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A Survey on Medical Image Analysis using Deep Learning Techniques

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***Abstract*: Deep learning algorithms, in particular convolution networks, have rapidly become a methodology of choice for analyzing medical images. Deep learning architectures such as deep neural networks, deep belief networks and recurrent neural networks have been applied to analyze medical images. This survey reviews the major deep learning concepts pertinent to medical image analysis and explains the use of deep learning for image classification, object detection, segmentation, registration, and other tasks. Concise overviews are provided of studies per application area: neuro, retinal, pulmonary, digital pathology, breast, cardiac, abdominal, musculoskeletal. This survey also discusses about different databases used for medical image analysis. Finally, it discusses briefly about issues and research challenges faced by researchers along with future direction.**

***Keywords*: Deep Learning, Convolutional networks, Medical Image**

1. Introduction

Initially, from the 1970s to the 1990s, medical image analysis was done with sequential application of low-level pixel processing and mathematical modeling to construct compound rule-based systems that solved particular tasks. At the end of the 1990s, supervised techniques, where training data is used to develop a system, were becoming increasingly popular in medical image analysis. Examples include active shape models atlas methods and the concept of feature extraction and use of statistical classifiers [3]. Thus, we have seen a shift from systems that are completely designed by humans to systems that are trained by computers using example data from which feature vectors are extracted. Computer algorithms determine the optimal decision boundary in the high-dimensional feature space. Let computers learn the features that optimally represent the data for the problem at hand. This concept lies at the basis of many deep learning algorithms: models composed of many layers that transform input data to outputs (e.g. while learning increasingly higher level features. The most successful type of models for image analysis to date are convolution neural networks (CNNs)[2]. CNNs contain many layers that transform their input with convolution filters of a small extent [3]. In computer vision, deep convolutional networks have now become the technique of choice.

A. Deep learning

Deep learning (also known as deep structured learning or hierarchical learning) is part of a broader family of machine learning methods based on learning data representations, as opposed to task-specific algorithms. Learning can be supervised, semi-supervised or unsupervised Deep learning architectures such as deep neural networks, deep belief networks and recurrent neural networks have been applied to fields including computer vision, speech recognition, natural language processing, audio recognition, social network filtering, machine translation, bioinformatics, drug design, medical image analysis, material inspection and board game programs. use a cascade of multiple layers of nonlinear processing units for feature extraction and transformation. Each successive layer uses the output from the previous layer as input.

B. Approaches in deep learning

Deep learning then can be defined as neural networks with a large number of parameters and layers. different deep learning approaches are,

- Unsupervised Pre-trained Networks
- Convolutional Neural Networks
- Recurrent Neural Networks
- Recursive Neural Networks
- Deep Auto Encoder(DAE)
- Stacked Auto Encoder(SAE)
- Deep Belief Network

C. Learning algorithm for deep learning

1) Neural network

Neural networks are a type of learning algorithm which forms the basis of deepest learning methods. A neural network is comprised of neurons or units with some activation a and parameters = {W, B}, where W is a set of weights and B set of biases. The activation represents a linear combination of the input $\mathbf{x}$ to the neuron and the parameters, followed by an element-wise non- linearity σ(·), referred to as a transfer function:

$$a = \sigma(\mathbf{w}\ T\ \mathbf{x} + b)$$

2) Convolution neural network

CNNs weights in the network are shared in such a way that the network performs convolution operations on images. This way, the model does not need to learn separate detectors for the same object occurring at different positions in an image, making the network equivariant with respect to translations of the input. It also drastically reduces the amount of parameters (i.e. the number of weights no longer depends on the size of the input image) that need to be learned. At each layer, the input image is convolved with a set of K kernels W = {W1, W2 , . . . , WK } and added biases B = { b1 , . . . , bK } , each generating a new feature map Xk . These features are subjected to an element-wise non-linear transform σ(·) and the same process is repeated for every convolutional layer l.

3) Recurrent Neural Network (RNNs)

Traditionally, RNNs were developed for discrete sequence analysis. They can be seen as a generalization of MLPs because both the input and output can be of varying length, making them suit- able for tasks such as machine translation where a sentence of the source and target language are the input and output.

The plain RNN maintains a latent or hidden state h at time t that is the output of a non-linear mapping from its input x t and the previous state h t−1:

$$h_t = \sigma(Wx_t + Rh_{t-1} + b)$$

where weight matrices W and R are shared over time. For classification, one or more fully-connected layers are typically added followed by a softmax to map the sequence to a posterior over the classes. P (y | x1, x2 , . . . , xT ;) = softmax (h T ;W out, b out) . Since the gradient needs to be back propagated from the out- put through time, RNNs are inherently deep (in time) and consequently suffer from the same problems with training as regular deep neural networks.

