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Deep Learning Performance on Medical Image, Data and Signals

A Review of Recent Studies

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Abstract

In this study, the recent medical studies with deep learning between 2009-2019 have been researched for observing the performance of deep learning on medical images, data and signal. Recent studies attained from Web of Science have been evaluated and selected according to the citation numbers. Studies have been listed as a table, according to the publication year, deep network structure, database used training and testing, evaluation metric and results. The studies have also been classified into the organs and the types of important diagnosis. The results have shown that the deep learning network structures, applied on fundus images, have attained nearly %99 percent accuracy. Although most of the studies between the range, made by Radiology and Nuclear Medicine Imaging, the accuracy of the results are 80-90% range. The current studies especially focus on automatic detection or classification of the tumor as benign or malign. Studies are mostly on medical CT, ultrasound, radiography and MRI images. This results show that computer aided medical diagnosis systems will be used in a very near future with fully performance.

Keywords: medical data, deep learning, convolutional neural networks

Tıbbı Görüntü, Veri ve Sinyaller Üzerinde Derin Öğrenme Performansları

Öz

Bu çalışmada, 2009-2019 yılları arasında Tıpta derin öğrenme ile ilgili yapılmış çalışmalar, derin öğrenmenin Tıbbı görüntü, veri ve sinyaller üzerine başarısını gözlemlemek için araştırılmıştır. Web of Science'tan elde edilen çalışmalar değerlendirilmiş ve atıf sayısına göre seçilmişlerdir. Çalışmalar yayın yılı, derin ağ yapısı, kullanılan veritabanı ve değerlendirme kriterine göre tablo haline getirilmiştir. Çalışmalar organlara göre ve tanılara göre de sınıflandırılmıştır. Sonuçlar retinal fundus görüntüleri uygulanan derin öğrenme ağ yapılarının doğruluklarının %99'lara ulaştığını göstemektedir. Bu aralıktaki çalışmaların çoğu radyoloji ve nükleer tıp alanında yapılmış olsa de sonuçlar henüz %80-90 aralığında görülmektedir. Yapılan çalışmalar özellikle tümörlerin otomatik tesbiti veya tümörlerin iyi veya kötü huylu olarak sınıflandırılması üzerinedir. Çalışmalar çoğunlukla tıbbı tomografi, ultrases, radyografi ve manyetik resonans görüntüler üzerinedir. Bu sonuçlar bilgisayar destekli teşhis sistemlerinin çok yakın bir gelecekte tam performans ile kullanılacağını göstermektedir.

Anahtar kelimeler: Tıbbi veri, derin öğrenme, konvolusyonel sinirsel ağlar

1. Introduction

Learning can be thought of as a "Two-step process involving the reception and processing of information. In the reception step, external information and internal information become available and a learner, who select the material he/she will process and ignore the rest. The processing step involves simple memorization or inductive or deductive reasoning, reflection or action, and introspection or interaction with others." The outcome is that the material is either "learned" or not learned [1].

Machine learning is also defined as two-step process, similar to the educational definition of learning. In the first step, external data is shown to the machine. But different from the human, machine can't select the features which are useful for learning. So feature extraction is applied, before the learning process. For example, a student, listening her/his teacher in order to learn a topic, takes notes for increasing the percentage of learning. But, machine learning methods process the extracted features of the data. So machine learning methods require the help of human.

Representation learning allows a machine to be fed with raw data and to automatically discover the representations needed for detection or classification like human. Deep-learning methods are representation-learning methods. Multiple levels of layers, extract feature and abstract data. As a result, very complex functions can be learned [2]. Since deep learning methods requires a very little effort for learning process, there is an increasing trend using deep learning in medical studies in recent years.

This review focuses especially the deep learning methods in Medical Studies. So the other, artificial intelligence methods used in the medical studies are excluded. But researchers can reach a very detailed manuscript, published by Kononenko [3]. Studies between 2009-2019 have been researched. Researches have been done with the "Medical deep learning" keywords in Web of Science [4]. While the total 1923 studies are from 1991 to 2019, the number of the studies between 2009-25.03.2019 is 1735. The studies are categorized into different criterias. 1032 articles and 593 conference papers and 103 reviews have been published between this range. Average citation per item has been found as 7.55.

