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DEEPANALYSIS OF MEDICAL IMAGES USING MACHINE LEARNING

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Abstract:

Healthcare sector is totally different from other industry. It is on high priority sector and people expect highest level of care and services regardless of cost. In terms of image interpretation by human expert, it is quite limited due to its subjectivity, complexity of the image; extensive variations exist across different interpreters, and fatigue. After the success of deep learning in other real world application, it is also providing exciting solutions with good accuracy for medical imaging and is seen as a key method for future applications in health sector. Deep neural networks are now the state-of-the-art machine learning models across a variety of areas, from image analysis to natural language processing, and widely deployed in academia and industry. These developments have a huge potential for medical imaging technology ,medical data analysis, medical diagnostics and healthcare in general, slowly being realized. We provide a short overview of recent advances and some associated challenges in machine learning applied to medical image processing and image analysis. As this has become a very broad and fast expanding field we will not survey the entire landscape of applications, but put particular focus on deep learning in MRI.

1. INTRODUCTION

Machine Learning (ML) and Artificial Intelligence (AI) have progressed rapidly in recent years. Techniques of ML and AI have played important role in medical field like medical image processing, computer-aided diagnosis, image interpretation, image fusion, image registration, image segmentation, image- guided therapy, image retrieval and analysis Techniques of ML extract information from the images and represents information effectively and efficiently. The ML and AI facilitate and assist doctors that they can diagnose and predict accurate and faster the risk of diseases and prevent them in time. These techniques enhance the abilities of doctors and researchers to under- stand that how to analyze the generic variations which will lead to disease. These techniques composed of conventional algorithms without learning like Support Vector Machine (SVM), Neural Network (NN), KNN etc. and deep learning algorithms such as Convolution Neural Network (CNN), Recur-rent neural Network (RNN), Long Short term Memory (LSTM), Extreme Learning Model (ELM), Generative Adversarial Networks (GANs) etc. Former algorithms are limited in processing the natural images in their raw form, time consuming, based on expert knowledge and requires a lot of time for tuning the features. The later algorithms are fed with raw data, automatic features learner and fast. These algorithms try to learn multiple levels of abstraction, representation and information automatically from large set of images that exhibit the desired behavior of data. Although automated detection of diseases based on conventional methods in medical imaging has been shown significant accuracies around for decades, but new advances in machine learning techniques have ignited a boom in the deep learning. Deep learning based algorithms showed promising performance as well speed in different do-mains like speech recognition, text recognition, lips reading, computer-aided diagnosis, face recognition, drug discovery. The study about deep learning based algorithms in medical image analysis, provides the fundamental knowledge and the state of the art approaches about deep learning in the domain of medical image processing and analysis.

2. LITERATURESURVEY

The symbolic AI paradigm ofthe1970s led to the development of rule-based, expert systems. One early implementation in medicine was the MYCIN system by Shortleaf, which suggested different regimes of antibiotic therapies for patients. Parallel to these developments, AI algorithms moved from heuristics-based techniques to manual, hand-crafted feature extraction techniques. and then to supervised learning techniques. Unsupervised machine learning methods are also being researched, but the majority of the algorithms from 2015-2017 in the published literature have employed supervised learning methods, namely Convolution Neural Networks (CNN). Aside from the availability of large labeled data sets being available, hardware advancements in Graphical Processing Units (GPUs) have also led to improvements in CNN performance, and their widespread use in medical image analysis.

