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Deep Learning for Medical Diagnosis

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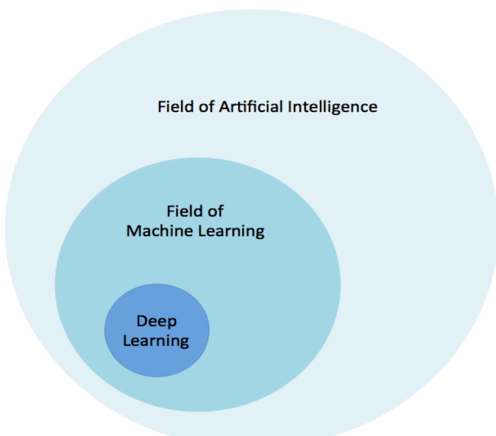
Abstract: **Deep Learning is a sub-area of Machine Learning, which deals with the recognition, processing, interpretation and classification of images, text, speech, etc. Disease identification and diagnosis of ailments is at the forefront of ML research in medicine. It is especially interesting for the medical field, which conducts the analysis and diagnostics based mainly on images. A wide variety of technologies and tools are involved in the diagnostic process like the Health IT. Health IT plays key roles in various aspects of the diagnostic process: capturing information about a patient that informs the diagnostic process, including the clinical history and interview, physical exam, and diagnostic testing results; shaping a clinician's workflow and decision making in the diagnostic process; and facilitating information exchange. This iterative, time-consuming process is costly as it causes threat to many people's lives. Deep Learning aims at delivering faster, accurate medical diagnostic services for patients. The potential of this technique not only assists in medical decisions and the accuracy of the diagnosis, but also assists the medical specialist to suggest treatment measures to improve speed and performance.**

INTRODUCTION

Embedding a secret image is an efficient and robust Recruitment is a core function of human resources
With massive amounts of computational power, machines can now recognize objects and translate speech in real time. Artificial intelligence is finally getting smart. Deep 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, partially supervised or unsupervised.



When programmable computers were first conceived, people wondered whether such machines might become intelligent, over a hundred years before one was built. Today, artificial intelligence (AI) is a thriving field with many practical applications and active research topics. We look to intelligent software to automate routine labor, understand speech or images, make diagnoses in medicine and support basic scientific research.

WHAT IS MEDICAL DIAGNOSIS?

Medical diagnosis is the process of determining which disease or condition explains a person's symptoms and signs It is most often referred to as diagnosis with the medical context being implicit. The information required for diagnosis is typically collected from a history and physical examination of the person seeking medical care. Often, one or more diagnostic procedures, such as diagnostic tests are also done during the process.

MEDICAL DIAGNOSIS AND ITS IMPORTANCE IN THE HEALTH FIELD

A diagnostic error may result in the patient being denied timely, effectively therapy or being administered potentially toxic, incorrect medications. Where a prompt treatment could have returned a patient to full health, the consequences of a wrong diagnosis can be devastating. Getting the right diagnosis is key for the patient. In addition to being made in timely fashion, the diagnosis and implications must be communicated effectively. The key issues are timeliness and accuracy. Timing may be minutes in acute situations or weeks in relation to sub-acute disorders. Over diagnosis is also a concern. This is when a condition is diagnosed that does not go to cause any symptoms or ill health. This can result in the blurring of the borders between health and disease. While over diagnosis is not an error, it can result in harm, over treatment and unnecessary anxiety. It is increasingly being accepted that patients are central to the solution and that good diagnostic systems are collaborative effort. It is more frequently being asked whether doctors spend sufficient time talking to patients in order to pick up important cures about their symptoms. Studies have found

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that experienced nurses accumulate more cues from a patient than their novice counterparts.

MEDICAL IMAGING:- COMPUTERAIDED DETECTION/DIAGNOSIS

Background: -

The practice of radiology consists of (a) looking at an image (visual perception) and then (b) interpreting what is seen (cognition). Numerous studies have shown that radiographic abnormalities that are clearly present on an image are, at times, not reported. To address this, strategies such as double reading have been selectively used, such as in screening mammography, which yield an increase in the cancer detection rate. This, however, is labor intensive and is thus not widely used, except when mandated by medical or government agencies.

The primary goal of CAD is to increase the detection of disease by reducing the false negative rate due to observational oversights. The use of a computer rather than a second human observer has the advantage of not increasing the demands on the radiologist (or trained observer) pool. An important aspect of either approach is to increase disease detection without an undo impact on the recall and work up rates. Finally, in some applications CAD, with its associated automated software tools, has the potential to provide workflow efficiencies. This latter application is beyond the scope of this overview.

