Recent Advances in Deep Learning Techniques and Its Applications: An Overview

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Abstract Learning with images and their classification, segmentation, localization, annotation, and abnormally detection is one of the current challenging and exciting task for the researchers. Recently deep learning techniques give excellent performance in Object Detection, Speech Recognition, Abnormality Detection, Business Analysis, and almost all other domains. But one important implication of deep learning techniques can found in Medical Image Analysis. Deep learning techniques beat the human-level performance and come with a better solution in the medical domain. Among different deep learning techniques Convolutional Neural Network, Recurrent Neural Network, Long Short-Term Memory, Deep Belief Network models are topmost priority for the researchers. In this paper, we briefly examine different application area of deep learning techniques and some current state-of-the-art performances of it. Moreover, we also discuss some of the limitations of Deep Learning techniques. As expected this paper creates a clear understanding of Deep Learning techniques and its applications.

Keywords Deep learning · CNN · RNN · Health care

1 Introduction

Neuroscience researchers examine that visual representation of brain can be done in two pathways, Dorsal pathway and Ventral pathway. The information of location movement observation follows the dorsal pathway and detection, color, texture shape,

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such information follow the ventral pathway. In 1959 Hubel and Wiesel (Hubel and Wiesel 1968) first observe that visual cortex's in brain mainly responsible for detecting lights. Inspired by this innovation LeCun et al. (Le Cun et al. 1990) in 1990 first make a handwritten character recognition system. This was the first neural network architecture which tried to learn and recognize characters. Since 90s many researchers come with their deep advance architecture which solves many real-time applications. AlexNet (Krizhevsky et al. 2012), VGGNet (Simonyan and Zisserman 2015), ResNet (He et al.2015c), models break all the previous performance in various domains.

Recently Deep Learning Techniques come with a better solution for analyzing different kinds of data. The idea of deep learning has a very old history. Because of its high computation power and colossal amount of data, deep learning techniques were not so popularly used back then. But in late 20s deep learning techniques accelerate its performance with the help of Graphical Processing Unit and massive amount of data. Deep Learning techniques gives state-of-the-art performance in almost all the domains like Object Detection, Speech Recognition, Fraud Detection, Face Recognition, Sentiment Analysis. Currently, deep learning techniques give excellent performance in medical image analysis. From 2015, research in deep learning for medical domain has increases exponentially. The number of research papers, journals, and articles in this domain are increasing day by day. It means this field is gaining interests gradually at a very rapid rate. There are special issues in almost all the journals with deep learning as a keyword. These are the primary motivation for us to work in this particular field. In this paper, we briefly examine different application area of deep learning techniques. Our search list contains "Deep Learning" either in the title or the keyword in various articles, journals good conference proceedings which are mainly focused on this field only. In this review, we try to scrutinize all the popular related papers published till 30 March 2018. We expect that this paper makes a brief overview of deep learning techniques in all the domains.

Our main aim for this review:

- To show deep learning techniques and its performance.
- To display current research Scenarios.
- To highlight some of the current research challenges.

The rest of the paper structured as follows. In Sect. 2 we introduce some essential deep learning techniques. Section 3 describes some popular application area of deep learning techniques. Section 4 narrates the deep learning implementation tools. Section 5 shows an essential overview discussion in medical imaging. Finally, conclusion and feature work were speculated in Sect. 6.

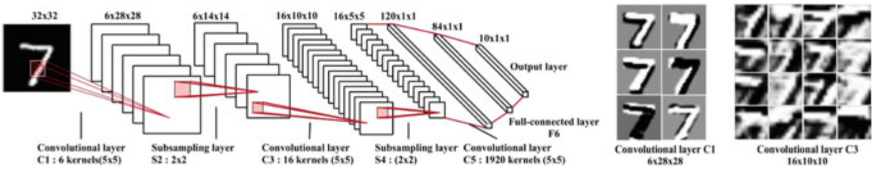

Fig. 1 Famous LeNet-5 network architecture with intermediate visual representation

2 Overview of Deep Learning Techniques

In recent times deep learning techniques are widely used in all the domains like Object Detection (Yoo et al. 2015), Sentiment Analysis (Wang et al. 2016c), Medical Image Analysis (Lo et al. 1995), Speech Recognition (Waibel et al. 1990), Self-Driving car, Automatic Machine Translation, Automatic Text Generation (He et al. 2015b), advertising, and many more. With the advancement of GPU based systems, several deep learning techniques are also introduced to address different kinds of problems. Convolutional Neural Network, Recurrent Neural Network, Restricted Boltzmann Machine, LSTM, Deep Autoencoder networks are current state of the learning algorithm. In this section, our main aim is to address some of the most popular deep learning techniques which create a huge impact on current research.

2.1 Convolutional Neural Network

Convolutional Neural network (CNN) (Vincent et al. 2008) is one of the most popular learning algorithms in computer vision field. Currently, many researchers come with their individual CNN architecture though there is a similarity between all the networks. Basically convolutional neural network consists of four types of layers. Convolutional layer, Activation layer, Pooling layer, and Fully Connected layer. LeNet-5 as presented in Fig. 1, was the first generalizes neural network architecture (Le Cun et al. 1990) which is still popularly used in current times. Convolutional layer takes information from the input data and produces a feature map with the help of kernels. The number of convolutional layers is vary from architecture to architecture. Generally first level of convolutional layers learns low-level features like dark and bright pixels, second layer of convolutional layers may learn horizontal edges, vertical edges, next level of convolutional layer learns some more complex functions like ears, nose mouth. As the number of layers increased neural network learns even more complex functions like face, object, and characters. These feature maps are passed through a nonlinear activation function which gives acceleration to the CNN to understand complex functions. Finally one or more number of fully connected layers which summarize the learnable information and put into a softmax classifier. The softmax classifier gives the output probability of each and every class for the given input.

2.2 Recurrent Neural Network

Recurrent neural network (RNN) (Poultney 2006) is one of the most interesting neural network architecture. RNN is interesting because of its use in many applications and is also notable performance under challenging applications. RNN is mostly trained by a sequence of data like sentence and make subsequent similar sentences which are most likely used in chatbots. RNN is widely used in several applications like image captioning, generating review, generating feedback, generating Music. Feedforward neural networks are not designed for sequence/time-series data, hence results with time series/sequence data are inadequate and moreover, they cannot design for storing memory. To address this problem, recurrent neural network was designed. Recurrent neural networks are the type of networks designed for capturing information from sequence/time series data. In RNN sequences is feed as current input, calculate a hidden state, and compute the output. For the next time step, the network takes new information as well as information from the previously hidden state to compute the current hidden state to predict the next output. Finally, a loss functions to improve the accuracy of RNN. This types of networks use in time series prediction like weather forecasting, Stock prediction, and sequence of data generating application like music, video.

2.3 Long Short-Term Memory

Long short-term memory (LSTM) is a type of recurrent neural network. LSTM is the next logic step in the progression of neural network Learning. It is technique of learning sequence of data or video frame and capable of learning long-term dependencies. One interesting idea of weighted self-loop to introduce path where Gradient flow for a long time in Long short-term memory. By addition of self-loops current hidden layers are controlled by previously computed hidden layers. Even for fixed parameters, the time scale of integration can be changed according to the input time is the output of this model. Different researchers found that LSTM networks are incredibly successful in many applications such as speech recognition, music generation, machine translation, image captioning, handwritten recognition.

