List of Deep Learning Models

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Abstract. Deep learning (DL) algorithms have recently emerged from machine learning and soft computing techniques. Since then, several deep learning (DL) algorithms have been recently introduced to scientific communities and are applied in various application domains. Today the usage of DL has become essential due to their intelligence, efficient learning, accuracy and robustness in model building. However, in the scientific literature, a comprehensive list of DL algorithms has not been introduced yet. This paper provides a list of the most popular DL algorithms, along with their applications domains.

Keywords: Deep learning, machine learning, convolutional neural networks (CNN) recurrent neural networks (RNN), denoising autoencoder (DAE), deep belief networks (DBNs), long short-term memory (LSTM), review, survey, state of the art,

1 Introduction

There has been an enormous evolution in system modeling and intelligence after introducing the early models for deep learning [1-8]. Deep learning methods very fast emerged and expanded applications in various scientific and engineering domains. Health informatics, energy, urban informatics, safety, security, hydrological systems modeling, economic, bioinformatics, and computational mechanics have been among the early application domains of deep learning. State of the art surveys on the data-driven methods and machine learning algorithms, e.g., [9-26], indicates that deep learning, along with the ensemble and hybrid machine learning methods are the future of data science. Further comparative studies, e.g., [26-42], report that deep learning models and hybrid machine learning models often outperform conventional machine learning models. Figure 1 represents the rapid rise in the applications of various deep learning methods during the past five years.

Deep learning methods are fast evolving for higher performance. Literature includes adequate review papers on the progressing algorithms in particular application domains, e.g., renewable energy forecasting, cardiovascular image analysis, super-resolution imaging, radiology, 3D sensed data classification, 3D sensed data classification, multimedia analytics, sentiment classification, text detection, transportation systems, activity recognition in radar, hyperspectral, medical ultrasound analysis, image cytometry, and apache spark [43-59]. However, a simplified list of deep learning methods has not been communicated so far. Thus, there is a gap in research in introducing the deep learning methods and summarize the methods and application in a brief, yet communicative paper. Consequently, this paper aims at providing a comprehensive list of the most popular deep learning methods and their notable applications. In every section, one deep learning method is introduced and the notable applications related to that method are listed. The description of each deep learning method and the function of each building block is explained.

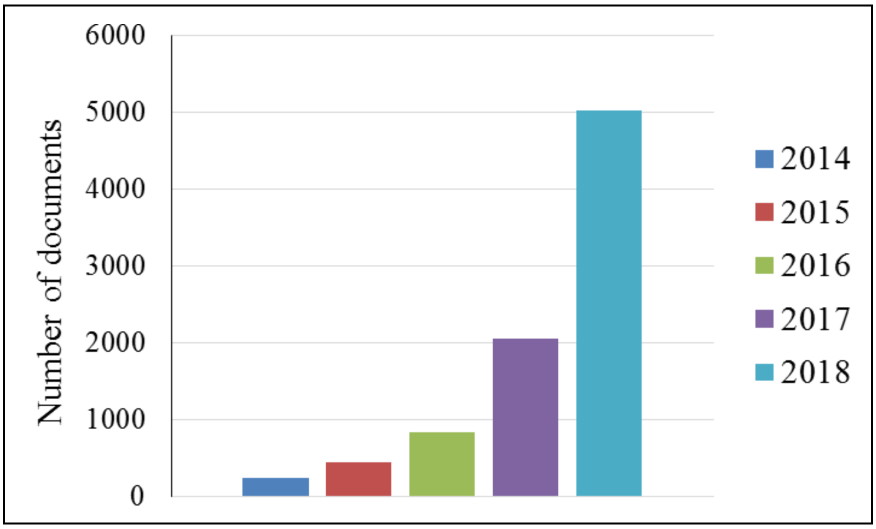

Fig. 1. The rapid increase of using DL models in various application domains (source: web of science)

2 Deep learning methods

Convolutional neural network (CNN) Recurrent neural network (RNN), Denoising autoencoder (DAE), deep belief networks (DBNs), Long Short-Term Memory (LSTM) are the most popular deep learning methods have been widely used. In this section, the description of each method is described along with the notable applications.