4) Unsupervised models

Auto-encoders (AEs) and stacked auto-encoders (SAEs)

AEs are simple networks that are trained to reconstruct the in- put x on the output layer x _ through one hidden layer h. They are governed by a weight matrix W x, h and bias b x, h from input to hid- den state and W h, x with corresponding bias b h,x_ from the hidden layer to the reconstruction. A non-linear function is used to compute the hidden activation:

$$h = \sigma(W_{x,h}x + b_{x,h})$$

Additionally, the dimension of the hidden layer | h | is taken to be smaller than | x |. This way, the data is projected onto a lower dimensional subspace representing a dominant latent structure in the input. Regularization constraints can be employed to enhance the discovery process. If the hidden layer had the same size as the input and no further non-linearity were added, the model would simply learn the identity function.

The denoise auto encoder is another solution to prevent the model from learning a trivial solution. Here, the model is trained to reconstruct the input from a noise corrupted version (typically salt-and-pepper-noise). SAEs (or deep AEs) are formed by placing auto-encoder layers on top of each other. In medical applications surveyed in this work, auto-encoder layers were often trained individually (‘greedily’) after which the full network was fine-tuned using supervised training to make a prediction

D. Restricted Boltzmann machines (RBMs) and deep belief networks (DBNs)

RBMs are a type of Markov Random Field (MRF), constituting an input layer or visible layer x = (x1, x2, . . . , xN) and a hidden layer h = (h1 , h2 , . . . , hM) that carries the latent feature representation. The connections between the nodes are bi- directional, so given an input vector x one can obtain the latent feature representation h and also vice versa. As such, the RBM is a generative model, and we can sample from it and generate new data points. In analogy to physical systems, an energy function is defined for a particular state (x, h) of input and hidden units: E(x , h) = h T Wx−c T x −b T h , with c and b bias terms. The probability of the ‘state’ of the system is defined by passing the energy to an exponential and normalizing.

E. Medical imaging process using deep learning

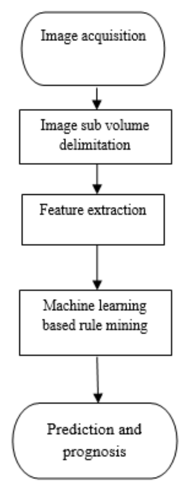

Fig. 1. Flowchart of medical imaging process using deep learning

2. Conclusion

After reviewing so many papers one would expect to be able to distill the perfect deep learning method and architecture for each individual task and application area. Although convolutional neural networks (and derivatives) are now clearly the top performers in most medical image analysis competitions, one striking conclusion we can draw is that the exact architecture is not the most important determinant in getting a good solution. Several researchers have shown that designing architectures incorporating unique task-specific properties can obtain better results than straightforward CNNs. Two examples which we encountered several times are multi-view and multi-scale networks.

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Table 1
Data Collection

Title	Year	Name of author	Approach used	Dataset	Disease predicted
Protein Sequence Based Anomaly Detection for Neuro-Degenerative Disorders Through Deep Learning Techniques [1]	2019	Shomona Gracia Jacob and R. Rajavel	Deep Auto Encoder(DAE)	Kyoto Encyclopedia of Genes and Genomes (KEGG)	Neuro-Degenerative brain Disorders
Nifty Net: a deep-learning platform for medical imaging[2]	2018	Eli Gibson et al	Deep neural network with shallow learning curve	Nitynet	Provide software infrastructure for medical image analysis and computer-assisted intervention
Identifying Medical Diagnoses and Treatable Diseases by Image-Based Deep Learning[3]	2018	Daniel S. Kermany et al	Convolutional Neural Network(CNN)	Optical coherence tomography images	Retinal diseases
A Deep Learning Algorithm for Prediction of Age-Related Eye[4] Disease Study Severity Scale for Age-Related Macular Degeneration from Colour Fundus Photography	2018	Felix Grassmann et al	Convolution deep neural network	Age-Related Eye Disease Study (AREDS)	Age related macular degeneration
Neuroimaging and Machine Learning for Dementia Diagnosis: Recent Advancements and Future Prospects[5]	2018	Md. Rishad Ahmed et al	Deep Ensemble Sparse Regression Network	Alzheimer's Disease Neuroimaging Initiative(ADNI) Open Access Series of Imaging Studies (OASIS)	Dementia – declination of brain function
3D Deep Learning in Medical Image Analysis [6]	2017	Dinggang Shen et al	Deep Boltzman machine	ImageNet Large Scale Visual Recognition Challenge (ILSVRC)	Analysis of medical images
3D Deep Learning for Multi-modal Imaging-Guided Survival Time Prediction of Brain Tumor Patients [7]	2016	Han Zhang et al	Convolutional neural network, Support vector machine	Pubmed	Glioma Brain tumor
De-noising of Contrast-Enhanced MRI Sequences by an Ensemble of Expert Deep Neural Networks [8]	2016	Yoshuabengio et al	Recurrent Neural Network	Pubmed	Mri image analysis

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