There are several deep learning techniques like Deep Autoencoder (Salakhutdinov and Hinton 2009; Rifai et al. 2011; Masci et al. 2011; Chen et al. 2013), Boltzmann Machine (Younes 1999; Center Berkeley 2016), and Deep belief networks are also popularly used in various domains.

3 Applications of Deep Learning Techniques

Currently, deep learning techniques are giving an excellent performance in Action Recognition, Significant Data Analysis, Sentiment Analysis, Medical Image Analysis, Character Recognition, Image Classification, Object Detection, Object Tracking, Pose Estimation, Visual Salient Detection Sense leveling, Speech Recognition, Natural Language Processing, Remote Sensing. In this segment, we try to introduce some of the current research application of deep learning techniques as illustrated in Fig. 2.

3.1 Action and Gesture Recognition

One of the interesting application of Deep learning techniques is in action recognition. Most of the Companies are using some action recognition for their internal security purpose. Because of its high demand and current challenges attract deep learning researchers in this field. This field has been examining from last decades and reported huge progress within the computer vision field. RNN (Le Cun et al. 1990), LSTM (Rowley et al. 1998), 3D convolutional neural network (Yang et al. 2017a), pertained features are the topmost priorities of deep learning researchers. Mainly three types of network model were used for action and texture recognition. 3D convolutional layer (de Brebisson and Montana 2015; Gao et al. 2015; Lo et al. 1995; Chen et al. 2017; Gao 2016; Tarando et al. 2016; Zhu et al. 2017; Xu et al. 2016b; Dittrich et al. 2011), motion-based input feature (Alexe et al. 2012; Zhao et al. 2016; Xu et al. 2016b; Chen et al. 2017; Hinton and Salakhutdinov 2006) and temporal methods which is the combination of 2d or 3d CNN networks. Though RNN is one of the important deep learning architecture particularly used for this task, this kind of network suffers from short-term memory loss. To address this problem LSTM (Anavi et al. 2015) was introduced. LSTM works in the inner layer of RNN. B-RNN (Goodfellow et al. 2014), H-RNN (He et al. 2015a), D-RNN (Janowczyk et al. 2017) are some extended, modified version of LSTM. Moreover fusion-based deep learning techniques (Lo et al. 1995; Pluim et al. 2003; Ngo et al. 2017; Yan et al. 2014; Chen et al. 2017; Center Berkeley 2016) are also popularly used for action recognition.

3.2 Deep Learning for Big Data

Big Data refers considerable amount of datasets (Philip Chen and Zhang 2014) which can synthesize specific patterns. Deep learning techniques are widely used for analyzing big data and succeeded to find certain hidden pattern that was impossible so far. Proper knowledge plays a critical role for success in many companies as well. This need can be satisfied by combining this two domain: Deep Learning and Big Data.

Big companies like Facebook, Google, and Yahoo used deep learning techniques and getting benefited from it. The analysis of big data can be subdivided into three phase: Big Data processing, Big Data storage, Big Data management. For better decision making we need large and good quality of data which requires data preprocessing (Hinton and Salakhutdinov 2006; Witten et al. 2016; Riabov and Liu 2006; Han et al. 2014; Siddiqa et al. 2016; Michael and Miller 2013; McAfee et al. 2012). Data cleansing, transmission sequencing are some of the intermediate steps of data processing. Storing big data in PT scale is not a feasible solution for researchers and interesting communities. Though recent advances of cloud computing anyhow reduce some problem. The main interesting thing in it is to create a storage management system which provides enough data and utilizes information retrieval (Dittrich et al. 2011), replication, indexing are the intermediate steps of storing big data (Li et al. 2008; Deng et al. 2014; Chen 2010) processing is one of the challenging tasks. There are several processing issues in managing big data. Recently AI companies invested a huge amount of money in big data processing (Buza et al. 2014; Porkar 2012; Jafari et al. 2016; Waibel et al. 1990). For addressing such problem, many machine learning (ML) researchers come with their handcraft feature learning techniques but fails to give a good result in practical aspects. But deep learning techniques give a better solution for handling both labeled and unlabeled datasets.

3.3 Deep Learning for Sentiment Analysis

Deep Learning Techniques (Morin and Bengio 2005; Mikolov et al. 2013a, b; Mnih and Kavukcuoglu 2013; Moraes et al. 2013; Johnson and Zhang 2015) are also useful for analyzing emotions. Though understanding of human emotion and explain it in terms of words is a challenging task for the computer vision researchers. Sometimes words are not enough to correctly explain our emotions as some emotions has no language translation. But deep learning techniques assistance to understand human emotional data which helps to take optimal decisions. There are mainly two basic approaches of sentiment analysis. Lexicon-based approach and AI-based Approach. In lexicon-based approach for given sentence words are split into small tokens also knows as tokenization. Bag of words is the count the number of frequencies of each word. Based on this it decides positive and negative sentences. AI-based deep learning techniques are the current trend research in sentiment analysis. For a large dataset deep learning techniques were trained and also be applied for real-time applications. CNN (Kalchbrenner et al. 2014; Kim 2014; dos Santos and Gatti 2014; Wang et al. 2016b, c; Guggilla et al. 2016; Mishra et al. 2017; Bengio et al. 2013; Qian et al. 2015), RNN (Tang et al. 2015; Guan et al. 2016; Yu and Jiang 2016) LSTM (Tang et al. 2016; Salakhutdinov and Hinton 2009; Qian et al. 2017; Li et al. 2017; Wang et al. 2015c; Huang et al. 2017; Le and Mikolov 2014; Glorot et al. 2011) models are popularly used in this task. Though deep learning-based sentiment analysis is a hard process of computation but these techniques give better result than traditional techniques. Document-level Sentiment classification (Wang et al. 2015c; Williams and Zipser 1989; Liu and Zhang 2017; Masci et al. 2011), Sentence level sentiment classification (Loshchilov and Hutter 2016; Wang et al. 2016c), aspect level sentiment classification (Liu and Zhang 2017; Yang et al. 2017b) are some of the intermediate steps of sentiment analysis. Large social media companies like Facebook twitter google has deep learning-based approaches for analyzing customers perspective.