CAD algorithms are developed to search for the same features that a radiologist looks for during case review. Thus, for breast cancer on mammograms, the CAD algorithms search for macrocalcifications and masses (both spiculated and non-speculated, architectural distortions and asymmetries). On chest radiographs and CT scans, current CAD applications search for pulmonary densities that possess certain physical characteristics, e.g. sphericity, that might represent lung nodules.

Clinical implementation of CAD

The CAD algorithms require a digital data set of the image for analysis. If the image is acquired on x-ray film, such as a film-screen mammogram, the analog image must first be digitized. However, the CAD algorithms can directly analyze images acquired in digital format, such as with digital mammography (FFDM) and CT.

In current practice (and as required by the FDA), the exam should first be reviewed and interpreted in the usual fashion. Only then are the CAD marks displayed, following which the radiologist re-reviews those areas that are prompted by the CAD system. Two important principles must be adhered to:

- Current CAD systems do not mark all actionable findings. Therefore, the absence of a CAD mark on a finding the radiologist was concerned about on his/her pre-CAD review must not deter further evaluation.
- Current CAD systems generate many more false CAD marks than true CAD marks. Therefore, it is the responsibility of the radiologist to determine if a CAD mark warrants further evaluation.

TISSUE CLASSIFICATION

As skin is the exterior organ of human body, cosmetic industry advances year by year. To reveal the details of skin tissue, three-dimensional medical imaging is required. Based on the idea of "readout instead of write", a new scheme named spectral classification imaging (SCI) is proposed in the present study to reduce the invasiveness by applying the reflection spectra of the sample points for three-dimensional medical imaging. Broad-band light source and the spectrometer were employed to collect the spectra curves of scanned region, which were classified into several tissue types by their cross-correlations. A colorful tissue tomography can finally be obtained by filling in each image pixel the color indicating the corresponding tissue type. The lateral/longitudinal resolutions and penetration depth were analyzed to characterize the SCI system. The lateral resolution is based on the source's diffraction limit, the longitudinal resolution is by its depth-of-focus, and the penetration depth is equivalent to its skin depth. The imaging results of an amethyst of 0.6 mm (chi-direction) x 0.6 mm (y-direction) with a total of 120 x 120 pixels per frame and a guppy fish of 3.2 mm (chi-direction) x 2.4 mm (y-direction) of 160 x 120 pixels, are presented to show the image quality. The effects of the cross-correlation coefficient and the number of source wavelengths on the imaging results were explored. The value of cross-correlation threshold determines the required time for imaging, the resulted number of tissue groups, and the variety of tissue colors in the imaging resultRGB LEDs possess merits of broad bandwidth, low cost, long lifetime, small volume, and are ready to be integrated into a multi-color source module. Replacing the wide-band light source and the spectrometer module with a composite RGB LED with discrete wavelengths and a micro-spectrometer for spectra retrieval, the system has great potential to be minimized as a hand-held product for noninvasive medical imaging. It leads to reduced use of non-eco-friendly cosmetics and extended advance of cosmetic dermatology.

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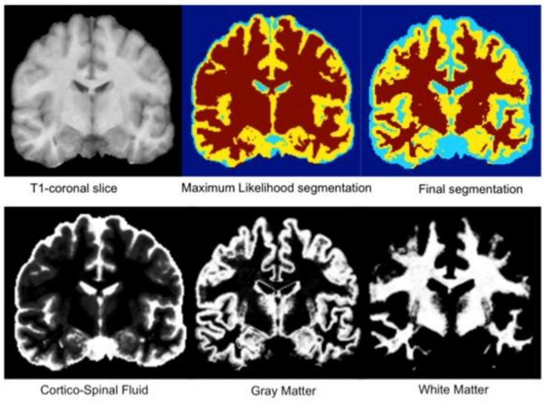

IMAGE SEGMENTATION

Segmentation is the process dividing an image into regions with similar properties such as gray level, colour, texture, brightness, and contrast. The role of segmentation is to subdivide the objects in an image; in case of medical image segmentation the aim is to:

- Study anatomical structure
- Identify Region of Interest i.e. locate tumor, lesion and other abnormalities
- Measure tissue volume to measure growth of tumor (also decrease in size of tumor with treatment)
- Help in treatment planning prior to radiation therapy; in radiation dose calculation

Automatic segmentation of medical images is a difficult task as medical images are complex in nature and rarely have any simple linear feature. Further, the output of segmentation algorithm is affected due to

- partial volume effect.
- intensity inhomogeneity
- presence of artifacts
- closeness in gray level of different soft tissue

