to another, making it possible to communicate with people from different linguistic backgrounds.
- **Sentiment analysis:** Deep learning models can analyse the sentiment of a piece of text, making it possible to determine whether the text is positive, negative, or neutral. This is used in applications such as customer service, social media monitoring, and political analysis.
- **Speech recognition:** Deep learning models can recognize and transcribe spoken words, making it possible to perform tasks such as speech-to-text conversion, voice search, and voice-controlled devices.
- **3. Reinforcement learning:**
- In reinforcement learning, deep learning works as training agents to take action in an environment to maximize a reward. Some of the main applications of deep learning in reinforcement learning include:
- **Game playing:** Deep reinforcement learning models have been able to beat human experts at games such as Go, Chess, and Atari.
- **Robotics:** Deep reinforcement learning models can be used to train robots to perform complex tasks such as grasping objects, navigation, and manipulation.
- **Control systems:** Deep reinforcement learning models can be used to control complex systems such as power grids, traffic management, and supply chain optimization.

Challenges in Deep Learning

- Deep learning has made significant advancements in various fields, but there are still some challenges that need to be addressed. Here are some of the main challenges in deep learning:
- **Data availability:** It requires large amounts of data to learn from. For using deep learning it’s a big concern to gather as much data for training.
- **Computational Resources:** For training the deep learning model, it is computationally expensive because it requires specialized hardware like GPUs and TPUs.
- **Time-consuming:** While working on sequential data depending on the computational resource it can take very large even in days or months.
- **Interpretability:** Deep learning models are complex, it works like a black box. it is very difficult to interpret the result.
- **Overfitting:** When the model is trained again and again, it becomes too specialized for the training data, leading to overfitting and poor performance on new data.

Advantages of Deep Learning

- **High accuracy:** Deep Learning algorithms can achieve state-of-the-art performance in various tasks, such as image recognition and natural language processing.
- **Automated feature engineering:** Deep Learning algorithms can automatically discover and learn relevant features from data without the need for manual feature engineering.
- **Scalability:** Deep Learning models can scale to handle large and complex datasets, and can learn from massive amounts of data.
- **Flexibility:** Deep Learning models can be applied to a wide range of tasks and can handle various types of data, such as images, text, and speech.
- **Continual improvement:** Deep Learning models can continually improve their performance as more data becomes available.

Disadvantages of Deep Learning

- **High computational requirements:** Deep Learning AI models require large amounts of data and computational resources to train and optimize.

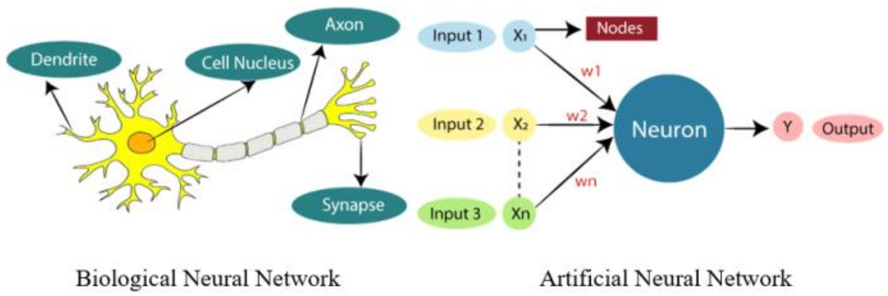
- **Requires large amounts of labelled data:** Deep Learning models often require a large amount of labelled data for training, which can be expensive and time- consuming to acquire.
- **Interpretability:** Deep Learning models can be challenging to interpret, making it difficult to understand how they make decisions. Overfitting: Deep Learning models can sometimes overfit to the training data, resulting in poor performance on new and unseen data.
- **Black-box nature:** Deep Learning models are often treated as black boxes, making it difficult to understand how they work and how they arrived at their predictions.

Artificial Neural Network

- The term "Artificial Neural Network (ANN)" refers to a biologically inspired sub-field of artificial intelligence modelled after the brain.
- An ANN is usually a computational network based on biological neural networks that construct the structure of the human brain.
- Similar to a human brain has neurons interconnected to each other, artificial neural networks also have neurons that are linked to each other in various layers of the networks. These neurons are known as nodes.

What is Artificial Neural Network?

- The term "Artificial Neural Network" is derived from Biological neural networks that develop the structure of a human brain.



- Dendrites from Biological Neural Network represent inputs in Artificial Neural Networks, cell nucleus represents Nodes, synapse represents Weights, and Axon represents Output.

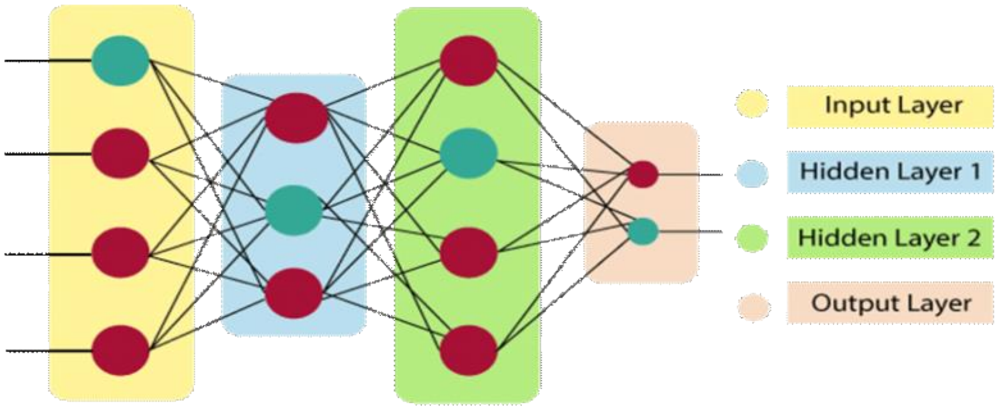
Relationship between Biological neural network and artificial neural network:

