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Deep Learning: A Brief Study on Its Architectures and Applications

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Abstract

Deep learning (DL) is a specialized branch of machine learning (ML) and artificial intelligence (AI) that uses multilayered neural networks, and teaches computers to process data in a way inspired by the functionality of human brain. It is based on "deep" neural networks comprising millions to billions of parameters organized into hierarchical layers that mimic human brain. It is a set of methods that uses deep architectures to learn high-level feature representations that allows the learning of more complex models compared to shallow architectures. Deep neural networks are a type of artificial neural network that have many layers in between (deep) the input and output layer. The DL has become one of the most popular and visible areas of ML due to its success in a variety of applications, such as computer vision, natural language processing, and reinforcement learning. Recently, it has become increasingly popular due to the advances in processing power and the availability of large datasets. The aim of this review is to provide an overview on DL frameworks in briefly.

Keywords: deep learning, neural networks, architectures, cyber-security

1. Introduction

Deep learning (DL) is a class of machine learning techniques that involves a neural network as a part of the thinking process for an artificial intelligence (AI), such as pattern recognition by passing input through various layers of the neural network (Drori, 2022; Mohajan, 2025b). It is the concept of computers simulating process of a human brain to analyze, think, and learn. It is a set of learning methods that attempt to model data with complex architectures combining different non-linear transformations (Yu & Deng, 2011). It focuses on utilizing multilayered neural networks that take inspiration from biological neuroscience and is centered on stacking artificial neurons into layers of interconnected neurons that collaborate to process input data to perform works, such as classification, regression, and representation learning (LeCun et al., 2015). It has achieved significant success in various fields, such as image recognition, computer vision, phonetic recognition, sound and image processing, voice search, audio processing, hand-writing recognition, facial recognition, speech and image feature coding, visual object recognition, text classification, semantic utterance classification, natural language processing, speech recognition, and recommendation systems (Sutskever et al., 2013).

The word "deep" in DL refers to the number of layers through which the data is transformed that have a substantial credit assignment path (CAP) depth. The term "deep learning" was introduced to the machine learning community by American distinguished professor of computer science Rina Dechter in 1986 with artificial neural networks by Ukrainian computer scientist Igor Aizenberg in 2000 (Schulz & Behnke, 2012). The DL has covered the research areas of neural network, graphical modeling, optimization, pattern recognition, and signal processing. Recent DL methods are developed since 2006. Modern DL provides training stability, generalization, and scalability with big data (Deng, 2014).

Training in DL especially in deep neural networks (DNNs) requires a large amount of data and computational resources. But, the availability of cloud computing and the development of specialized hardware, such as graphics processing units (GPUs) has made it easier to train DL (Goodfellow et al., 2016). The DL algorithms are complex mathematical structures with several processing layers that can separate the features of data or representations into various abstraction layers. Some of the popular DL architectures are convolutional neural networks (CNNs), recurrent neural networks (RNNs), and deep belief networks (DBNs) (LeCun et al., 1998).

2. Literature Review

A literature review is an overview of previously published works, such as scholarly articles, books, and theses on a particular topic (Creswell, 2013). A good literature review has a proper research question, a proper theoretical framework, and a chosen research methodology. It is also a common portion in a research proposal or prospectus (Baker, 2000). It provides an outline of current knowledge to identify relevant theories, methods, and gaps in the existing research. It analyzes, synthesizes, and critically evaluates the research area to give a clear picture of the state of knowledge on the subject (Galvan, 2015).

Kamal Choudhary and his coauthors have realized that DL is one of the fastest growing topics in materials data science with rapidly emerging applications spanning atomistic, image-based, spectral, and textual data modalities. They have presented a high-level overview of DL methods followed by a detailed discussion of recent developments of DL in atomistic simulation, materials imaging, spectral analysis, and natural language processing (Choudhary et al., 2022). Jenny Gu and her coauthors have presented a nice overview on recent advances of CNNs, multiple variants of CNN, DL architectures, regularization methods and functionality, and applications in various fields (Gu et al., 2015). Li Deng has reviewed some selected applications of DL in broad areas of signal and information processing, such as speech and image detection and processing, multimodality, language modeling, natural language processing, and information retrieval (Deng, 2014).