2.1 Convolutional neural network (CNN)

CNN is one of the most known architectures of DL techniques. This technique is generally employed for image processing applications. CNN contains three types of layers with different convolutional, pooling, and fully connected layers (Fig. 1). In each CNN, there are two stages for the training process, the feed-forward stage, and the back-propagation stage. The most common CNN architectures are ZFNet [60], GoogLeNet [61], VGGNet [62], AlexNet [63], ResNet [64].

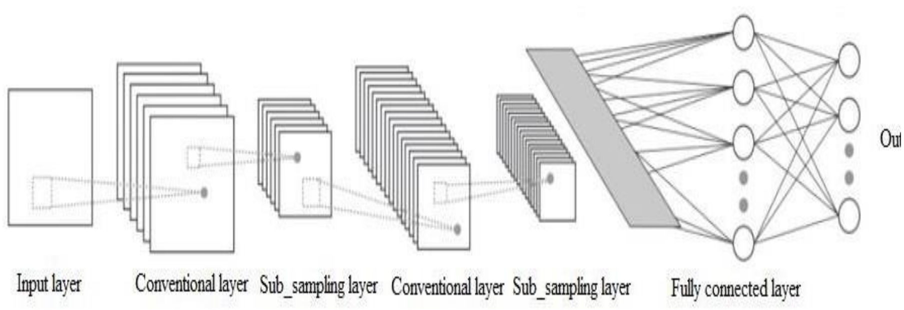

Fig. 2. CNN Architecture

Table 1. The CNN notable applications

Reference	Application	Journal
Kong et al. 2020 [65]	Condition monitoring of wind turbines	Renewable Energy

Lossau et al. 2019 [66]	Motion estimation and correction of medical imaging	Computerized Medical Imaging and Graphics
Bhatnagar et al. 2019 [67]	Prediction of aerodynamic flow	Computational Mechanics
Nevavuori et al. 2019 [68]	Crop yield prediction	Computers and Electronics in Agriculture
Ajami et al. 2019 [69]	Advanced image processing	Remote Sensing

Although CNN is primarily known for image processing applications, the literature includes other application domains, e.g., energy, computational mechanics, electronics systems, remote sensing, etc.

2.2 Recurrent neural networks (RNN)

RNN is designed to recognize sequences and patterns such as speech, handwriting, text, and such applications. RNN benefits cyclic connections in the structure which employ recurrent computations to sequentially process the input data [70]. RNN is basically a standard neural network that has been extended across time by having edges which feed into the next time step instead of into the next layer in the same time step. Each of the previous inputs data are kept in a state vector in hidden units, and these state vectors is utilized to compute the outputs. Fig 2 shows the architecture of RNN.

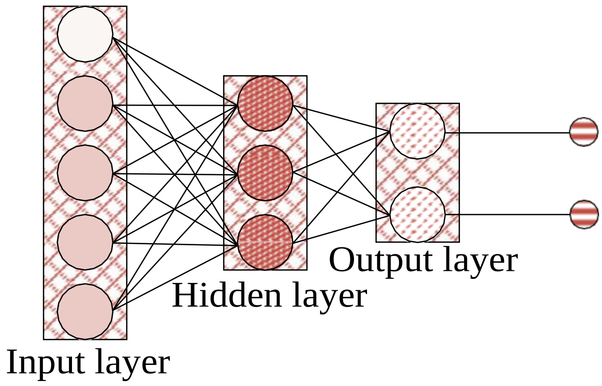

Fig. 3. RNN Architecture

Table 2. Notable RNN applications

Reference	**Application**	**Journal**
Zhu et al. 2019 [71]	Wind speed prediction	Energy Conversion and Management
Pan et al. 2019 [72]	Tropical cyclone intensity prediction	Electronics Letters
Bisharad et al. 2019 [73]	Music genre recognition	Expert Systems

Zhong et al. 2019 [74]	Ship Trajectory Restoration	Journal of Navigation
Jarrah et al. 2019 [75]	Stock price trends predict	Advanced Computer Science and Applications

RNN is relatively newer deep learning method. This is why the application domains are still young and plenty of rooms remains for research and exploration. The energy, hydrological prediction, expert systems, navigation, and economics are the current applications reported in the literature.