Most of the studies with deep learning are related to ophthalmology [5-9]. The studies on deep learning have been published by the departments of radiolaogy, nuclear medicine, optics, surgery and obstetrics gynecology, respectively. The studies are classified into detection [9,10], recognition[11], classification [12], and segmentation [13].

The detection studies are mostly on automatic detection via deep learning. Detection of diabetic retinopaty [5], chest patology detection [30], microcalcification detection [47], pulmonary nodule detection [48,49], lesion detection [50], lung nodule detection [51], pulmonary cancer detection [52], detection of thyroid nodules [53], polyp detection [54] are some of the detection studies. Some of the studies on recognition are body parts recognition [55], automatic recognition of severity level for diagnosis of diabetic retinopathy[11], different cardiac diases pattern recognition[56] and teeth recognition[57]. Classification studies consist ECG signal classification[31], lung pattern classification[25], Mammographic tumor classification[35]. Most of the recent studies focus on segmentation, such as brain tumor segmentation [27],pancreas segmentation[33] and left ventricle segmentation[39].

The network architecture, used in these studies, are generally, CNN(Convolutional Neural Network)[23-25], RNN(Recurrent Neural Network), AE(Auto Encoders)[40] and DBN(Deep Blief Network)[39].

The rest of this review is detailed as followed. In Section 2, deep learning is introduced. In Section 3, deep learning in medical studies is overviewed. And lastly, the results of the articles reviewed here have been interpreted with a general perspective.

2. Deep Learning

Deep learning is a general definition of a class of algorithms which optimize the neural network to be able to work with unstructured data [14]. Neural learning networks have been based on synapses of a general type described by Hebb and Eccles [15-17]. The classical neural learning network is combination of the perceptron, which composed of inputs, weights, activation function and output. Networks are designed as multi-layers. Each layer consists of a number of perceptrons. Neural network, used for classification, requires processed data, to be able to perform well. In visual processing, for example, feature extraction should previously have been done [17]. Deep-network architecture is a multilayer neural network to be able to accept unstructured raw data, such as images, voice, videos and text. In the CNN architecture, Convolutional Layers, Rectified Linear Unit (RELU), Pooling Layers and Fully Connected Layers are used for creating a multi-layer deep convolutional neural network. Convolution layer, compute the output of neurons that are connected to the input. RELU is the activation function. Pooling layers, progressively reduce the spatial size of the representation to reduce the computation. The Fully connected layers calculate the output label percentage [18]. Convolutional Neural netwok (CNN), Unsupervised Pretrained Networks (UPN), Recurrent Neural Networks (RNN) and Recursive Neural Networks are deep neural network architectures. A sample Convolutional Neural Network architecture has been shown in Figure 1.

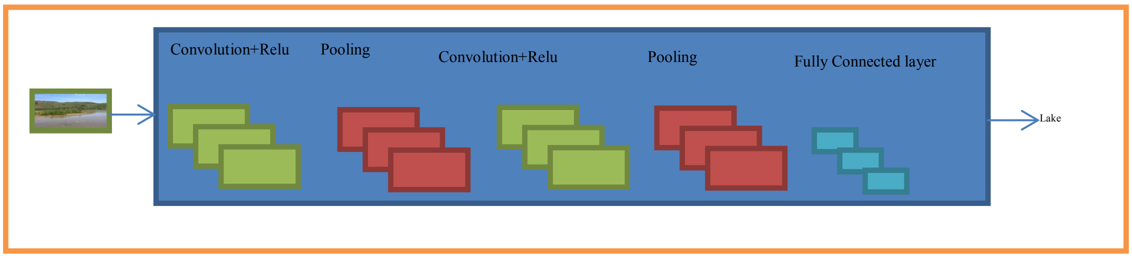

Figure 1 Convolutional Neural Network Layers

In recent years, a lot of pre-trained CNNs are available for researchers to implement their studies. These networks have been trained with millions of images, such as ImageNet[19]. The most popular ones are Mathworks, AlexNET, GoogLeNet, VGG-Net and ResNets[20].

The learning process of network has two main steps as training and testing. In training step, inputs are fed with data and output labels are shown.