3.4 Deep Learning for Medical Image Analysis

Analysis of medical images and their classification localization segmentation annotation abnormally detection are one of the current research interest. Since 2014 after the development of GPU based systems deep learning techniques give excellent performance in medical domain. Many researchers collect their data and make available for research purpose. Different research shows that CNN (Suk and Shen 2016; de Brebisson and Montana 2015; Choi and Jin 2016; Zhang et al. 2015a; Birenbaum and Greenspan 2016; Brosch et al. 2016) based deep learning models are most widely used in medical engineering. Apart from CNN, RBM, RNN (Stollenga et al. 2015; Andermatt et al. 2016) Autoencoder based models are also popularly different health care applications like brain image analysis(Sarraf and Tofighi 2016; Chen et al. 2016; Ghafoorian et al. 2016a, b), retinal image analysis (Gulshan et al. 2016; Zilly et al. 2017; Chen et al. 2015; Abràmoff et al. 2016; Lu et al. 2016a; van Grinsven et al. 2016; Gulshan et al. 2016; Gao et al. 2015), chest x-ray image analysis (Lo et al. 1995; Anavi et al. 2015; Anavi et al. 2016; Lin et al. 2014; Vaillant et al. 1994; Hwang et al. 2016; Kim and Hwang 2016; Rajkumar et al. 2017; Yang et al. 2017a), CT chest x-ray image analysis (Wang et al. 2017; Charbonnier et al. 2017; Shen et al. 2015a; Chen et al. 2017; Dou et al. 2017; Setio et al. 2016; Sun et al. 2016; Anthimopoulos et al. 2016; Christodoulidis et al. 2017; Gao 2016; Tarando et al. 2016; van Tulder and de Bruijne 2016; Avendi et al. 2016), pathology image analysis (Xie et al. 2016; Wang et al. 2016e; Xu et al. 2016a, b; Chang et al. 2017; Çiçek et al. 2016; Chen et al. 2017; Janowczyk et al. 2017; Hubel and Wiesel 1968), cardiac image analysis (Emad et al. 2015; Ngo et al. 2017; Poudel et al. 2016; Tran 2016; Prasoon et al. 2013), abdominal image analysis (Li et al. 2015; Vivanti et al. 2015; Wang and Gupta 2015; Yu et al. 2017; Zhu et al. 2017; Zhao et al. 2016), musculoskeletal image analysis (Shen et al. 2015b; Suzani et al. 2015; Antony et al. 2016). Figure 2 shows the pictorial application area of deep learning techniques in medical science.

3.5 Deep Learning for Text Detection and Recognition

Character and text recognition is one of the current time research and had been studied in the computer vision field from long time. Optical character recognition also popularly known as OCR recognition is one of the fundamental academic research. CNN is the main building block architecture for recognition of characters. We also divide this

Fig. 2 Application area of deep learning techniques in health care sector (Masci et al. 2011)

task into three subcategories: Text detection, text recognition from small region, and combination of text detection and recognition. CNN models are widely used for text detection (Zhang et al. 2015b). There are several standard handwritten and optical character available in almost all the languages in worldwide. One improvement of this work is the combination of CNN and Maximally Stable External Regions (MSER) (Goodfellow et al. 2014; Zhang et al. 2015b), Bag-of-Words (BoG) and CNN based sliding Non-Maximal suppression (NMS) (He et al. 2015b) based CNN structures are also popularly used. Similar to text detection, Text recognition is also popular research area Good fellow et al. (Shi et al. 2015) proposed a multilevel CNN classifier for character recognition from multidigit input string. Conditional Random Fields (CRF) based CNN, feature extraction based CNN (Gers et al. 2000), Sliding window-based LSTM (Jaderberg et al. 2014), and feature extraction based text recognition (Jaderberg et al. 2015) are also some popular techniques of text recognition. End-to-End text spotting with bounding box (Lawrence et al. 1997; Simard et al. 2003) is also the popular research interest in computer vision field. According to Ethnologies catalog of world languages, there is 6909 number of registered script language exist and most of the counties have their own official languages. Thus character recognition field has its own separate interest. Currently, automatic character recognition is used in machine translation, postal systems, identification recognition, image translations.

3.6 Deep Learning for Image Classification

Deep Learning Techniques gives a tremendous performance for classification of the object from a large dataset. Though CNN was used for image classification long back (He et al. 2015b), but it creates a remarkable performance in recent times with the advances of Graphical processing units and a large amount of data (He et al. 2015b; Lawrence et al. 1997; Everingham et al. 2014; Deng et al. 2009). In 2012 AlexNet creates a huge impact for mage classification of large-scale images which also wins the ILSVRC 2012 challenge. Taking this motivation of the work many researchers take their interest in increasing the classification accuracy by tuning the hyper parameters in the neural network. Several researchers come up with their new classification technique which sometimes works well. Hierarchy based image classification is a common technique for classifying a large class of images (Wang et al. 2015a). Hierarchy of CNN in discriminate feature learning for sharing their hierarchy of information to share among the classes (Xiao et al. 2014). Fine-gained feature learning (Yan et al. 2014), trained hierarchal network (Nilsback and Zisserman 2008), embedding CNN into a subcategory of the hierarchy methods are also popularly used to reducing the classification error. Subcategory image classification datasets (Yu and Grauman 2014; Yang et al. 2015) also takes lots of interest. CNN (Uijlings et al. 2013), R-CNN (Pluim et al. 2003; Lin et al. 2015b) Deep LAC (Lin et al. 2015a) based object part classification is also popularly used. Create a subnetwork, localize a region, and estimate the predictive class (Krause et al. 2015) also helps to improve classification accuracy. Both supervised and unsupervised learning techniques on annotated data are popular to fine-tuned (Dalal and Triggs 2005) the class. Ensemble the localization (Rowley et al. 1998), co-segmentation (Rowley et al. 1998), leveling by simplicity, visual attention based CNN models are also popularly used for image classification.

3.7 Deep Learning for Object Detection

One of the current time computer vision problems is object detection. There are many research issues for detecting objects from video or images. Though CNN based object detection techniques started in early 90s. However, due to lack of computational power and a small amount of data breaks the progress of CNN-based system. Recently in 2012 after the huge success in ImageNet challenge (Deng et al. 2009) this field gets back interested from the research community. In earlier times CNN based object detection (Lin et al. 2014; Vaillant et al. 1994) using sliding window were so popular, but these techniques require high computational power which makes them unreliable for massive datasets. Like VOC (He et al. 2015b), IMAGENET (Lawrence et al. 1997), MSCOCO (Alexe et al. 2012). To address this issue, Object proposal based technique introduced. Different literature (Carreira and Sminchisescu 2012; Pluim et al. 2003) shows that object proposal based techniques are the most generic measure of the test, a generic window is used to propose whether an object present or not., then passes it to next level of generic detection to understand objects are belonging to the same class or not. Region-based CNN (R-CNN) (Sermanet et al. 2013) is one of the popular objection technique. A pertained CNN is used on a selective search to extract feature and SVM used to classify objects. Several improvements were done to improve the performance. Feature extraction (He et al. 2015a; Carreira and Sminchisescu 2012; Sermanet et al. 2013), SPP net (Yoo et al. 2015), pyramidal R-CNN (Felzenszwalb et al. 2010), bounding box (Redmon et al. 2016), bootstrapping (Liu et al. 2015), Yolo, SDD, top-down search (Gidaris and Komodakis 2015) methods are introduced for better performance in dynamically challenging environments (Liu et al. 2015; Loshchilov and Hutter 2016; Lu et al. 2016b).

3.8 Deep Learning for Object Tracking

Another success of deep learning techniques can be found in object tracking. CNN and RNN based models are popular in this particular task. CNN based object tracking, target specific (Li et al. 2014) object tracking, temporal adaptation mechanism (Li et al. 2014), tracking based (Plis et al. 2014), similarity-based visual tracking (Hong et al. 2015), are most popular. In almost all the small/big companies and institutes use some kinds of tracking system for detecting persons, counting vehicles, finding missing elements, video surveillance.

4 Software and Implementation Tools

Table 1 shows some of the deep learning implementation tools. Keras, Tensorflow, Theano, PyTorch tools are widely used for implementation of AI techniques. Most of the tools use python as their underlying framework. The number of libraries for supporting the python is increased with the acceleration of GPU based systems. One of the main reasons for development of deep learning techniques is the Nvidia Corporation. Almost all the researchers use GPU based systems for accelerating their training time. In Table 1 we try to introduce the interdependencies of different learning techniques.