2.3 Denoising AutoEncoder (DAE)

DAE has been extended from AE as asymmetrical neural network for learning features from noisy datasets. DAE consists of three main layers, including input, encoding, and decoding layers [76]. DAE is able to be aggregated for taking high-level features. Stacked Denoising AutoEncoder (SDAE), as an unsupervised algorithm, is generated by the DEA method, which can be employed for nonlinear dimensionality reduction. This method is a type of feed-forward neural network and employs a deep architecture with multiple hidden layers and a pre-training strategy [77, 78]. Fig. 3 presents the architecture of DEA methodology.

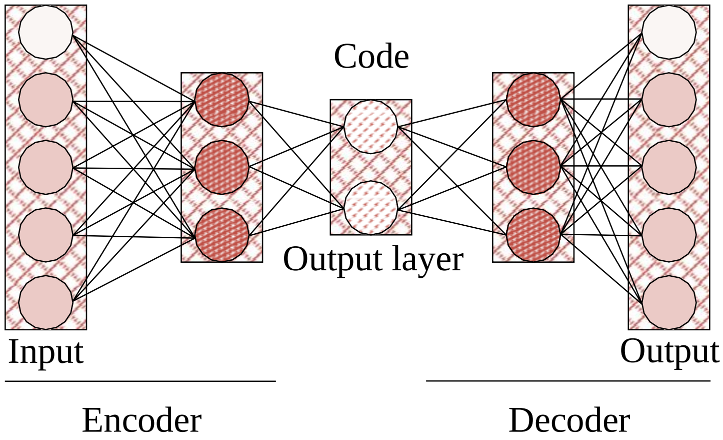

Fig. 4. DEA Architecture

Table 3. The notable DEA applications

Reference	**Application**	**Journal**
Chen et al. 2019 [79]	Improving the cyber-physical systems	Journal on Wireless Communications
Liu et al. 2019 [80]	Electric load forecasting	Energies
Nicolai et al. 2018 [81]	Laser-based scan registration	IEEE Robotics and Automation

Yue, et al. 2018 [82]	Collaborative Filtering	Computer Science and Technology
Roy et a. 2018 [83]	Noisy image classification	Journal of Information and Communication Technology
Tan et al. 2018 [84]	Robust Speaker Verification	IEEE Transactions on Audio Speech

DEA is slowly starting to be known among researchers as an efficient DL algorithm. DEA has already been used in various application domains with promising results. The energy forecasting, cybersecurity, banking, fraud detection, image classification, and speaker verification are among the current popular applications of DEA.

2.4 The deep belief networks (DBNs)

DBNs are employed for high dimensional manifolds learning of data. This method contains multiple layers, including connections between the layers except for connections between units within each layer. DBNs can be considered as a hybrid multi-layered neural network, including directed and undirected connections. DBNs contains restricted Boltzmann machines (RBMs) which are trained in a greedy manner. Each RBM layer communicates with both the previous and subsequent layers [78, 85, 86]. This model is consists of a feed-forward network and several layers of restricted Boltzmann machines or RBM as feature extractors [87]. A hidden layer and visible layer are only two layers of an RBM [88]. Fig. 4 presents the architecture of the DBN method.

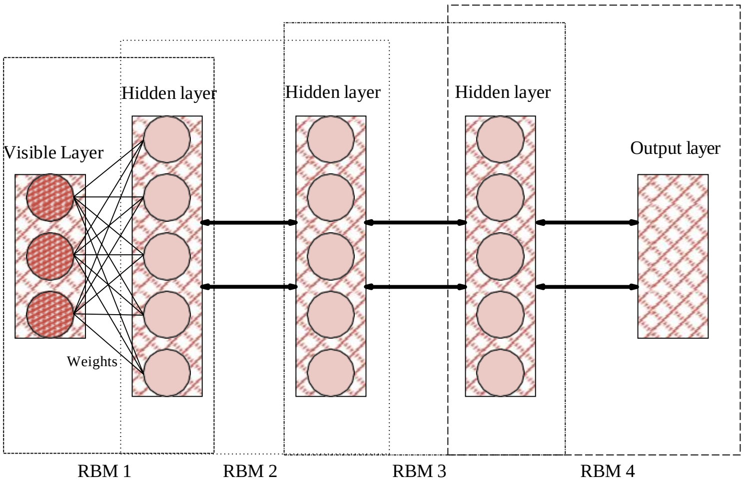

Fig. 5. DBN Architecture

Table 4. The notable DBN applications

Reference	**Application**	**Journal**
Hassan et al. 2019 [89]	Human emotion recognition	Information Fusion
Cheng et al. 2019 [90]	Time series prediction	IEEE Internet of Things