The training is to adapt the network weights to provide the desired output for a given input. Each layer has been trained for a number of sweeps through the training set, which is called “epochs” [21]. The performance of the learning is tested with test data. Specifity, Sensitivity, accuracy and AUC(Area of ROC Curve) are most used performance evaluation metrics. Specifity, Sensitivity and Accuracy formulations have been given in Equation 1, 2 and 3 respectively. AUC is more preferred than accuracy [22].

$$Specifity = \frac{TN}{TN + FP} \tag{1}$$

$$Sensitivity = \frac{TP}{TP + FN} \tag{2}$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{3}$$

TP: Positives correctly classified

TN: Negatives correctly classified

FP: Negatives incorrectly classified

FN: Positives incorrectly classified

AUC was proposed for evaluation of machine learning performance in recent years, even if it was popular for medical diagnosis studies[22].

3. Deep Learning in Medical Studies

Deep learning is a subclass of machine learning methods that are increasing their accuracy in a lot of different areas, including computer vision, speech recognition, natural language processing[58]. The articles found with medical deep learning keywords at WebofScience have been evaluated in this study. In Medical deep learning studies between 2009-2019 have been classified as given in figure 2.

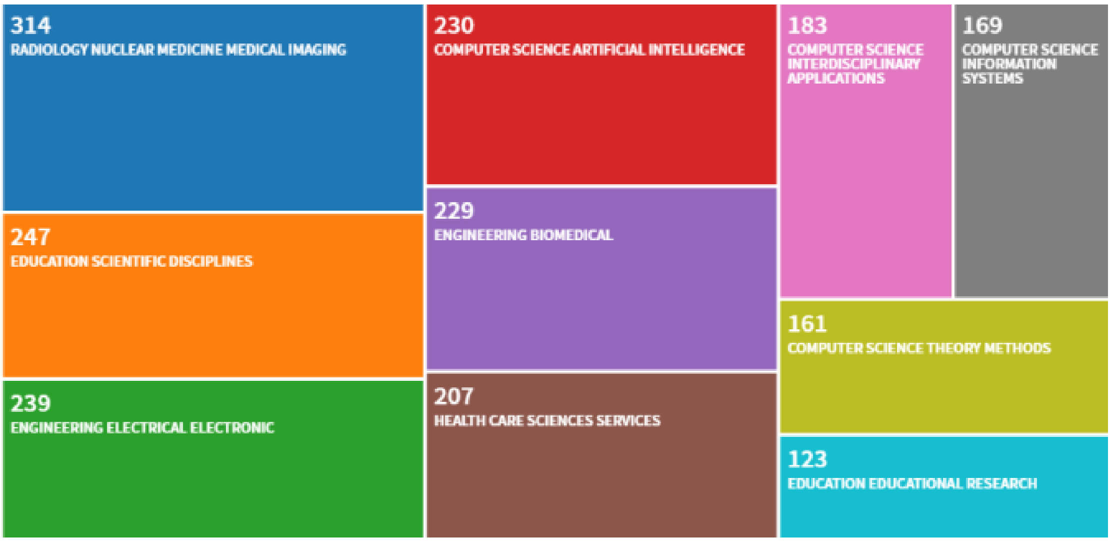

Figure 2 The Categories of Medical Deep Learning Studies[4]

As it has been seen in the Figure 2, the higher percentage of the studies has been done in Radiology and Nuclear Medicine Medical Imaging. The number of the studies published in each year between the ranges has been shown in Figure 3.