Biological Neural Network	Artificial Neural Network
Dendrites	Inputs
Cell nucleus	Nodes
Synapse	Weights
Axon	Output

- An Artificial Neural Network in the field of Artificial intelligence where it attempts to mimic the network of neurons makes up a human brain so that computers will have an option to understand things and make decisions in a human-like manner. The artificial neural network is designed by programming computers to behave simply like interconnected brain cells.
- There are around 1000 billion neurons in the human brain. Each neuron has an association point somewhere in the range of 1,000 and 100,000. In the human brain, data is stored in such a manner as to be distributed, and we can extract more than one piece of this data, when necessary, from our memory parallelly. We can say that the human brain is made up of incredibly amazing parallel processors.
- We can understand the artificial neural network with an example, consider an example of a digital logic gate that takes an input and gives an output. "OR" gate, which takes two inputs. If one or both the inputs are "On," then we get "On" in output. If both the inputs are "Off," then we get "Off" in output. Here the output depends upon input. Our brain does not perform the same task. The outputs to inputs relationship keep changing because of the neurons in our brain, which are "learning."

The architecture of an artificial neural network:

- To understand the concept of the architecture of an artificial neural network, we have to understand what a neural network consists of. In order to define a neural network that consists of a large number of artificial neurons, which are termed units arranged in a sequence of layers. Let's us look at various types of layers available in an artificial neural network. Artificial Neural Network primarily consists of three layers:



Input Layer:

- As the name suggests, it accepts inputs in several different formats provided by the programmer.

Hidden Layer:

- The hidden layer presents in-between input and output layers. It performs all the calculations to find hidden features and patterns.

Output Layer:

- The input goes through a series of transformations using the hidden layer, which finally results in output that is conveyed using this layer.
- The artificial neural network takes input and computes the weighted sum of the inputs and includes a bias. This computation is represented in the form of a transfer function.

$$\sum_{i=1}^{n} Wi * Xi + b$$

- It determines weighted total is passed as an input to an activation function to produce the output. Activation functions choose whether a node should fire or not. Only those who are fired make it to the output layer. There are distinctive activation functions available that can be applied upon the sort of task we are performing.

Computational Model of Neurons

- A computational model of a neuron, often referred to as an artificial neuron or perceptron, is a simplified mathematical representation of a biological neuron. These models are the fundamental building blocks of artificial neural networks (ANNs), which are used in machine learning and deep learning.

Key Components of a Computational Neuron:

1. **Inputs (Dendrites):**
    - Like dendrites in a biological neuron that receive signals from other neurons, the artificial neuron receives inputs (features) from other neurons or the external environment. Each input has an associated weight that determines its influence on the neuron's output.
2. **Weights (Synaptic Strengths):**
    - Weights in the computational model represent the synaptic strengths of connections between neurons. These weights are adjustable parameters that are learned during the training process.
3. **Weighted Sum (Aggregation):**
    - The neuron computes a weighted sum of its inputs, similar to how a biological neuron integrates incoming signals. Mathematically, this is represented as:

$$z = \sum_{i=1}^{n} w_i x_i + b$$

    - Where x_i are the inputs, w_i are the corresponding weights, and b is the bias term.
4. **Bias (Threshold):**
    - The bias is an additional parameter that helps in adjusting the output along with the weighted sum of the inputs. It is similar to the neuron's threshold for firing an action potential.

5. **Activation Function (Firing Mechanism):**
   - The weighted sum is passed through an activation function to produce the neuron's output. This function introduces non-linearity into the model, allowing it to solve complex problems. Common activation functions include the sigmoid, hyperbolic tangent (tanh), and rectified linear unit (ReLU).

$$y = \phi(z)$$

   - where ϕ is the activation function and y is the output of the neuron.

Mimicking Biological Neurons:

- **Signal Reception and Transmission:**
  - Biological neurons receive signals through dendrites and transmit them through axons. Similarly, computational neurons receive inputs and produce an output that can be transmitted to other neurons.
- **Synaptic Weights:**
  - The synaptic strength between biological neurons is analogous to the weights in artificial neurons. These weights are adjusted during learning, much like synaptic strengths are modified during biological learning and memory formation.
- **Integration and Firing:**
  - Biological neurons integrate incoming signals and fire an action potential if the integrated signal surpasses a certain threshold. The computational model mimics this by summing the weighted inputs and applying an activation function to determine if the neuron "fires" (produces a significant output).
- **Learning and Adaptation:**
  - Just as biological neurons adapt through synaptic plasticity (changes in synaptic strength), artificial neurons learn by adjusting their weights through algorithms like gradient descent during the training process.

Example: Perceptron Model

- The perceptron is the simplest form of a computational neuron, which can be described as:

1. **Inputs and Weights:**

$$x = (x_1, x_2, \ldots, x_n), \quad w = (w_1, w_2, \ldots, w_n)$$

2. **Weighted Sum:**

$$z = \sum_{i=1}^{n} w_i x_i + b$$

3. **Activation Function (Step Function):**

$$y = \begin{cases} 1 & \text{if } z > 0 \\ 0 & \text{otherwise} \end{cases}$$