Yu et al. 2019 [91]	wind speed prediction	IEEE Transactions on Electrical Engineering
Zheng et al. 2019 [92]	Exchange rate forecasting	Neural Computing and Applications
Ahmad et al. 2019 [93]	Automatic Liver Segmentation	IEEE Access
Ronoud et al. 2019 [94]	Breast cancer diagnosis	Soft Computing

DBN is one of the most reliable deep learning methods with high accuracy and computational efficiency. Thus, the application domains have been divers, including exciting application in a wide range of engineering and scientific problems. Human emotion detection, time series prediction, renewable energy prediction, economic forecasting, and cancer diagnosis have been among the public application domains.

2.5 Long Short-Term Memory (LSTM)

LSTM is an RNN method which benefits feedback connections to be used as a general-purpose computer. This method can of for both sequences and patterns recognition and image processing applications. In general, LSTM contains three central units, including input, output, and forget gates. LSTM can control on deciding when to let the input enter the neuron and to remember what was computed in the previous time step. One of the main strength of the LSTM method is that it decides all these based on the current input itself. Fig. 6 presents the architecture of the LSTM method.

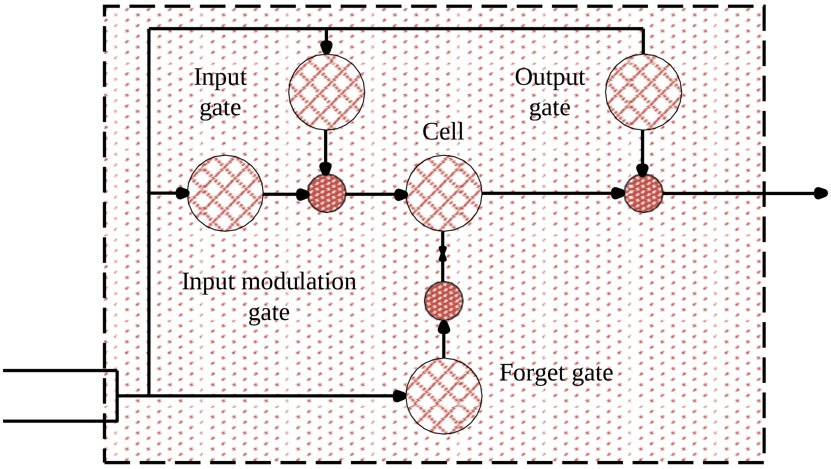

Fig. 6. LSTM Architecture

Table 5. The notable applications of LSTM

Reference	**Application**	**Journal**
Ghimire et al. 2019 [95]	Solar radiation forecasting	Applied Energy
Liu 2019 [3]	Volatility forecasting	Expert Systems with Applications

Hong et al. 2019 [96]	Fault prognosis of battery systems	Applied Energy
Krishan 2019 [97]	Air quality prediction	Air Quality and Atmosphere
Zhang et al. 2019 [98]	Structural seismic prediction	Computers and Structures
Hua et al. 2019 [99]	Time Series Prediction	IEEE Communications
Zhang et al. 2019 [100]	Wind turbine power prediction	Applied Energy
Vardaan et al. 2019 [101]	Earthquake trend prediction	Electrical and Computer Engineering

LSTM has shown great potential in environmental applications, e.g., geological modeling, hydrological prediction, air quality, and hazard modeling. Due to the generalization ability of the LSTM architecture, it can be suitable for many application domains. Energy demand and consumption, wind energy industry, and solar power modeling are the other application domains of LSTM. Further investigation is essential to explore the new deep learning methods and explore the application domains, as it has been done for machine Learning methods [102-109].

3 Conclusions

Deep learning methods are fast-evolving. Some of them have advanced to be specialized in a particular application domain. However, there is a gap in research in introducing the deep learning methods and summarize the methods and application in a single paper. Consequently, this paper aims at providing a comprehensive list of the most popular deep learning methods and provide notable applications. CNN, RNN, DAE, DBNs, LSTM methods have been identified as the most popular deep learning method. The description of each deep learning method and the function of each building block of them is explained.

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