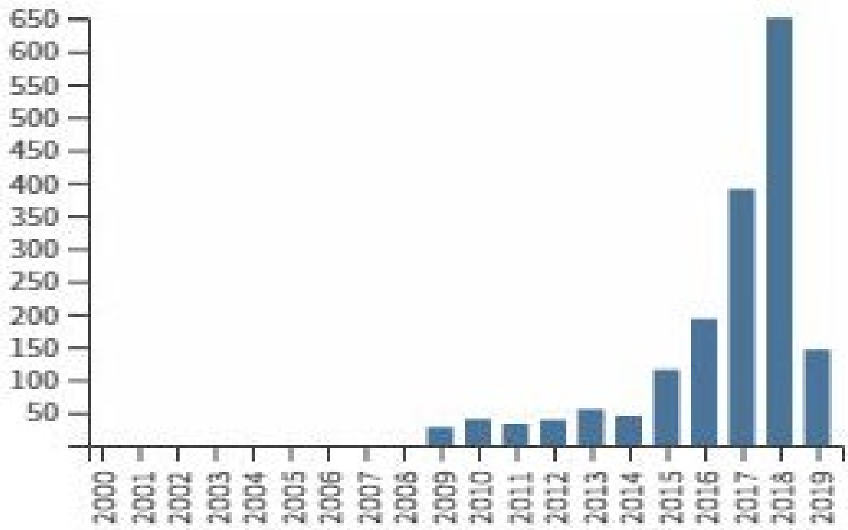

Figure 3 Total Publications by Year[4]

As seen in the Figure 3, the studies on deep learning have boomed in last year. According to this graphic, it is certain that, this trend will also increase in 2019. The studies mostly are carried out last four years. The most cited articles have been given in the Table 1.

Table 1 The Most Cited Medical Deep Learning Studies

No	**Pub. Year, Cited by**	**Topic**	**Network and Dataset**	**Success**
[5]	12-2016, *429*	Detection of diabetic retinopathy in retinal fundus images	CNN EyePACS-1 Mesidor-2	Sensitivity:0.975 Sensitivity:0.961
[24]	2-2017, *249*	Brain lesion segmentation	3D CNN BRATS 2015 ISLES 2015	Sensitivity:0.885 Sensitivity: 0. 876

Table 1 The Most Cited Medical Deep Learning Studies (Continue)

No	Pub. Year, Cited by	Topic	Network and Dataset	Success
[25]	5-2016, *145*	Lung pattern classification	CNN 14696 image ,120 CT scans	Accuracy:0.855
[26]	2013, *130*	Knee cartilage segmentation	CNN 114 MRI	Specifity:0.9997
[27]	5-2016, *250*	Brain Tumor Segmentation	CNN BRATS 2013 BRATS 2015	Sensitivity:0.89 Sensitivity:0.78
[28]	01-2017, *261*	Brain Tumor Segmentation	DNN BRATS2013	Specifity:0.88
[29]	10-2016, *155*	Volumetric Medical Image Segmentation	Fully CNN PROMISE 2012	Dice:0.869
[30]	2015, *62*	Pathology detection	CNN Chest X-Ray dataset	AUC:0.87-0.94
[31]	2016, *77*	ECG classification	DNN MIT-BIH Arrhythmia Database	AUC:0.996
[32]	2015, *337*	DNA sequence prediction	Deep Network -	DeepFind AUC: 0.73
[33]	2015, *71*	Pancreas Segmentation	Deep CNN ConvNet Medical Image Dataset	Dice:0.836 training 0. 718 test
[34]	9-2015, *67*	Standard plane localization in fetal ultrasound	CNN 1991 positive samples 3160 negative	Accuracy:0.904
[35]	9-2016, *49*	Mammographic tumor classification	CNN 219 breast lesions (607 image)	AUC:0.81
[7]	6-2017, *44*	Identification of diabetic retinopathy	DR Deep learning tool Messidor 2 E-Optha	AUC:0.97
[37]	2016, 37	Retinal vessel segmentation	Fully-connected conditional random fields DRIVE STARE	Accuracy:0.9470 Accuracy:0.9545
[38]	3-2018, 38	Prediction of cardiovascular risk	Soft-attention UK Biobank clinical validation set EyePACS-2K clinical validation set	AUC:0.97
[39]	3-2012, *51*	Left ventricle segmentation	Deep Blief Network 400 annoted image	AUC:0.95
[40]	12-2018, *5*	ECG signal compression	MIT-BIH Deep convolutional autoencoder	Compression ratio:32.25%

This table shows that the most cited and successful studies are on retinal fundus images. Medical image segmentation studies are lively topic for deep learning, since the accuracy is nearly 80-90%. And the most cited reviews have been given in Table 2.

