Deep learning is a subset of machine learning that focuses on utilizing neural networks to perform tasks such as classification, regression, and representation learning. The field takes inspiration from biological neuroscience and is centered around stacking artificial neurons into layers and "training" them to process data. The adjective "deep" refers to the use of multiple layers (ranging from three to several hundred or thousands) in the network. Methods used can be either supervised, semi-supervised or unsupervised.  
Some common deep learning network architectures include fully connected networks, deep belief networks, recurrent neural networks, convolutional neural networks, generative adversarial networks, transformers, and neural radiance fields. These architectures have been applied to fields including computer vision, speech recognition, natural language processing, machine translation, bioinformatics, drug design, medical image analysis, climate science, material inspection and board game programs, where they have produced results comparable to and in some cases surpassing human expert performance.  
Early forms of neural networks were inspired by information processing and distributed communication nodes in biological systems, particularly the human brain. However, current neural networks do not intend to model the brain function of organisms, and are generally seen as low-quality models for that purpose.  
Overview  
Most modern deep learning models are based on multi-layered neural networks such as convolutional neural networks and transformers, although they can also include propositional formulas or latent variables organized layer-wise in deep generative models such as the nodes in deep belief networks and deep Boltzmann machines.  
Fundamentally, deep learning refers to a class of machine learning algorithms in which a hierarchy of layers is used to transform input data into a progressively more abstract and composite representation. For example, in an image recognition model, the raw input may be an image (represented as a tensor of pixels). The first representational layer may attempt to identify basic shapes such as lines and circles, the second layer may compose and encode arrangements of edges, the third layer may encode a nose and eyes, and the fourth layer may recognize that the image contains a face.  
Importantly, a deep learning process can learn which features to optimally place at which level on its own. Prior to deep learning, machine learning techniques often involved hand-crafted feature engineering to transform the data into a more suitable representation for a classification algorithm to operate on. In the deep learning approach, features are not hand-crafted and the model discovers useful feature representations from the data automatically. This does not eliminate the need for hand-tuning; for example, varying numbers of layers and layer sizes can provide different degrees of abstraction.  
The word "deep" in "deep learning" refers to the number of layers through which the data is transformed. More precisely, deep learning systems have a substantial credit assignment path (CAP) depth. The CAP is the chain of transformations from input to output. CAPs describe potentially causal connections between input and output. For a feedforward neural network, the depth of the CAPs is that of the network and is the number of hidden layers plus one (as the output layer is also parameterized). For recurrent neural networks, in which a signal may propagate through a layer more than once, the CAP depth is potentially unlimited. No universally agreed-upon threshold of depth divides shallow learning from deep learning, but most researchers agree that deep learning involves CAP depth higher than two. CAP of depth two has been shown to be a universal approximator in the sense that it can emulate any function. Beyond that, more layers do not add to the function approximator ability of the network. Deep models (CAP > two) are able to extract better features than shallow models and hence, extra layers help in learning the features effectively.

Deep learning architectures can be constructed with a greedy layer-by-layer method. Deep learning helps to disentangle these abstractions and pick out which features improve performance.  
Deep learning algorithms can be applied to unsupervised learning tasks. This is an important benefit because unlabeled data are more abundant than the labeled data. Examples of deep structures that can be trained in an unsupervised manner are deep belief networks.  
The term Deep Learning was introduced to the machine learning community by Rina Dechter in 1986, and to artificial neural networks by Igor Aizenberg and colleagues in 2000, in the context of Boolean threshold neurons. Although the history of its appearance is apparently more complicated.  
Interpretations  
Deep neural networks are generally interpreted in terms of the universal approximation theorem or probabilistic inference.  
The classic universal approximation theorem concerns the capacity of feedforward neural networks with a single hidden layer of finite size to approximate continuous functions. In 1989, the first proof was published by George Cybenko for sigmoid activation functions and was generalised to feed-forward multi-layer architectures in 1991 by Kurt Hornik. Recent work also showed that universal approximation also holds for non-bounded activation functions such as Kunihiko Fukushima's rectified linear unit.  
The universal approximation theorem for deep neural networks concerns the capacity of networks with bounded width but the depth is allowed to grow. Lu et al. proved that if the width of a deep neural network with ReLU activation is strictly larger than the input dimension, then the network can approximate any Lebesgue integrable function; if the width is smaller or equal to the input dimension, then a deep neural network is not a universal approximator.  
The probabilistic interpretation derives from the field of machine learning. It features inference, as well as the optimization concepts of training and testing, related to fitting and generalization, respectively. More specifically, the probabilistic interpretation considers the activation nonlinearity as a cumulative distribution function. The probabilistic interpretation led to the introduction of dropout as regularizer in neural networks. The probabilistic interpretation was introduced by researchers including Hopfield, Widrow and Narendra and popularized in surveys such as the one by Bishop.