McCulloch and Pitts described the artificial neuron in 1943, which developed into the perception posited by Rosenblatt [6] in 1958. In essence, an artificial neural network is a layer of connected perceptions linking inputs and outputs, and deep neural networks are multiple layers of artificial neural networks. The advantage of a deep neural network is its ability to automatically learn significant low level features (such as lines or edges), and amalgamate them to higher level features (such as shapes) in the subsequent layers. Interestingly, this is how the mammalian and human

Visual cortices are thought to process visual information and recognize objects. CNNs may have their origins in the Neo cognition concept proposedbyFukushimain1982,butitwasLecun *et al.* who formalized CNNs and used the error back propagation described by Rumelhart*et al.*, to successfully perform the automatic recognition of hand-written digits. The widespread use of CNNs in image recognition came about after Krizhevsky *et al.* [11] won the 2012 Image net Large Scale Visual Recognition Challenge (ILSVRC) with a CNN that had a 15% error rate. The runner up had almost double the error rate at 26%. Krizhevsky *et al.* introduced signicant concepts that are used in CNNs today, including the use of Rectified Linear Unit (RELU) functions in CNNs, data augmentation and dropout. Since then, CNNs have featured as the most used architecture in every ILSVRC competition, surpassing human performance at recognizing images in 2015. Correspondingly, There has been a dramatic increase in the number of research papers published on CNN architecture and applications, such that CNNs have become the dominant architecture in medical image analysis.

3. PROPOSEDWORK

Traditionally, machine learning models are trained to per-form useful tasks based on manually designed features extracted from the raw data, or features learned by other simple machine learning models. In deep learning, the computers learn useful representations and features automatically, directly from the raw data, bypassing this manual and difficult step. By far the most common models in deep learning are various variants of artificial neural networks, but there are others. The main common characteristic of deep learning methods is their focus on feature learning: automatically learning representations of data. This is the primary difference between deep learning approaches and more “classical” machine learning. Discovering features and performing a task is merged into one problem, and therefore both improved during the same training process.

In medical imaging the interest in deep learning is mostly triggered by Convolutional neural networks (CNNs), a powerful way to learn useful representations of images and other structured data. Before it became possible to use CNN sufficiently, these features typically had to be engineered by hand, or created by less powerful machine learning models. Once it became possible to use features learned directly from the data, many of the handcrafted image features were typically left by the wayside as they turned out to be almost worthless compared to feature detectors found by CNNs. There are some strong preferences embedded in CNNs based on how they are constructed, which helps us understand why they are so powerful. Let us therefore take a look at the building blocks of CNNs.

Convolutional neural networks

When applying neural networks to images one can in principle use the simple feed forward neural networks discussed above. However, having connections from all nodes of one layer to all nodes in the next is extremely inefficient. A careful pruning of the connections based on domain knowledge, i.e. the structure of images, leads to much better performance. A CNN is a particular kind of artificial neural network aimed at preserving spatial relationships in the data, with very few connections between the layers. The input to a CNN is arranged in a grid structure and then fed through layers that preserve these relationships, each layer operation operating on a small region of the previous layer (Fig. 2). CNNs are able to form highly efficient representation of the input data,16 well-suited for image-oriented tasks. A CNN has multiple layers of convolutions and activations, often interspersed with pooling layers, and is trained using back propagation and gradient descent as for standard artificial neural networks.

Convolutional layers:

In the Convolutional layers the activations from the previous layers are convolved with a set of small

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parameterized *filters*, frequently of size 3 × 3, collected in a tensor $W^{(j,i)}$, where j is the filter number and i is the layer number. Byhaving each filter share the exact same weights across the whole input domain, i.e. translational equivariance at each layer, one achieves a drastic reduction in the number of weights that need to

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be learned. The motivation for this weight- sharing is that features appearing in one part of the image likely also appear in other parts.

Activation layer:

The feature maps from a Convolutional layer are fed through nonlinear activation functions. This makes it possible for the entire neural network to approximate almost any nonlinear function.

Pooling:

Each feature map produced by feeding the data through one or more convolutional layer is then typically pooled in a *pooling layer*. Pooling operations take small grid regions as input and produce single numbers for each region. The number is usually computed by using the max function (*max-pooling*) or the average function (*average pooling*).Since a small shift of the input image results in small changes in the activation maps, the pooling layers gives the CNN some translational invariance.