Yann LeCun and his coworkers have shown that DL allows computational models that are composed of multiple processing layers to learn representations of data with multiple levels of abstraction that have dramatically improved the state-of-the-art in speech recognition, visual object recognition, object detection, and many other domains, such as drug discovery and genomics (LeCun et al., 2015). Iqbal H. Sarker has shown that DL is a branch of ML and AI, and is considered as a core technology of fourth industrial revolution. He has discussed the structured and comprehensive view on DL techniques including a taxonomy considering various types of real-world tasks like supervised or unsupervised. He has aimed to draw a big picture on DL modeling that can be used as a reference guide for both academia and industry professionals (Sarker, 2021). Geert Litjens and his coworkers have studied the major DL concepts pertinent to medical image analysis. They have used DL for image classification, object detection, segmentation, registration, and other tasks; and provide concise overviews of studies per application area (Litjens et al., 2017).

Jurgen Schmidhuber has studied the deep supervised learning, unsupervised learning, reinforcement learning and evolutionary computation, and indirect search for short programs encoding deep and large networks. His study has focused on the narrower, but now commercially important, subfield of DL in artificial neural networks (ANNs) (Schmidhuber, 2015). Yoshua Bengio has focused on the context of the unsupervised and transfer learning challenge, on why unsupervised pre-training of representations can be useful, and how it can be exploited in the transfer learning scenario (Bengio, 2012). Rene Y. Choi and his coworkers have wanted to provide an overview of current ML methods and their use in medical research, focusing on select ML techniques, best practices, and DL (Choi et al., 2020). Abhishek Hazra and his coworkers have briefly examined different application area of DL techniques and some current state-of-the-art performances of it. They have also discussed some of the limitations of DL techniques (Hazra et al., 2020).

3. Research Methodology of the Study

Research is a systematic investigation to describe, explain, predict, and control the observed phenomenon. It involves inductive and deductive methods (Cohen & Arieli, 2011; Mohajan, 2018a). It is an essential and powerful tool in leading a person towards progress. It tries to collect and analyze data to increase understanding of a specific topic with a focus on controlling sources of bias and error (Pandey & Pandey, 2015). It attempts to develop new knowledge through the use of existing knowledge in a new and creative way so as to generate new concepts (Creswell, 2013). There are two major types of empirical research design: qualitative research and quantitative research. The qualitative research is a type of research that aims to gather and analyze non-numerical data (Silverman, 2011; Mohajan, 2018b). It is used to explore complex phenomena to gain insight into people's experiences and perspectives on a particular topic (Berg, 2009). The quantitative research designs are experimental, correlational, and survey that deal data of numerical form, such as statistics, percentages, etc. (Goertzen, 2017; Mohajan, 2020).

Methodology is the systematic approach to conduct research, gather information to reach in a specific goal. It is a system of principles and general ways of organizing and structuring theoretical and practical activity (Oduor, 2010). Research methodology covers the systematic procedures and techniques used to conduct research, ensuring that studies are valid, reliable, and address research questions effectively. It describes the techniques and procedures used to identify and analyze information regarding a specific research topic (Groh, 2018; Mohajan, 2017).