Artifacts present in MR and CT images can be divided into three categories on the basis of image processing technique needed to rectify them: (i) artifacts needing appropriate filtering technique. For example, noise artifact, susceptibility artifact and presence of no sharp edges in the image (ii) artifact needing appropriate image restoration techniques for example motion artifacts and (iii) artifact needing specific algorithm are; partial volume, intensity inhomogeneity.
Although a number of algorithms have been proposed in the field of medical image segmentation, medical image segmentation continues to be a complex and challenging problem. Different researchers have done the classification of segmentation techniques in one or another way. At present, from the medical image processing point of view we have done the classification of segmentation techniques on the basis of gray level based and textural feature based techniques. Further, we consider artificial intelligence as tools to optimize these basic techniques to achieve accurate segmentation results. Thus, the broad classification of techniques available for segmentation of an image classified into two classes is as follows:

Methods based on gray Level features

a. Amplitude segmentation based on histogram features
b. Edge based segmentation
c. Region based segmentation

Methods based on texture features
Method based on gray level features
Amplitude segmentation based on histogram features
This includes segmentation of an image based on thresholding of histogram features and gray level thresholding is perhaps the simplest example of this technique. This is particularly suitable for an image with region or object of uniform brightness placed against a back ground of different gray level, A threshold can be applied to segment the object and background. Mathematically the threshold can be defined as follows.

ri,j={10pi,j≥Tpi,j≺T

(1)

Where $r_{i,j}$ is the resulting pixel at co-ordinate *(i, j)*, $p_{i,j}$ is the pixel of input image and *T* is the value of threshold.

Equation 1gives good results for segmentation of image with bi-modal histogram and fails in the case of an image with multi-modal histogram. Thresholding operation, defined by equation 1 is very basic and simple, and works well only when the object and background have uniform brightness of distinct gray level values respectively. This simple threshold operation does not work well at segmentation of images with multiple objects each having distinct gray level value varying over a band of values. To overcome this limitation, band thresholding based multiple thresholding operation is applied as follows:

ri,j=1 for T1<pi,j≤T2=2 for T2<pi,j≤T3=3 for T3<pi,j≤T4=k for Tk<pi,j≤Tk=0 otherwise

(2)

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Here, the K^{th} band is corresponding to object/region having pixel values in the range of T_k to T_{k+1} where T_k is the lower limit of gray level and T_{k+1} is the upper limit of Gray level band.

For application of thresholding based segmentation technique, it is required to apply the correct threshold values in order to achieve proper segmentation results, otherwise results are poor. The histogram of an image is particularly used to determine the value of threshold. The histogram of abdomen CT image is shown in Figure 1. There are three peaks (maxima) separated by two minima. The values of these minima are selected as threshold for segmentation of image; the original Abdomen CT image and corresponding segmentation result are shown in figure 2 and 3 respectively.

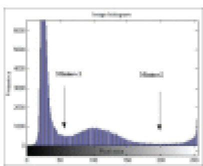

Figure 1
Image Histogram (three peaks separated by two minima)

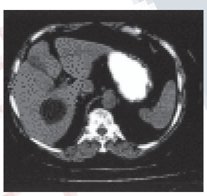

Figure 2
Original Abdomen CT Image

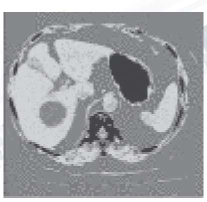

Figure 3
Segmentation of Abdomen (CT image using threshold technique)

Object 1 belongs (0 to 55)

Object 2 belongs (55 to 200)

Object 3 belongs (200 to 255)

For histogram-based optimal segmentation of images numbers of methods have been proposed by different researchers. Frank et al, have used optimal threshold selection method for segmentation of T1 weighted MR brain image to segment grey matter, white matter, and cerebra spinal fluid.

Edge based segmentation

Edge based segmentation is the most common method based on detection of edges i.e. boundaries which separate distinct regions. Edge detection method is based on marking of discontinuities in grey level, colour etc., and often these edges represent boundaries between objects. This method divides an image on the basis of boundaries.
Number of edge detecting operators based on gradient (derivative) function are available e.g. Prewitt, Sobel, Roberts (1st derivative type) and Laplacian (2nd derivative type), Canny, Marr-Hilclrath edge detector. Further, in edge based segmentation method, it is required to build the border by combining the detected edges into a edge chain in this process the spurious, or fake edges, weak edges are removed by thresholding operation. The different edge based segmentation algorithms are:

- Edge relaxation
- Border detection method
- Hough transform based

The generalized algorithm for edge based segmentation has the following steps.

1. Apply the derivative operator to detect edges of the image
2. Measure the strength of edges by measuring amplitude of the gradient
3. Retain all edge having magnitude greater than threshold T (removal of weak edge)
4. Find the position of crack edges; the crack edge is either retained or rejected based on the confidence it receives from it predecessor and successor edges
5. Step 3 and 4 are repeated with different values of threshold so as to find out the closed boundaries; segmentation of an image is achieved

Figure 4 shows the result of edge based segmentation of abdomen CT image [Figure 2], in the present result canny edge detector has been employed.