5 Discussion Overview

Our research query also exploits one common problem "what are the best possible ways of training a neural network." To find this answer to the question, we examine some breakthrough performances and general intuitions for understanding a neural network. We found out that there are mainly two ways we can train our neural network: first is to create own neural network architecture and the second is by using

Table 1 Some of the popular deep learning implementation tools

Tools	Platform	Support	Interface
Caffe (Williams and Zipser 1989)	Windows, Linux, Mac OSX	CNN, RNN	Python, C++, Matlab, Cuda
Tensorflow (Salakhutdinov and Hinton 2009)	Windows, Linux, Mac OSX, Android	Almost support all deep learning techniques	Python
Theano (Younes 1999)	Windows, Linux, Mac OSX	Almost support all deep learning techniques	Python, Cuda
Torch (Microsoft 2016)	Windows, Linux, Mac OSX	Almost support all deep learning techniques	Lua
Keras (Delakis and Garcia 2008)	Windows, Linux, Mac OSX	Almost support all deep learning techniques	Cross-platform, Cuda
PyTorch (Xu and Su 2015)	Linux, Mac OSX	Almost support all deep learning techniques	Python, C, Cuda

transfer learning. In the previous section, we already examine some unique deep learning architecture. Now in this segment, we will try to understand the transfer learning techniques. There are mainly three ways of using pre-trained model and train neural network: Fixed feature extractor, Fine-tuning the model, and pertained the model(Choudhary and Hazra 2019).

Fixed feature extraction: It is one of the early ML algorithms. First, use a technique which summarize the features and then apply on a classifier for predicting output levels. Also, the same way we can train neural network at first choose a convolutional neural network trained on big dataset like ImageNet and by removing last fully connected layer the network can be treated as a fixed feature extractor. Once the feature was extracted then the neural network trains on a classifier for new dataset.

Fine-Tuning the ConvNet: Another important strategy in deep learning is not only retrained as the classifier over new dataset but also to replace and fine-tune the learning experiences of the neural network. It may also be possible to train all the layers or keep some of the earlier layer fixed and fine-tune the upper layers. One notable thing to mention, the earlier layer of convolutional layer contain more generic low-level information's which can be advantageous for new dataset. Different experiments show that layer-wise fine-tuning of a ConvNet for a big data performs better than making a neural network from the sketch. There are certain intuitions when and how to fine-tune a network, deciding choosing a perfect transfer learning technique on a new dataset is a bit challenging task. There are several strategies one should take care, but the important two are the size of the new dataset and similarity between old and new datasets. In the lower level of ConvNet contain a lower level of generic information and upper level of the network contain more specific information related to the dataset. Some thumb rule for fine-tuning the new dataset are:

- If the dataset is small in size, then fine-tuning a ConvNet over a small dataset will not be a good idea as the deep neural network may suffer from overfitting problem. Hence, using a linear classifier on a small dataset might be a good idea.
- If the dataset is large and there is a similarity between two datasets then using a pre-trained model will give more confidence not to be overfitting the network, hence chances of increasing the performance of the network.
- If the new data is small and differ from original data, then using a linear classifier may not always work, instead use of support vector machine classifier may be beneficial for new dataset as the network contain data specific information.
- If the data is large and differs from original data, then fine-tuning a residual neural network sometimes helpful because it is found out that exploring vanishing gradient can lead some problem for weight updation. Even though making a neural network from scratch also works depending on the dataset.

Pretrain Models: Training a neural network on a large image dataset like ImageNet may take ~2–3 weeks for training on a Search Results Web results Graphics processing unit (GPU) based systems. Researchers sometimes release their final work for helping others. Using a pretrain model a fuse of different deep neural network sometimes also beneficial for Training a neural network.

6 Conclusion and Future Work

All the challenging issues discussed in the previous section were not been tackled yet by the researchers. Though some successes were achieved by using deep learning techniques. From this survey one observation we can make, many researchers' uses pretrained networks for evaluate their model. ResNet, VGGNet, GoogleNet networks are the top listed architectures for the researchers. Even though it is not clear that these models will work in all the domains. Recently some good results were achieved by making a fused model of different networks. Though there are some limitations of deep learning techniques, still it is widely used for solving real-time problems. Convolutional neural networks, RNN, LSTM networks create a benchmark performance in computer vision, robotics, speech recognition, and all the domains. In this literature, we also try to introduce the capabilities of different deep learning techniques. As this research field is new, there is a massive gap for improvement. In conclusion, we can say deep learning techniques are the current state of the learning algorithms. We expect that, in feature by using deep learning techniques researchers can solve many unsolved problems. Our work still in progress, in recent features we are trying to detect different chest diseases by using deep learning techniques.

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References

Abràmoff MD, Lou Y, Erginay A, Clarida W, Amelon R, Folk JC, Niemeijer M (2016) Improved automated detection of diabetic retinopathy on a publicly available dataset through integration of deep learning. Invest Ophthalmol Vis Sci 57(13):5200–5206. https://doi.org/10.1167/iovs.16-19964

Alexe B, Deselaers T, Ferrari V (2012) Measuring the objectness of image windows. In: PAMI

Anavi Y, Kogan I, Gelbart E, Geva O, Greenspan H (2015) A comparative study for chest radiograph image retrieval using binary texture and deep learning classification. In: 2015 37th annual international conference of the IEEE engineering in medicine and biology society (EMBC), Milan, pp 2940–2943. https://doi.org/10.1109/EMBC.2015.7319008

Anavi Y, Kogan I, Gelbart E, Geva O, Greenspan H (2016) Visualizing and enhancing a deep learning framework using patients age and gender for chest x-ray image retrieval. In: Proceedings of the SPIE 9785, medical imaging 2016: computer-aided diagnosis, vol 978510, 7 July 2016. https://doi.org/10.1117/12.2217587

Andermatt S, Pezold S, Cattin P (2016) Multi-dimensional gated recurrent units for the segmentation of biomedical 3D-data. In: Proceedings of the deep learning in medical image analysis (DLMIA). Lecture Notes in Computer Science, vol 10008, pp 142–151

Anthimopoulos M, Christodoulidis S, Ebner L, Christe A, Mougiakakou S (2016) Lung pattern classification for interstitial lung diseases using a deep convolutional neural network. IEEE Trans Med Imaging 35(5):1207–1216. https://doi.org/10.1109/TMI.2016.2535865

Antony J, McGuinness K, Connor NEO, Moran K (2016) Quantifying radiographic knee osteoarthritis severity using deep convolutional neural networks. arXiv:1609.02469

Avendi M, Kheradvar A, Jafarkhani H (2016) A combined deep-learning and deformable-model approach to fully automatic segmentation of the left ventricle in cardiac MRI. Med Image Anal 30:108–119

Bengio Y, Courville A, Vincent P (2013) Representation learning: a review and new perspectives. IEEE Trans Pattern Anal Mach Intell (2013)