4. Objective of the Study

Deep learning is a family of methods in AI and ML that uses deep architectures to learn high-level feature representations. It has emerged as a game-changing technique within the arena of data-driven analytics due to its revolutionary success in several traditionally hard AI applications (Agrawal & Choudhary, 2019). It has proven useful in many software disciplines, such as computer vision, speech and audio processing, natural language processing, robotics, bioinformatics, chemistry, video games, search engines, online advertising, and finance (Goodfellow et al., 2016). It is based on multi-layered neural networks, such as artificial neural networks (ANNs), convolutional neural networks (CNNs), recurrent neural networks (RNNs), and deep belief networks (DBNs) (LeCun et al., 1998). Major objective of the study is to discuss the aspects of deep learning, such as basic idea, recent development, and applications. Other minor objectives of the study are as follows:

1) to highlight on architectures of DL,
2) to focus on neural networks, and
3) to discuss application and drawbacks of DL.

5. Architectures of DL

Deep learning architectures are multilayer non-linear repetition of simple architectures, and in most of the cases these help to obtain highly complex functions out of the inputs (LeCun et al., 2015). These can be constructed with a greedy layer-by-layer method, and most of them are based on neural networks that can be considered as a generalization of a linear or logistic regression (Tealab, 2018). The neural networks are inspired by the structure and function of the biological neurons of human brain, and these are designed to learn from large amounts of data (Bengio et al, 2007). The human brain consists of tens of billions of small processing units known as neurons that are connected to each other via synapses (Arel et al., 2009).

Some common DL network architectures are fully connected networks, deep belief networks, recurrent neural networks, convolutional neural networks, generative adversarial networks, transformers, and neural radiance fields (Cho & Chen, 2013). The DL models are able to automatically learn features from the data that makes them well-suited for tasks, such as computer vision, image recognition, speech recognition, natural language processing, machine translation, bioinformatics, drug design, medical image analysis, climate science, material inspection, and board game programs (Deng, 2014). The most widely used architectures in DL are feed-forward neural networks (FNNs), convolutional neural networks (CNNs), deep neural networks (DNNs), and recurrent neural networks (RNNs) (Bengio, 2009).

6. Neural Networks

Human nervous system contains cells, such as neurons that are connected to one another with the use of axons and dendrites, and are referred to as synapses. It consists of more than a billion of neural cells that process information. The computational units of it are connected to one another through weights that serve the same role as the strengths of synaptic connections in biological organisms (Szegedy et al., 2013). There are four types of neural networks: i) artificial neural networks (ANNs), ii) convolutional neural networks (CNNs), iii) deep neural networks (DNNs), and iv) recurrent neural networks (RNNs). Among these four neural networks, two architectures: convolutional neural networks (CNNs) and recurrent neural networks (RNNs) are currently most popular (Litjens et al., 2017).

A neural network is a graph with neurons, such as input and output nodes, units, etc. that are connected by links and communicate with other nodes via connections, and work similar to the human nervous system. It can be used for regression or classification (Nielsen, 2015). The neurons are organized in layers; an input layer (first layer), one or more hidden layers connected one after the other, and an output layer (last layer). Each neuron receives input from the previous layer neurons, and this process continues until the final layer produces the output of the network. The input layer receives data from the outside world which the neural network needs to analyze or learn about (Hastie et al., 2009).

6.1 Artificial Neural Networks (ANNs)

The ANN computing systems are inspired by the biological neural networks that are arranged in a series of layers and constitute animal brains that generally work without task-specific programming. An ANN contains a layer of input nodes, three hidden layers, and an output layer. It is built on the principles of the structure and operation of human neurons known as units (Hastie et al., 2009). It also contains nodes that communicate with other nodes via connections. Different layers can perform different kinds of transformations on their inputs (Brocardo et al., 2017). Signals travel from the input to the output layer, possibly after traversing the layers multiple times. The goal of ANN is to solve problems in the same way that a human brain would (Bishop & Bishop, 2024).

Each neuron is a mathematical processing unit, which is combined with all other neurons, and is designed to learn the relationship between the input features and the output (Georgevici & Terblanche, 2019). The first model of an artificial neuron was proposed by American neurophysiologist and cybernetician Warren McCulloch and American self-taught logician and cognitive psychologist Walter Pitts in 1943 that was the first mathematical model of a neural network (McCulloch & Pitts, 1943). Artificial neurons are elementary units in an ANN that are non-linear mathematical functions with many parameters. Each of these consists of three basic components: weights, thresholds, and a single activation function (Goodfellow et al., 2016).