Figure 4

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Result of Edge-based Segmentation of Abdomen (CT image)

The limitations of edge based method are:

- Performance is affected by the presence of noise
- fake edges and weak edges may be present in the detected edge image which may have a negative influence on segmentation results
- Edge detection techniques are required to be used in conjunction with region-based technique for complete segmentation.

Region based segmentation

Region based methods are based on the principle of homogeneity - pixels with similar properties are clustered together to form a homogenous region. The criteria for homogeneity is most of the time grey level of pixels and this criterion can be specified by following conditions

$R1 \cup .R2 \cup . R3 \cup .... \cup . Ri=I$

where R1, R2, R3, …Ri are the region in the image I,

and further, $R1 \cap R2 \cap R3 \cap ... \cap Ri=0$

This is as per the set theory of homogeneity.

Region based segmentation is further divided into three types based on the principle of region growing:

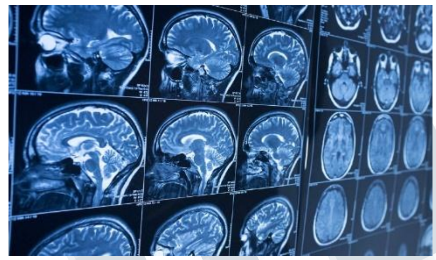
a. Region merging
b. Region splitting
c. Split and merge

Medical imaging in personalized medicine

The future of medicine lies in early diagnosis and individually tailored treatments, a concept that has been designated 'personalized medicine' (PM), which aims to deliver the right treatment to the right patient at the right time. Medical imaging has always been personalized and is fundamental to almost all aspects of PM. It is instrumental in solving clinical differential diagnoses. Imaging procedures are tailored to the clinical problem and patient characteristics. Screening for preclinical disease is done with imaging. Medical imaging procedures are tailored to the clinical problem of the patient and to patient characteristics. The main aims are to perform the right diagnostic procedure for an individual problem, to optimize the quality of the diagnostic examination and to reduce the side effects of the diagnostic procedure. All these aims fit in the concept of PM.

Lesion Detection

Computer-aided detection (CAD) is a well-established area of medical image analysis that is highly amenable to deep learning. In the standard approach to CAD, candidate lesions are detected, either by supervised methods or by classical image processing techniques such as filtering and mathematical morphology. Candidate lesions are often segmented, and described by an often-large set of hand-crafted features. A classifier is used to map the feature vectors to the probability that the candidate is an actual lesion. The straightforward way to employ deep learning instead of hand-crafted features is to train a CNN operating on a patch of image data centered on the candidate lesion.



BENEFITS OF DEEP LEARNING IN MEDICAL DIAGNOSIS

The value of deep learning systems in healthcare comes only in improving accuracy and/or increasing efficiency. Healthcare, today, is a human—machine collaboration that may ultimately become a symbiosis or even cyborg relationship. We are still at the stage, however, that we have both humans and machines each performing both tasks at which they are suboptimal. As deep learning systems develop and evolve they will more and more assist humans with those tasks at which humans are not good. So, for example, humans are very good at processing information from their senses including vision. They are very good at perceiving human emotions. But humans are not so good at remembering things, searching for and organizing data and not too good at correlating and reasoning about that data. DL systems that will make physicians and other providers faster and smarter in their diagnoses and reduce uncertainty in their decisions thereby avoiding costs and hazards and saving time.

MEDICAL IMAGING IS GOING THROUGH A DATA REVOLUTION

Worldwide, the number of medical imaging procedures being performed is increasing several times faster than the number of doctors who can interpret them. Each scan is much more complex and information-rich than it used to be. Physician workload keeps increasing, as does the amount of information that they need to process before reaching a diagnosis. In this setting, the chance of human error increases, and doctors may miss a diagnosis that is evident in hindsight.

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CONCLUSION

We consider the use of AI in medical imaging; we anticipate this technological innovation to serve as a collaborative medium in decreasing the burden and distraction from many repetitive and humdrum tasks, rather than replacing radiologists. The use of deep learning and AI in radiology is currently in the stages of infancy. One of the most important factors for the development of AI and its proper clinical adoption in radiology would be a good mutual understanding of the technology, and the most appropriate form of radiology practice and workflow by both radiologists and computer scientists/engineers. With the recent technological innovations by ImageNet, large and fully annotated databases are needed for advancing AI development in medical imaging. This will be vital for training the deep learning network, and also for its evaluation. The active involvement of many radiologists is also essential for establishing a large medical imaging database. Furthermore, there are various other issues and technical problems to solve and overcome. Finally, ethical, regulatory, and legal issues raised in the use of patient clinical image data for the development of AI should be carefully considered.

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