Birenbaum A, Greenspan H (2016) Longitudinal multiple sclerosis lesion segmentation using multi-view convolutional neural networks. In: Proceedings of the deep learning in medical image analysis (DLMIA). Lecture notes in computer science, vol 10008, pp 58–67. https://doi.org/10.1007/978-3-319-46976-8_7

Brosch T, Tang LY, Yoo Y, Li DK, Traboulsee A, Tam R (2016) Deep 3D convolutional encoder networks with shortcuts for multiscale feature integration applied to multiple sclerosis lesion segmentation. IEEE Trans Med Imaging 35(5):1229–1239. https://doi.org/10.1109/TMI.2016.2528821

Buza K, Nagy GI, Nanopoulos A (2014) Storageoptimizing clustering algorithms for high-dimensional tick data. Expert Syst Appl 41:4148–4157

Carreira J, Sminchisescu C (2012) CPMC: automatic object segmentation using constrained parametric min-cuts. In: PAMI

Center Berkeley (2016) Caffe. http://caffe.berkeleyvision.org/

Chang H, Han J, Zhong C, Snijders A, Mao J-H (2017) Unsupervised transfer learning via multi-scale convolutional sparse coding for biomedical applications. IEEE Trans Pattern Anal Mach Intell https://doi.org/10.1109/TPAMI.2017.2656884

Charbonnier J-P, van Rikxoort EM, Setio AAA, Schaefer-Prokop CM, van Ginneken B, Ciompi F (2017) Improving airway segmentation in computed tomography using leak detection with

convolutional networks. Med Image Anal 36:52–60. ISSN 1361-8415. https://doi.org/10.1016/j.media.2016.11.001
Chen X (2010) Google big table
Chen W, Corso JJ (2015) Action detection by implicit intentional motion clustering. In: Proceedings of the IEEE international conference on computer vision, pp 3298–3306
Chen J, Chen Y, Xiaoyong D, Li C, Jiaheng L, Zhao S, Zhou X (2013) Big data challenge: a data management perspective. Front Comput Sci 7(2):157–164
Chen H, Dou Q, Yu L, Heng P-A (2016) Voxresnet: deep voxelwise residual networks for volumetric brain segmentation. arXiv:1608.05895
Chen S, Qin J, Ji X, Lei B, Wang T, Ni D, Cheng J-Z (2017) Automatic scoring of multiple semantic attributes with multi-task feature leverage: a study on pulmonary nodules in CT images. IEEE Trans Med Imaging 36(3):802–804. https://doi.org/10.1109/TMI.2016.2629462
Choi H, Jin KH (2016) Fast and robust segmentation of the striatum using deep convolutional neural networks. J Neurosci Methods 274:146–153. https://doi.org/10.1016/j.jneumeth.2016.10.007
Choudhary P, Hazra A (2019) Chest disease radiography in twofold: using convolutional neural networks and transfer learning. Evol Syst 1–13
Christodoulidis S, Anthimopoulos M, Ebner L, Christe A, Mougiakakou S (2017) Multisource transfer learning with convolutional neural networks for lung pattern analysis. IEEE J Biomed Health Inform 21(1):76–84. https://doi.org/10.1109/JBHI.2016.2636929
Çiçek Ö, Abdulkadir A, Lienkamp SS, Brox T, Ronneberger O (2016) 3D U-Net: learning dense volumetric segmentation from sparse annotation. In: Proceedings of the medical image computing and computer-assisted intervention. Lecture notes in computer science, vol 9901. Springer, pp 424–432. arXiv:1606.06650v1
Dalal N, Triggs B (2005) Histograms of oriented gradients for human detection. In: CVPR
de Brebisson A, Montana G (2015) Deep neural networks for anatomical brain segmentation. In: Proceedings of the computer vision and pattern recognition, pp 20–28
Delakis M, Garcia C (2008) Text detection with convolutional neural networks. In: VISAPP
Deng J, Dong W, Socher R, Li L, Li K, Li F (2009) Imagenet: a large-scale hierarchical image database. In: CVPR
Deng L, Yu D et al (2014) Deep learning: methods and applications. Found Trends R Signal Process 7(3–4):197–387
Dittrich J, Blunschi L, Salles MAV (2011) Movies: indexing moving objects by shooting index images. Geoinformatica 15(4):727–767
dos Santos CN, Gatti M (2014) Deep convolutional neural networks for sentiment analysis for short texts. In: Proceedings of the international conference on computational linguistics (COLING 2014)
Dou Q, Chen H, Yu L, Qin J, Heng PA (2017) Multilevel contextual 3-D CNN's for false positive reduction in pulmonary nodule detection. IEEE Trans Biomed Eng 64(7):1558–1567. https://doi.org/10.1109/tbme.2016.2613502
Emad O, Yassine IA, Fahmy AS (2015) Automatic localization of the left ventricle in cardiac MRI images using deep learning. In: Proceedings of the IEEE engineering in medicine and biology society, pp 683–686. https://doi.org/10.1109/embc.2015.7318454
Everingham M, Eslami SA, Van Gool L, Williams CK, Winn J, Zisserman A (2014) The pascal visual object classes challenge: a retrospective. In: IJCV
Felzenszwalb PF, Girshick RB, McAllester D, Ramanan D (2010) Object detection with discriminatively trained part-based models. In: PAMI
Gao M et al (2016) Segmentation label propagation using deep convolutional neural networks and dense conditional random field. In: 2016 IEEE 13th international symposium on biomedical imaging (ISBI), Prague, pp 1265–1268. https://doi.org/10.1109/ISBI.2016.7493497
Gao X, Lin S, Wong TY (2015) Automatic feature learning to grade nuclear cataracts based on deep learning. IEEE Trans Biomed Eng 62(11):2693–2701. https://doi.org/10.1109/TBME.2015.2444389

