

# Deep learning

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**Deep learning** (also known as **deep structured learning**) is part of a broader family of [machine learning](#) methods based on [artificial neural networks](#) with [representation learning](#). Learning can be [supervised](#), [semi-supervised](#) or [unsupervised](#).<sup>[1][2][3]</sup>

Deep-learning architectures such as [deep neural networks](#), [deep belief networks](#), [deep reinforcement learning](#), [recurrent neural networks](#) and [convolutional neural networks](#) have been applied to fields including [computer vision](#), [speech recognition](#), [natural language processing](#), [machine translation](#), [bioinformatics](#), [drug design](#), [medical image analysis](#), material inspection and [board game](#) programs, where they have produced results comparable to and in some cases surpassing human expert performance.<sup>[4][5][6][7]</sup>

[Artificial neural networks](#) (ANNs) were inspired by information processing and distributed communication nodes in [biological systems](#). ANNs have various differences from biological [brains](#). Specifically, artificial neural networks tend to be static and symbolic, while the biological brain of most living organisms is dynamic (plastic) and analogue.<sup>[8][9][10]</sup>

The adjective "deep" in deep learning refers to the use of multiple layers in the network. Early work showed that a linear [perceptron](#) cannot be a universal classifier, but that a network with a nonpolynomial activation function with one hidden layer of unbounded width can. Deep learning is a modern variation which is concerned with an unbounded number of layers of bounded size, which permits practical application and optimized implementation, while retaining theoretical universality under mild conditions. In deep learning the layers are also permitted to be heterogeneous and to deviate widely from biologically informed [connectionist](#) models, for the sake of efficiency, trainability and understandability, whence the "structured" part.

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## Definition

Deep learning is a class of [machine learning algorithms](#) that<sup>[12]:199–200</sup> uses multiple layers to progressively extract higher-level features from the raw input. For example, in [image processing](#), lower layers may identify edges, while higher layers may identify the concepts relevant to a human such as digits or letters or faces.

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## Overview

Most modern deep learning models are based on [artificial neural networks](#), specifically [convolutional neural networks](#) (CNN)s, 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](#).<sup>[13]</sup>

In deep learning, each level learns to transform its input data into a slightly more abstract and composite representation. In an image recognition application, the raw input may be a [matrix](#) of pixels; the first representational layer may abstract the pixels and encode edges; 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 in which level *on its own*. This does not completely eliminate the need for hand-tuning; for example, varying numbers of layers and layer sizes can provide different degrees of abstraction.<sup>[1][14]</sup>

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.<sup>[2]</sup> 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 2. CAP of depth 2 has been shown to be a universal approximator in the sense that it can emulate any function.<sup>[15]</sup> Beyond that, more layers do not add to the function approximator ability of the network. Deep models (CAP > 2) 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.<sup>[16]</sup> Deep learning helps to disentangle these abstractions and pick out which features improve performance.<sup>[1]</sup>

For [supervised learning](#) tasks, deep learning methods eliminate [feature engineering](#), by translating the data into compact intermediate representations akin to [principal components](#), and derive layered structures that remove redundancy in representation.

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 neural history compressors<sup>[17]</sup> and [deep belief networks](#).<sup>[1][18]</sup>

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## Deep-Learning Revolution

In 2012, a team led by George E. Dahl won the "Merck Molecular Activity Challenge" using multi-task deep neural networks to predict the [biomolecular target](#) of one drug.<sup>[95][96]</sup> In 2014, Hochreiter's group used deep learning to detect off-target and toxic effects of environmental chemicals in nutrients, household products and drugs and won the "Tox21 Data Challenge" of [NIH](#), [FDA](#) and [NCATS](#).<sup>[97][98][99]</sup>

Significant additional impacts in image or object recognition were felt from 2011 to 2012. Although CNNs trained by [backpropagation](#) had been around for decades, and GPU implementations of NNs for years, including CNNs, fast implementations of CNNs on GPUs were needed to progress on computer vision.<sup>[89][91][43][100][2]</sup> In 2011, this approach achieved for the first time superhuman performance in a visual pattern recognition contest. Also in 2011, it won the ICDAR Chinese handwriting contest, and in May 2012, it won the ISBI image segmentation contest.<sup>[101]</sup> Until 2011, CNNs did not play a major role at computer vision conferences, but in June 2012, a paper by Ciresan et al. at the leading conference CVPR<sup>[5]</sup> showed how max-pooling CNNs on GPU can dramatically improve many vision benchmark records. In October 2012, a similar system by Krizhevsky et al.<sup>[6]</sup> won the large-scale [ImageNet competition](#) by a significant margin over shallow machine learning methods. In November 2012, Ciresan et al.'s system also won the ICPR contest on analysis of large medical images for cancer detection, and in the following year also the MICCAI Grand Challenge on the same topic.<sup>[102]</sup> In 2013 and 2014, the error rate on the ImageNet task using deep learning was further reduced, following a similar trend in large-scale speech recognition.

Image classification was then extended to the more challenging task of [generating descriptions](#) (captions) for images, often as a combination of CNNs and LSTMs.<sup>[103][104][105][106]</sup>

Some researchers state that the October 2012 ImageNet victory anchored the start of a "deep learning revolution" that has transformed the AI industry.<sup>[107]</sup>

In March 2019, [Yoshua Bengio](#), [Geoffrey Hinton](#) and [Yann LeCun](#) were awarded the [Turing Award](#) for conceptual and engineering breakthroughs that have made deep neural networks a critical component of computing.

Primary Component Analysis selects the best features that contribute more to diabetic retinopathy classification and deep neural network performs better than random forest and support vector machine algorithms.<sup>[108]</sup>