Let us reformulate the input vector $x = \{x_1, x_2, \ldots, x_n\}$ as a set of features, and a set of weights of the neuron as $w = \{w_1, w_2, \ldots, w_n\}$. The output of the neuron that can be calculated by applying the activation function over the net input as (Gulshan et al., 2016),

$$y = f\left(\{x_1, x_2, \ldots, x_n\}.\{w_1, w_2, \ldots, w_n\} + b\right)$$

$$y = f\left(x_1 w_1 + x_2 w_2 + \ldots + x_n w_n + b\right)$$

$$y = f\left(x.w + b\right),$$

where b is the "bias" term that is the information which can impact output without being dependent on any feature. Here f is an activation function that is extremely important feature of the ANN. It basically decides whether a neuron should be activated or not, and it limits the output signal to a finite value. The function f is differentiable and monotonic, but the derivative of f is non-monotonic (Ghosh et al., 2019).

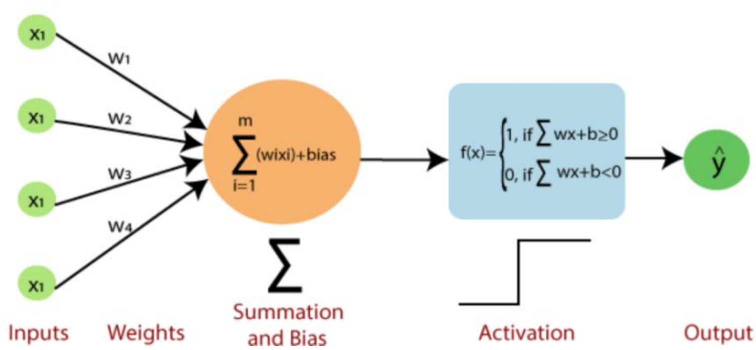

Figure 1. Three basic components of ANN: weights, thresholds, and a single activation function

Source: Qamar & Zardari (2023).

Without an activation function *f*, the neural network is just a linear regression model, as it performs only summation of product of input and weights. Each node in an ANN contains an activation function (Yegnanarayana, 2009). The ANNs are used on a variety of tasks, such as computer vision, image classification, speech recognition, machine translation, social network filtering, playing board and video games, medical diagnosis, and natural language processing (Silver et al., 2016).

6.2 Convolutional Neural Network (CNN)

A CNN is a type of feed-forward neural network that learns features through filter optimization, which can be applied to process and make predictions from many different types of data, such as text, images, and audio. It is introduced by French-American Chief AI Scientist at Facebook and JT Schwarz Professor Yann LeCun (LeCun et al., 2015). It detects local conjunctions from features and pooling layers merge similar features into one. It is composed by several kinds of layers, such as convolutional layers, pooling layers, and fully connected layers that allow reducing the dimension by taking the mean or the maximum on patches of the image, which act on small patches of the image. It is the most popular and successful variants among sparsely connected networks (Rumelhart et al., 1986). It is the most commonly used deep network that provides the benefit of automatically learning high-level useful features directly without having to extract handcrafted features. It can afford a semantic segmentation by associating each pixel of the input image to a label, and jointly optimize numerous related tasks together (Zhao et al., 2019). It is trained on either the entire image or on image patches and the important features are learned by optimizing a specific loss function. It takes advantage of the multidimensional structure of images capturing the spatial relationships between pixels (Krizhevsky et al., 2012).