Drop out regularization:

A simple idea that gave a huge boost in the performance of CNNs. By averaging several models in an ensemble one tend to get better performance than when using single models. Dropout [62] is an aver-aging technique based on stochastic sampling of neural networks.[20] By randomly removing neurons during training one ends up using slightly different networks for each batch of training data, and the weights of the trained network are tuned based on optimization of multiple variations of the network.

Batch normalization:

These layers are typically placed after activation layers, producing normalized activation maps by subtracting the mean and dividing by the standard deviation for each training batch. Including batch normalization layers forces the network to periodically change its activations to zero mean and unit standard deviation as the training batch hits these layers, which works as a regularize for the network, speeds up training, and makes it less dependent on careful parameter initialization.

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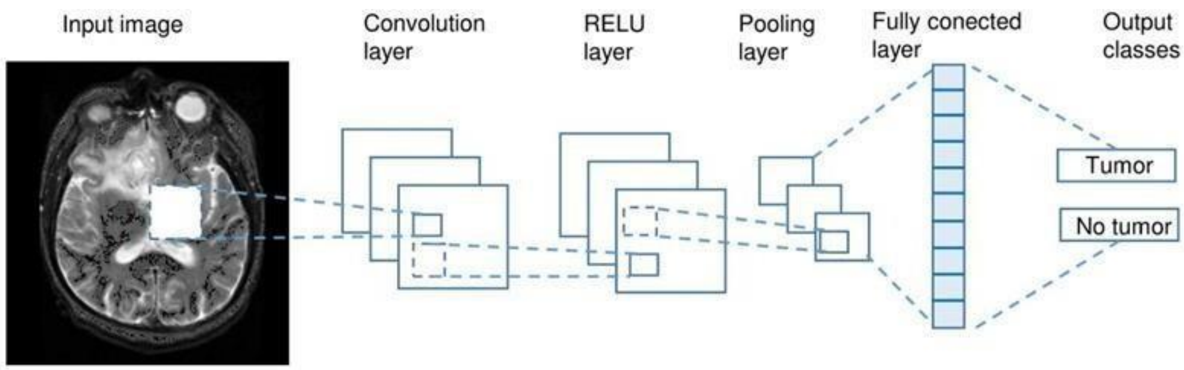

Fig: Basic Structure of CNN

Deep learning, medical imaging and MRI

Deep learning methods are increasingly used to Improve clinical practice, and the list of examples are long, growing daily. We will not attempt a comprehensive overview of deep learning in medical imaging, but merely sketch some of the landscape before going into a more systematic exposition of deep learning in MRI.

A.CLASSIFICATION

Using *variation networks* for single-shot fast spin-echo MRI with variable density sampling, Chenet al.enabled real-time(200msper section) image reconstruction, outperforming conventional parallel imaging and compressed sensing reconstruction. The authors explored the potential for *transfer learning* (pertained models) and assessed the generalization of learned image reconstruction regarding image contrast, SNR, sampling pat-tern and image content, using a variation network and true measurement *k*-space data from patient knee MRI recordings and synthetic *k*-space data generated from images in the Berkeley Segmentation Data Set and Benchmarks. Employing least-squares generative adversarial networks (GANs) that learns texture details and suppresses high-frequency noise, created a novel compressed sensing framework that can produce diagnostic quality reconstructions "on the fly" (30 ms). A unified framework for image reconstruction, called *automated transform by manifold approximation* (AUTOMAP) consisting of a feed forward deep neural network with fully connected layers followed by a sparse Convolutional auto encoder, formulate image reconstruction generically as a data-driven supervised learning task that generates a mapping between the sensor and the image domain based on an appropriate collection of training data (e.g. MRI examinations collected from the Human Connective Project, transformed to the *k*-space sensor domain)

LOCALIZATION and DETECTION

Localization

Localization of normal anatomy is less likely to interest the practicing clinician although applications may arise in anatomy education. Alternatively, localization may and use in fully automated end-to-end applications, whereby the radiological image is autonomously analyzed and reported without any human intervention. Yan *et al.* looked at transverse CT image slices and constructed a two stage CNN where the rest stage identified local patches, and the second stage discriminated the local patches by various body organs, achieving better results than a standard CNN.