Gers FA, Schmidhuber J, Cummins F (2000) Learning to forget: continual prediction with LSTM. In: Neural computation
Ghafoorian M, Karssemeijer N, Heskes T, van Uden I, Sanchez C, Litjens G, de Leeuw F-E, van Ginneken B, Marchiori E, Platel B (2016a) Location sensitive deep convolutional neural networks for segmentation of white matter hyperintensities. arXiv:1610.04834
Ghafoorian M, Karssemeijer N, Heskes T, van Uden IWM, de Leeuw F-E, Marchiori E, van Ginneken B, Platel B (2016b) Non-uniform patch sampling with deep convolutional neural networks for white matter hyperintensity segmentation. In: Proceedings of the IEEE international symposium on biomedical imaging, pp 1414–1417. https://doi.org/10.1109/isbi.2016.7493532
Gidaris S, Komodakis N (2015) Object detection via a multi-region and semantic segmentation-aware CNN model. In: ICCV
Glorot X, Bordes A, Bengio Y (2011) Domain adaption for large-scale sentiment classification: a deep learning approach. In: Proceedings of the international conference on machine learning (ICML 2011)
Goodfellow IJ, Ibarz J, Arnoud S, Shet V (2014) Multi-digit number recognition from street view imagery using deep convolutional neural networks. In: ICLR
Guan Z, Chen L, Zhao W, Zheng Y, Tan S, Cai D (2016) Weakly-supervised deep learning for customer review sentiment classification. In: Proceedings of the international joint conference on artificial intelligence (IJCAI 2016)
Guggilla C, Miller T, Gurevych I (2016) CNN-and LSTM-based claim classification in online user comments. In: Proceedings of the international conference on computational linguistics (COLING 2016)
Gulshan V, Peng L, Coram M, Stumpe MC, Wu D, Narayanaswamy A, Venugopalan S, Widner K, Madams T, Cuadros J, Kim R, Raman R, Nelson PC, Mega JL, Webster DR (2016) Development and validation of a deep learning algorithm for detection of diabetic retinopathy in retinal fundus photographs. J Am Med Assoc 316:2402–2410. https://doi.org/10.1001/jama.2016.17216
Han H, Wen Y, Chua T-S, Li X (2014) Toward scalable systems for big data analytics: a technology tutorial. IEEE Access 2:652–687
He K, Zhang X, Ren S, Sun J (2015a) Spatial pyramid pooling in deep convolutional networks for visual recognition. In: PAMI
He P, Huang W, Qiao Y, Loy CC, Tang X (2015b) Reading scene text in deep convolutional sequences. In: CoRR
He K, Zhang X, Ren S, Sun J (2015c) Deep residual learning for image recognition. In: CVPR
Hinton GE, Salakhutdinov RR (2006) Reducing the dimensionality of data with neural networks. Science 313(5786):504–507
Hong S, You T, Kwak S, Han B (2015) Online tracking by learning discriminative saliency map with convolutional neural network. In: ICML
Huang M, Qian Q, Zhu X (2017) Encoding syntactic knowledge in neural networks for sentiment classification. ACM Trans Inf Syst
Hubel DH, Wiesel TN (1968) Receptive fields and functional architecture of monkey striate cortex. J Physiol
Hwang S, Kim H-E, Jeong J, Kim H-J (2016) A novel approach for tuberculosis screening based on deep convolutional neural networks. In: Proceedings of the SPIE, medical imaging 2016: computer-aided diagnosis, vol 9785, p 97852W, 24 Mar 2016. https://doi.org/10.1117/12.2216198
Jaderberg M, Vedaldi A, Zisserman A (2014) Deep features for text spotting. In: ECCV
Jaderberg M, Simonyan K, Vedaldi A, Zisserman A (2015) Reading text in the wild with convolutional neural networks. In: IJCV
Jafari M, Wang J, Qin Y, Gheisari M, Shahabi AS, Tao X (2016) Automatic text summarization using fuzzy inference. In: 2016 22nd international conference on automation and computing (ICAC). IEEE, pp 256–260

Janowczyk A, Basavanhally A, Madabhushi A (2017) Stain normalization using sparse autoencoders (STANOSA): application to digital pathology. Comput Med Imaging Graph 57:50–61
Johnson R, Zhang T (2015) Effective use of word order for text categorization with convolutional neural networks. In: Proceedings of the conference of the North American chapter of the association for computational linguistics: human language technologies (NAACL-HLT 2015)
Kalchbrenner N, Grefenstette E, Blunsom P (2014) A convolutional neural network for modelling sentences. In: Proceedings of the annual meeting of the association for computational linguistics (ACL 2014)
Kim Y (2014) Convolutional neural networks for sentence classification. In: Proceedings of the annual meeting of the association for computational linguistics (ACL 2014)
Kim H, Hwang S (2016) Scale-invariant feature Learning using deconvolutional neural networks for weakly-supervised semantic segmentation. arXiv:1602.04984
Krause J, Jin H, Yang J, Fei-Fei L (2015) Fine-grained recognition without part annotations. In: CVPR
Krizhevsky A, Sutskever I, Hinton GE (2012) Imagenet classification with Deep Convolutional neural networks. In: NIPS
Lawrence S, Giles CL, Tsoi AC, Back AD (1997) Face recognition: a convolutional neural-network approach. In: TNN
Le Cun BB, Denker JS, Henderson D, Howard RE, Hubbard W, Jackel LD (1990) Handwritten digit recognition with a back-propagation network. In: NIPS
Le Q, Mikolov T (2014) Distributed representations of sentences and documents. In: Proceedings of the international conference on machine learning (ICML 2014)
Li G, Ooi BC, Feng J, Wang J, Zhou L (2008) Ease: an effective 3-in-1 keyword search method for unstructured, semi-structured and structured data. In: Proceedings of the 2008 ACM SIGMOD international conference on management of data. ACM, pp 903–914
Li H, Li Y, Porikli F (2014) Deeptrack: learning discriminative feature representations by convolutional neural networks for visual tracking. In: BMVC
Li W, Jia F, Hu Q (2015) Automatic segmentation of liver tumor in CT images with deep convolutional neural networks. J Comput Commun 3(11):146–151
Li Z, Zhang Y, Wei Y, Wu Y, Yang Q (2017) End-to-end adversarial memory network for cross-domain sentiment classification. In: Proceedings of the international joint conference on artificial intelligence (IJCAI 2017)
Lin T-Y, Maire M, Belongie S, Hays J, Perona P, Ramanan D, Dollár P, Zitnick CL (2014) Microsoft COCO: common objects in context. In: ECCV (2014)
Lin T-Y, RoyChowdhury A, Maji S (2015a) Bilinear cnn models for fine-grained visual recognition. arXiv:1504.07889
Lin D, Shen X, Lu C, Jia J (2015b) Deep LAC: Deep localization, alignment and classification for fine-grained recognition. In: CVPR
Liu J, Zhang Y (2017) Attention modeling for targeted sentiment. In: Proceedings of the conference of the European chapter of the association for computational linguistics (EACL 2017)
Liu W, Anguelov D, Erhan D, Szegedy C, Reed S (2015) SSD: single shot multibox detector. In: ECCV
Lo SCB, Lou SLA, Lin J-S, Freedman MT, Chien MV, Mun SK (1995) Artificial convolution neural network techniques and applications for lung nodule detection. IEEE Trans Med Imaging 14(4):711–718. https://doi.org/10.1109/42.476112
Loshchilov I, Hutter F (2016) Online batch selection for faster training of neural networks. In: ICLR workshop
Lu Y, Javidi T, Lazebnik S (2016a) Adaptive object detection using adjacency and zoom prediction. In: CVPR
Lu X, Xu D, Liu D (2016b) Robust 3D organ localization with dual learning architectures and fusion. In: Proceedings of the deep learning in medical image analysis (DLMIA). Lecture notes in computer science, vol 10008, pp 12–20. https://doi.org/10.1007/978-3-319-46976-8_2