At each layer, the input image is convolved with a set of *k* kernels $W = \{w_1, w_2, \ldots, w_k\}$ and subsequently biases $B = \{b_1, b_2, \ldots, b_k\}$ are added, each generates a new feature map X_k. These features are repeated for every convolutional layer *l as*,

$$X_k^l = \sigma\left(W_k^{l-1} \otimes X^{l-1} + b_k^{l-1}\right).$$

The discrete convolution between two functions *f* and *g* is defined as,

$$(f * g)(x) = \sum_t f(t) g(x+t).$$

For 2-dimensional signals, such as images the 2D-convolutions is used as,

$$(K * I)(i, j) = \sum_{m,n} K(m, n) I(i+n, j+m)$$

where *K* is a convolution kernel applied to a 2D signal or image *I*. If the image has 3 channels and if $K_l(l = 1, 2, \ldots, C_0)$ denote 5×5×3 kernels, where C_0 is the number of output channels. The convolution with the image *I* with the kernel K_l corresponds to the formula,

$$(K_l * I)(i, j) = \sum_{c=0}^{2} \sum_{n=0}^{4} \sum_{m=0}^{4} K_l(n, m, c) I(i+n-2, j+m-2, c).$$

For example, for each neuron in the fully-connected layer, 10,000 weights would be required for processing an image sized 100×100 pixels. But, applying cascaded convolution kernels, only 25 weights for each convolutional layer are required to process 5×5 sized tiles (Habibi & Heravi, 2017).

The CNNs are applied in text processing, image and video recognition, recommender systems, image classification, image segmentation, face recognition, object detection, medical image analysis, natural language processing, brain-computer interfaces, image segmentation, and financial time series (Ronneberger et al., 2015). The CNN also has some drawbacks, such as it is complex with an enormous amount of training parameters and it can be difficult to interact with any single layer within the deep network. Sometimes it is viewed as a black-box that does not explain their predictions in a way that humans can understand (Brown et al., 2018).

6.3 Deep Neural Networks (DNNs)

The DNN is an ANN with multiple hidden layers (tens to hundreds) between the input and output layers that makes them more complex and resource-intensive compared to conventional neural networks, which consist of the same components, such as neurons, synapses, weights, biases, and mathematical functions; and these as a whole mimics the functions of the human brain (Schmidhuber, 2015). It is capable of classification and generalization. The extension of CNN is considered as DNN, usually it has more than 3 layers, including the output and input layers. The major advantages of DNN are the ability of dealing with raw, unstructured, and unlabeled data, and cluster and process them to similar forms. For example, it can take a billion images, and cluster them according to their similarities (Janowczyk & Madabhushi, 2016). The DNN has gained popularity in 2006, when the researchers have founded that greedily training DNNs layer-by-layer in an unsupervised manner, followed by supervised fine-tuning of the stacked network, could result in excellent pattern recognition tools (Litjens et al., 2017).

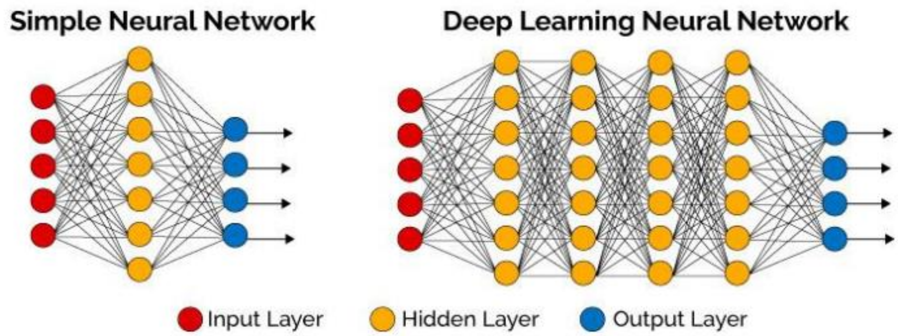

Figure 2. Summation and activation within single and deep neural networks

Source: Georgevici & Terblanche (2019).