Image segmentation

Image segmentation, the holy grail of quantitative image analysis, is the process of partitioning an image into multiple regions that share similar attributes, enabling localization and quantification.[39] It has an almost 50 years long history, and has become the biggest target for deep learning approaches in medical imaging. The multispectral tissue classification report by Vannier et al. in 1985, using statistical pat-tern recognition techniques (and satellite image processing software from NASA), represented one of the most seminal works leading up to today's machine learning in medical imaging segmentation. In this early era, we also had the opportunity to contribute with supervised and unsupervised machine learning approaches for MR image segmentation and tissue classification. An impressive range of segmentation methods and approaches have been reported (especiallyfor brain segmentation) and reviewed, e.g.. MR image segmentation using deep learning approaches, typically CNNs, are now penetrating the whole field of applications.

4. CONCLUSION

Medical image analysis is an active eld of research for machine learning, partly because the data is relatively structured and labeled, and it is likely that this will be the area where patient's rst interact with functioning, practical artificial intelligence systems. This is significant for two reasons. Firstly, in terms of actual patient metrics, medical image analysis is a litmus test as to whether artificial intelligence systems will actually improve patient outcomes and survival. Secondly, it provides a test bed for human-AI interaction, of how receptive patients will be towards health-altering choices being made, or assisted by a non-human actor. . The success of machine learning algorithms at computer vision tasks in recent years comes at an opportune time when medical records are increasingly digitalized. The use of electronic health records (EHR) quadrupled very high.

5. REFERENCES

[1] C.-J. Hsiao, E. Hing, and J. Ashman, ''Trends in electronic health record system use among of ce- based physicians: United states, 2007 2012,''Nat. Health Stat. Rep., vol. 75, pp. 1 18, May 2014.
[2] R. Smith-Bind man et al., ''Use of diagnostic imaging studies and asso-ciated radiation exposure for patients enrolled in large integrated health care systems, 1996 2010,'' JAMA, vol. 307, no. 22, pp. 2400 2409, 2012.
[3] E. H. Short liffe, Computer-Based Medical Consultations:MYCIN,vol.2.NewYork,NY, USA: Elsevier, 1976.
[4] G.Litjensetal.(Jun.2017).''Asurveyondeep learning in medical image analysis.'' [Online]. Available:https://arxiv.org/abs/1702.05747

[5] W.S.McCulloch and W.Pitts,''A logical calculus of the ideas immanent in nervousactivity,''Bull.Math.Biol.,vol.5,nos.4,pp. 115 133, 1943.

[6] F. Rosenblatt, ''The perception: A probabilistic model for information storage and organization in the brain,'' Psychol. Rev., vol. 65, no. 6, pp. 365 386, 1958.

[7]D. H. Hubel and T. N. Wiesel, ''Receptive elds, binocular interaction and functional architecture in the cat's visual cortex,'' J.Physiol., vol. 160, no. 1, pp. 106 154, 1962.

[8]K. Fukushima and S. Miyake, ''Neocognitron: A self-organizing neural network model for a mechanism of visual pattern recognition,'' in Compe-tition and Cooperation in Neural Nets. Berlin, Germany: Springer, 1982, pp.267 285.

[9]Y.LeCunetal.,''Back propagation applied to handwritten zip code recognition,'' Neural Comput., vol. 1, no. 4, pp. 541 551, 1989.

[10] D. E. Rumelhart, G. E. Hinton, and R. J. Williams, ''Learning repre-sentations by back- propagating errors,'' Nature, vol. 323, pp.533 536, Oct. 1986.

[11] A. Krizhevsky, I. Sutskever, and G.E. Hinton, ''Image Net classification with deep convolutional neural networks,'' in Proc. Adv. Neural Inf. Process. Syst., 2012, pp. 1097 1105.