Masci J, Meier U, Cireşan D, Schmidhuber J (2011) Stacked convolutional auto-encoders for hierarchical feature extraction. In: Proceedings of the international conference on artificial neural networks, pp 52–59
McAfee A, Brynjolfsson E, Davenport TH, Patil DJ, Barton D (2012) Big data. The management revolution. Harv Bus Rev 90(10):61–67
Michael K, Miller KW (2013) Big data: new opportunities and new challenges [guest editors' introduction]. Computer 46(6):22–24
Microsoft (2016) CNTK. https://github.com/Microsoft/CNTK
Mikolov T, Chen K, Corrado G, Dean J (2013a) Efficient estimation of word representations in vector space. In: Proceedings of international conference on learning representations (ICLR 2013)
Mikolov T, Sutskever I, Chen K, Corrado G, Dean J (2013b) Distributed representations of words and phrases and their compositionality. In: Proceedings of the annual conference on advances in neural information processing systems (NIPS 2013)
Mishra A, Dey K, Bhattacharyya P (2017) Learning cognitive features from gaze data for sentiment and sarcasm classification using convolutional neural network. In: Proceedings of the annual meeting of the association for computational linguistics (ACL 2017)
Mnih A, Kavukcuoglu K (2013) Learning word embeddings efficiently with noise-contrastive estimation. In: Proceedings of the annual conference on advances in neural information processing systems (NIPS 2013)
Moraes R, Valiati JF, Neto WP (2013) Document-level sentiment classification: an empirical comparison between SVM and ANN. Expert Syst Appl
Morin F, Bengio Y (2005) Hierarchical probabilistic neural network language model. In: Proceedings of the international workshop on artificial intelligence and statistics
Ngo TA, Lu Z, Carneiro G (2017) Combining deep learning and level set for the automated segmentation of the left ventricle of the heart from cardiac cine magnetic resonance. Med Image Anal 35:159–171. https://doi.org/10.1016/j.media.2016.05.009
Nilsback M-E, Zisserman A (2008) Automated flower classification over a large number of classes. In: ICVGIP
Philip Chen CL, Zhang C-Y (2014) Data-intensive applications, challenges, techniques and technologies: a survey on big data. Inf Sci 275:314–347
Plis SM, Hjelm DR, Salakhutdinov R, Allen EA, Bockholt HJ, Long JD, Johnson HJ, Paulsen JS, Turner JA, Calhoun VD (2014) Deep learning for neuroimaging: a validation study. Front Neurosci. https://doi.org/10.3389/fnins.2014.00229
Pluim JP, Maintz JA, Viergever M et al (2003) Mutual-information-based registration of medical images: a survey. In: T-MI
Porkar P (2012) Sensor networks challenges. In: 11th international conference on data networks, DNCOCO '12, 7–9 Sept 2012
Poudel RPK, Lamata P, Montana G (2016) Recurrent fully convolutional neural networks for multi-slice MRI cardiac segmentation. arXiv:1608.03974
Poultney C et al (2006) Efficient learning of sparse representations with an energy-based model. In: Proceedings of the advances in neural information processing systems, pp 1137–1144
Prasoon A, Petersen K, Igel C, Lauze F, Dam E, Nielsen M (2013) Deep feature learning for knee cartilage segmentation using a triplanar convolutional neural network. In: Proceedings of the medical image computing and computer-assisted intervention. Lecture notes in computer science, vol 8150, pp 246–253. https://doi.org/10.1007/978-3-642-40763-5_31
Qian Q, Tian B, Huang M, Liu Y, Zhu X, Zhu X (2015) Learning tag embeddings and tag-specific composition functions in the recursive neural network. In: Proceedings of the annual meeting of the association for computational linguistics (ACL 2015)
Qian Q, Huang M, Lei J, Zhu X (2017) Linguistically regularized LSTM for sentiment classification. In: Proceedings of the annual meeting of the association for computational linguistics (ACL 2017)
Rajkumar A, Lingam S, Taylor AG, Blum M, Mongan J (2017) High-throughput classification of radiographs using deep convolutional neural networks. J Digit Imaging 30:95–101. https://doi.org/10.1007/s10278-016-9914-9

Redmon J, Divvala S, Girshick R, Farhadi A (2016) You only look once: unified, real-time object detection. In: CVPR
Riabov A, Liu Z (2006) Scalable planning for distributed stream processing systems. In: ICAPS, pp 31–41
Rifai S, Vincent P, Muller X, Glorot X, Bengio Y (2011) Contractive auto-encoders: explicit invariance during feature extraction. In: Proceedings of the international conference on machine learning, pp 833–840
Rowley HA, Baluja S, Kanade T (1998) Neural network-based face detection. In: PAMI
Salakhutdinov R, Hinton GE (2009) Deep Boltzmann machines. In: Proceedings of the international conference on artificial intelligence and statistics, vol. 1, art no 3
Sarraf S, Tofighi G (2016) Classification of Alzheimer's disease using fMRI data and deep learning convolutional neural networks. arXiv:1603.08631
Sermanet P, Eigen D, Zhang X, Mathieu M, Fergus R, LeCun Y (2013) Overfeat: integrated recognition, localization and detection using convolutional networks
Setio AAA et al (2016) Pulmonary nodule detection in CT images: false positive reduction using multi-view convolutional networks. IEEE Trans Med Imaging 35(5):1160–1169. https://doi.org/10.1109/TMI.2016.2536809
Shen W, Zhou M, Yang F, Yang C, Tian J (2015a) Multi-scale convolutional neural networks for lung nodule classification. In: Ourselin S, Alexander D, Westin CF, Cardoso M (eds) Information processing in medical imaging. IPMI 2015. Lecture notes in computer science, vol 9123. Springer, Cham
Shen W, Yang F, Mu W, Yang C, Yang X, Tian J (2015b) Automatic localization of vertebrae based on convolutional neural networks. In: Proceedings of the SPIE on medical imaging, vol 9413, p 94132E
Shi B, Bai X, Yao C (2015) An end-to-end trainable neural network for image-based sequence recognition and its application to scene text recognition. In: CoRR
Siddiqa A, Hashem IAT, Yaqoob I, Marjani M, Shamshirband S, Gani A, Nasaruddin F (2016) A survey of big data management: taxonomy and state-of-the-art. J Netw Comput Appl 71:151–166
Simard PY, Steinkraus D, Platt JC (2003) Best practices for convolutional neural networks applied to visual document analysis. In: ICDAR
Simonyan K, Zisserman A (2015) Very deep convolutional networks for large-scale image recognition. In: ICLR
Stollenga MF, Byeon W, Liwicki M, Schmidhuber J (2015) Parallel multi-dimensional LSTM, with application to fast biomedical volumetric image segmentation. In: Proceedings of the advances in neural information processing systems, pp 2998–3006
Suk H-I, Shen D (2016) Deep ensemble sparse regression network for Alzheimer's disease diagnosis. In: Proceedings of the medical image computing and computer-assisted intervention. Lecture notes in computer science, vol 10019, pp 113–121. https://doi.org/10.1007/978-3-319-47157-0_14
Sun W, Zheng B, Qian W (2016) Computer-aided lung cancer diagnosis with deep learning algorithms. In: Proceedings of the SPIE, medical imaging 2016: computer-aided diagnosis, vol 9785, p 97850Z, 24 Mar 2016. https://doi.org/10.1117/12.2216307
Suzani A, Rasoulian A, Seitel A, Fels S, Rohling R, Abolmaesumi P (2015) Deep learning for automatic localization, identification, and segmentation of vertebral bodies in volumetric MR images. In: Proceedings of the SPIE medical imaging, vol 9415, p. 941514
Tang D, Qin B, Liu T (2015) Document modelling with gated recurrent neural network for sentiment classification. In: Proceedings of the conference on empirical methods in natural language processing (EMNLP 2015)
Tang D, Qin B, Feng X, Liu T (2016) Effective LSTMs for target-dependent sentiment classification. In: Proceedings of the international conference on computational linguistics (COLING 2016)
Tarando SR, Fetita C, Faccinetto A, Brillet P-Y (2016) Increasing CAD system efficacy for lung texture analysis using a convolutional network. In: Proceedings of the SPIE, medical imaging