6.4 Recurrent Neural Networks (RNNs)

The RNN is proposed by Kaiming He and his coauthors that consists of 152 layers, and has lower error and easily trained with residual learning. It is one of the most interesting neural network architecture. It is a special class of neural network allowing for an indefinite memory of previous events (He et al., 2015). It is a type of neural network that is able to process sequential data, such as time series and natural language (Ranzato, 2006). It is able to maintain an internal state that captures information about the previous inputs that make them well suited for tasks, such as speech recognition, natural language processing, and language translation. It has achieved better performance and is considered as an important advance in DL (Goodfellow et al., 2016). It is mostly trained by a sequence of data like sentence and makes subsequent similar sentences which are most likely used in chatbots. It is widely used in several applications, such as image captioning, generating review, generating feedback, and generating music (Rumelhart et al., 1986).

7. Application of DL

The DL is used in many aspects of our daily lives, such as image classification, recognition, colorization, and question answering; speech recognition, understanding, generation, and processing; sentence classification, modeling, and processing, etc. (LeCun et al., 2015; Mohajan, 2025a). It is also applied in many recent outstanding activities, such as word processing, video classification, document processing, photographic style transfer, question answering, person identification, object detection, face recognition and verification, playing Go, mobile and television vision, self-driving cars, web search, fraud detection, email and spam filtering, chip design, financial risk modeling, etc. (Silver et al., 2016; Wang et al., 2017).

The DL provides exciting new capabilities in numerous fields, such as navigation, particle physics, protein science, drug discovery, chemistry, physics, biology, materials science, astrophysics, etc. (Agrawal & Choudhary, 2019). In medical, modern DL tools show the high accuracy of detecting various diseases that improve the diagnosis efficiency. For example, these have been used for cancer detection and cell classification, lesion detection, X-ray CT reconstruction, organ segmentation, and image enhancement (Litjens et al., 2017).

DL algorithms can achieve the best performance in various tasks, such as image recognition and natural language processing. It can discover and learn relevant features from data without the need for manual feature engineering. It can scale to handle large and complex datasets (Deng & Yu, 2014). Since more data are available in DL; it can continually improve its performance day by day. It can be applied to a wide range of tasks and can handle various types of data, such as images, text, and speech (Kim et al., 2017).

8. Drawbacks and Challenges of DL

The DL is used successfully in image recognition, natural language processing, and autonomous systems. It is also used in neural networks to analyze and learn from large datasets. Despite its impressive capabilities it faces many challenges in data quality, computational demands, and model interpretability (Bengio, 2009). For example, it is difficult to estimate how much data are necessary to sufficiently and reliably train DL systems, because it depends both on the quality of the input training data as well as the complexity of the task (Choudhary et al., 2022). It is also suffered from the "black box" problem when input is supplied to the algorithm and an output emerges, but it is not exactly clear what features were identified or how they informed the model output (Wang et al., 2017).

The DL can inadvertently learn and perpetuate biases present in the training data that can lead to unfair outcomes and ethical concerns. It requires substantial computational resources, such as high-performance GPUs or TPUs. Access to such hardware can be a bottleneck for researchers and practitioners (Bengio et al., 2007). It can be used with full potential by enhancing data quality, leveraging advanced tools, and addressing ethical concerns. Continuous improvement and adaptation are necessary for the successful future use (Zeiler & Fergus, 2013).

9. Conclusions

In this study, I have briefly presented DL architecture and applications with the future challenges. The DL is one of the fastest growing topics in data science, computer science, medicine, and natural sciences. Recently, it becomes a research hotspot due to its powerful learning ability and advantages for dealing with complex patterns. During the past few years it has achieved an enormous improvement in computer vision, speech recognition, and text understanding. The DL provides a solid comprehensive foundation to any researcher interested in the current and future directions of DL research. Despite the empirical promising results of it reported so far, much need to be developed. The DL has advanced the world faster than ever, but there are many difficult problems for humanity to deal with.

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