Table 2 The Most Cited Reviews

Ref.	Publication Year	Cited by	Topic
[41]	5-2016	443	CNN in medical image analysis
[42]	12-2017	340	Deep learning in medical image analysis
[43]	5-2016	256	CNN in medical image analysis
[44]	5-2016	236	Deep learning in medical imaging
[45]	2017	158	Deep learning in medical image analysis
[46]	2016	28	MRI-based brain tumor image segmentation using deep learning methods

In order to evaluate the studies, brain, cardiac, pulmonary, hepatic and fundus keywords have been researched in the studies. The number of the studies for each organ has been given in Table 3.

Table 3 The Medical Deep Learning Studies Classification According to Organs

Organ	Most Cited Refs	Topics	Imaging Techniques + Network Architecture
Brain (167)	249	Brain lesion segmentation[24]	Multi Modal Brain MRI+CNN
	30	Brain Segmentation [59]	Brain MRI+Voxelwise residual network
	14	Brain region segmentation[60]	MRI+Ultrasound+Hough CNN
	5	Image Classification[61]	CT+ DNN(Deep Neural Network)
	12	Prediction of MGMT Methylation Status[62]	MRI+ResNET
	2	Brain Hemorrhage [63] .	CT+CNN
Cardiac (47)	50	Segmentation of left ventricle[64]	MRI+Level Set+DBN
	2	Ventricle segmentation[65]	MRI+CNN
	0	Assessment of myocardial infarction[66]	MR+CNN
Pulmonary (53)	97	Pulmonary nodule diagnosis[67]	CT+CNN
	37	Automatic detection of pulmonary nodules[68]	CT
	24	Detection of abnormalities on chest radiograph[69]	Radiograph+CNN
	21	Automatic scoring of multiple semantic attributes on pulmonary nodules[70]	CT
Hepatic Liver (8)	1	Classification of mice hepatic granuloma[71]	Microscopic Images+ CNN
	1	Liver lesion classification[72]	CNN
Retinal (58)	429	Detection of diabetic retinopathy in retinal fundus images[5]	Retinal fundus images+CNN
	63	Deep learning system for diabetic retinopathy[36]	DR Deep Learning Tool
	37	Retinal vessel segmentation[37]	Fully-connected conditional random fields
	1	Detecting diabetic retinopathy[23]	Retinal fundus images+CNN

According to the results, brain image segmentation is the mostly studied topic for tumor classification. 73 of the 167 studies are on segmentation. Studies have not been focused exactly on specific disease. But there are studies focused on epileptic seizure[73], Alzheimer[74] migraine [75] and Parkinson. The studies on cardiac are especially on ventricle segmentation [64,65] and tracking [76]. The studies carried out on lung are the lung nodule detection, classification and cancer detection on CT imaging and radiograph. The studies focus on diagnosis of some disease with deep learning. Table 4 shows some diagnosis keywords and the number of the studies carried out for this diagnosis on medical images. The number of the studies for each keyword given in Table 4, is not exactly different from each other. Some of the studies have been counted on more then one diagnosis item. The title of the studies combine the three subtitles given in the tables (Table 1,3,4). For example “Brain tumor segmentation” combines three classification categories given in the tables.

Table 4 Some Important Diagnosis Keywords and The Studies Carried Out For These Diagnoses with Deep Learning

Diagnosis	**The number of studies with Deep Learning**
Hemorrage [10]	13
Nodule[77]	63
Polyp[78]	20
Tumor[79]	115
Cancer[80]	244
Calcification[81]	8

Results

Even if convolutional neural networks have been proposed nearly for 25 years, due to the computers power, they have been popular for last decade. So in this study, the articles published between 2009-2019 have been researched. Recent studies on deep learning have shown promising results on medical data. So in the very near feature, the medical diagnosis support systems using deep learning will increase. The most successful studies are on retinal fundus images. The success of the recent studies on retinal fundus images is nearly 100%. The second success is belong to ECG signal classification studies. Tumor segmentation studies are between 80-90% successes. So, medical image segmentation will continue to be studied. Researchers focus on the detection of hemorrage, inflammation, nodule, polyp, calsification, cancer or tumor. The succes of those diagnosis will increase with the increasing rate of accuracy of segmentation on related medical images.

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