2016: computer-aided diagnosis, vol 9785, p 97850Q, 24 Mar 2016. https://doi.org/10.1117/12.2217752

Tran PV (2016) A fully convolutional neural network for cardiac segmentation in short-axis MRI. arXiv:1604.00494

Uijlings JR, van de Sande KE, Gevers T, Smeulders AW (2013) Selective search for object recognition. In: IJCV

Vaillant R, Monrocq C, Le Cun Y (1994) Original approach for the localisation of objects in images. In: IEE proceedings—vision, image and signal processing

van Grinsven MJJP, van Ginneken B, Hoyng CB, Theelen T, Sánchez CI (2016) Fast convolutional neural network training using selective data sampling: application to hemorrhage detection in color fundus images. IEEE Trans Med Imaging 35(5):1273–1284. https://doi.org/10.1109/TMI.2016.2526689

van Tulder G, de Bruijne M (2016) Combining generative and discriminative representation learning for lung CT analysis with convolutional restricted Boltzmann machines. IEEE Trans Med Imaging 35(5):1262–1272. https://doi.org/10.1109/TMI.2016.2526687

Vincent P, Larochelle H, Bengio Y, Manzagol P-A (2008) Extracting and composing robust features with denoising autoencoders. In: Proceedings of the international conference on machine learning, pp 1096–1103

Vivanti R, Ephrat A, Joskowicz L, Karaaslan O, Lev-Cohain N, Sosna J (2015) Automatic liver tumor segmentation in follow-up CT studies using convolutional neural networks. In: Proceedings of the patch-based methods in medical image processing workshop, MICCAI'2015, pp 54–61

Waibel A, Hanazawa T, Hinton G, Shikano K, Lang KJ (1990) Phoneme recognition using time-delay neural networks. In: Readings in speech recognition, pp 393–404

Wang X, Gupta A (2015) Unsupervised learning of visual representations using videos. In: ICCV

Wang Z, Wang X, Wang G (2015a) Learning fine-grained features via a cnn tree for large-scale classification. arXiv:1511.04534

Wang X, Liu Y, Sun C, Wang B, Wang X (2015c) Predicting polarities of tweets by composing word embeddings with long short-term memory. In: Proceedings of the annual meeting of the association for computational linguistics (ACL 2015)

Wang J, Yu L-C, Lai RK, Zhang X (2016b) Dimensional sentiment analysis using a regional CNN-LSTM model. In: Proceedings of the annual meeting of the association for computational linguistics (ACL 2016)

Wang X, Jiang W, Luo Z (2016c) Combination of convolutional and recurrent neural network for sentiment analysis of short texts. In: Proceedings of the international conference on computational linguistics (COLING 2016)

Wang S, Yao J, Xu Z, Huang J (2016e) Subtype cell detection with an accelerated deep convolution neural network. In: Proceedings of the medical image computing and computer-assisted intervention. Lecture notes in computer science, vol 9901, pp 640–648. https://doi.org/10.1007/978-3-319-46723-8_74

Wang C, Elazab A, Wu J, Hu Q (2017) Lung nodule classification using deep feature fusion in chest radiography. Comput Med Imaging and Graph 57:10–18. ISSN 0895-6111. https://doi.org/10.1016/j.compmedimag.2016.11.004

Williams RJ, Zipser D (1989) A learning algorithm for continually running fully recurrent neural networks. Neural Comput 1(2):270–280

Witten IH, Frank E, Hall MA, Pal CJ (2016) Data mining: practical machine learning tools and techniques. Morgan Kaufmann

Xiao T, Zhang J, Yang K, Peng Y, Zhang Z (2014) Error-driven incremental learning in deep convolutional neural network for large-scale image classification. In: ACMMM

Xie W, Noble JA, Zisserman A (2016) Microscopy cell counting and detection with fully convolutional regression networks. Comput Methods Biomech Biomed Eng Imaging Vis 1–10

Xu H, Su F (2015) Robust seed localization and growing with deep convolutional features for scene text detection. In: ICMR

Xu J, Luo X, Wang G, Gilmore H, Madabhushi A (2016a) A deep convolutional neural network for segmenting and classifying epithelial and stromal regions in histopathological images. Neurocomputing 191:214–223. https://doi.org/10.1016/j.neucom.2016.01.034

Xu Y, Li Y, Liu M, Wang Y, Lai M, Chang EI-C (2016b) Gland instance segmentation by deep multichannel side supervision. arXiv:1607.03222

Yan Z, Jagadeesh V, DeCoste D, Di W, Piramuthu R (2014) HD-CNN: hierarchical deep convolutional neural network for image classification. arXiv:1410.0736

Yang L, Luo P, Loy CC, Tang X (2015) A large-scale car dataset for fine-grained categorization and verification. In: CVPR

Yang W, Chen Y, Liu Y, Zhong L, Qin G, Lu Z, Feng Q, Chen W (2017a) Cascade of multi-scale convolutional neural networks for bone suppression of chest radiographs in gradient domain. Med Image Anal 35:421–433. ISSN 1361-8415. https://doi.org/10.1016/j.media.2016.08.004

Yang M, Tu W, Wang J, Xu F, Chen X (2017b) Attention-based LSTM for target-dependent sentiment classification. In: Proceedings of AAAI conference on artificial intelligence (AAAI 2017)

Yoo D, Park S, Lee J-Y, Paek AS, So Kweon I (2015) Attentionnet: Aggregating weak directions for accurate object detection. In: CVPR

Younes L (1999) On the convergence of markovian stochastic algorithms with rapidly decreasing ergodicity rates. Stoch: Int J. Probab Stoch Process 65(3/4):177–228

Yu A, Grauman K (2014) Fine-grained visual comparisons with local learning. In: CVPR

Yu J, Jiang J (2016) Learning sentence embeddings with auxiliary tasks for cross-domain sentiment classification. In: Proceedings of the conference on empirical methods in natural language processing (EMNLP 2016)

Yu L, Yang X, Chen H, Qin J, Heng PA (2017) Volumetric convnets with mixed residual connections for automated prostate segmentation from 3D MR images. In: Proceedings of the thirty-first AAAI conference on artificial intelligence

Zhang W, Li R, Deng H, Wang L, Lin W, Ji S, Shen D (2015a) Deep convolutional neural networks for multi-modality isointense infant brain image segmentation. Neuroimage 108:214–224. https://doi.org/10.1016/j.neuroimage.2014.12.061

Zhang C, Yao C, Shi B, Bai X (2015b) Automatic discrimination of text and non-text natural images. In: ICDAR

Zhao J, Zhang M, Zhou Z, Chu J, Cao F (2016) Automatic detection and classification of leukocytes using convolutional neural networks. Med Biol Eng Comput. https://doi.org/10.1007/s11517-016-1590-x

Zhu Y, Wang L, Liu M, Qian C, Yousuf A, Oto A, Shen D (2017) MRI Based prostate cancer detection with high-level representation and hierarchical classification. Med Phys 44(3):1028–1039. https://doi.org/10.1002/mp.12116

Zilly J, Buhmann JM, Mahapatra D (2017) Glaucoma detection using entropy sampling and ensemble learning for automatic optic cup and disc segmentation. Comput Med Imaging Graph 55:28–41. https://doi.org/10.1016/j.compmedimag.2016.07.012