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Abstract:-

Radiology has been playing a vital role since the advent of digital imaging. The quintessence of medical imaging lies in comprehension the relationship between examples of vitality radiating from tissues and the basic state, i.e., healthy or infected of those tissues. This essential worldview won't change later on the medical imaging. But, the way we think about natural tissues with various types of vitality and how we draw interpretation from image information will change ceaselessly at a persistent pace. In this pace, deep learning technology entered one step ahead and it will be changing the medical imaging in a most disruptive manner. In this article, mainly discussed how the future of computer vision can make a good influence on medical data exploration using quantitative and qualitative image analytics for renovated radiology.

1. INTRODUCTION

As we are presently living in a modern computerized world, the choices and results are analysed based on the information. For experts working in the health care domain, it has turned into significant apparatus for helping the people live healthier lives and achieve positive results. Due to the increasing digital image data has additionally turned into a new substance for enhancing the work process which is important to the total health care industry. In the medical image domain, different types of scanning information provide the insights to analysts for further analysis in the medical images such as X-Ray, MRI, CT-Scan etc. This process is known as quantitative image analytics. A well-trained expert commonly deciphers the images generated through the most of the medical image processes. But this may not be accurate all the times, due to the variation of each person perception and decision. So quantitative image analytics move one step ahead and looks to perform in-depth analysis to identify the hidden patterns, which never have been recognized at all. If we integrate electronic data with the quantitative and qualitative analysis results, doctors can easily interpret patient condition for the best treatment, also helps to predict future medical problems.

Deep learning is more demanding and advanced research field in image analysis field [1]. Deep learning is an enhanced version of artificial neural networks, which consists of more layers to allow deeper levels of abstraction and enhanced predictions from the data [2 & 3]. Especially, Convolutional Neural Networks (CNNs) turned out to be more influential tool for a wide range of computer vision applications. Deep CNNs can able to learn spontaneously at different levels of abstractions from the raw images. In medical image analytics, the correct diagnosis and assessment of a disease mainly depend on both image acquisition and interpretation. While the medical imaging is progressing rapidly, deep learning in health care and imaging is continuing to thrive. Training a deep CNN from initial stage is bit difficult, because at first, CNNs need huge quantity of labelled training data, which may be difficult in the medical field. Second, training a deep CNN requires large computational and memory resources, without which the training process would be extremely time-consuming. Third, training a deep CNN is often complicated by over fitting and convergence issues, which often require repetitive adjustments in the architecture or learning parameters of the network to ensure that all layers are learning with comparable speed. Given these difficulties, several new learning schemes, “transfer learning” and “fine-tuning”, came to provide solutions and are increasingly gaining popularity. The future of deep learning is mainly focusing on a full-fledged decision and diagnostic support system designed to assist radiologists in their interpretations and physicians in their treatment decisions.

2. RELATED WORKS

In general, candidate lesions are identified, either by supervised methods or by traditional image processing methods. Setio *et al.* [4] used three earlier methods with a mixture of various CNNs to classify every candidate with small enhancement. Roth *et al.* [5] applied CNNs to advance three current CAD structures for the detection of colonic polyps on CT colonography, sclerotic spine metastases on body CT and enlarged lymph nodes on body CT. The sensitivity for lesion detection enhanced almost 13 – 34% for all three CAD systems with the use of CNNs and these enhancements would have been nearly difficult to attain without deep learning classifiers. Dou *et al.* [6] discovered cerebral micro-bleeds from vulnerability weighted MRI scans using 3D CNNs with enhanced results. Sirinu kunwattana *et al.* [7] detected and classified nuclei in histo-pathological images using CNN with small patches as input and attained significant results compared to the traditional methods.

Brosch *et al.* [8], developed a 3D deep convolutional encoder system for brain lesion segmentation on MRI and performed the best state of the art methods. Brain tumor segmentation on MRI was studied in Pereira *et al.* [9] using various CNN architectures for low and high grade tumours and achieved best results. Whenever not enough data is available, then pre-train CNN as an initialization of the network[10-14]. In Tajbakhsh *et al.*, [15] additional analysis showed that deep fine tuning led to enhanced performance over shallow fine-tuning, and the importance of using fine-tuning increases with reduced size training sets. Albarqouni *et al.* [16] used modified network that combines an combination layer that is combined into the CNN to enable learning inputs from the crowds as part of the network learning method. Unsupervised feature learning for mammography threat scoring is discussed in Kallenberg *et al.* [17]. Yan *et al.* [18] designed a multi stage deep learning framework for image classification and applied it on body part recognition. In Miao *et al.* [19], a CNN regression method is discussed in detail for real-time 2-D/3-D registration with better accuracy. Golkov *et al.* [20] used deep learning to minimize the MRI data processing to a single enhanced stage.

3. KEY ISSUES AND MAIN PROMISES

Most of the existing works were used supervised learning, but for the unsupervised data it is difficult to give annotation due to various causes. First it is tough to get funding for the construction of data sets. Second, rare and costly medical expertise is required for better quality labelling of medical images. Third, the confidentiality concerns makes more difficult to share medical images. Fourth, the wide area of medical image applications require several different data sets required. So exploration should start working on semi supervised and unsupervised learning. This unsupervised deep learning will overcome the great challenges in the health care industry in the near future.

3.1 The key risks linked with applying deep learning techniques into aging

As we all know many people are passed away due to aging and age related diseases in each year. Practically there is no specific treatments/medications for long-lasting situations, so it is time to bring deep learning and additional AI techniques in healthcare to make remarkable advancement in curing the aging problems. But the problems are high level regulations and government involvement in medical practise may risks applying the AI in some of the areas. Also the lacking of particular area expertise people may also lead negative impact on society.

3.2 What Results Can Deep Learning Actually Drive towards?

In future, deep learning will develop in such a way that high school students also can use it to develop more interactive things by using transfer learning and reinforcement learning. Deep learning also be able to detect nutritious and life style interferences which are going to affect or benefit the specific person. In the future, many intelligent systems are going build to predict the specific disease accurately for the right treatment. Unsupervised representation learning techniques such as Restricted Boltzmann Machines (RBM) may overtake regular schemes.

In Reinforcement learning, the candidate has the chance to network with the setting to learn at its own pace, to review, postulate, try-out, plan, and think. Artificial intelligence (AI) will give privileges to monitor our own health without going to clinics for small and medium risk diseases. AI will also make us to recognise the reason to cancer, heart disease etc., and also what the precautions can be taken care for it. Robotic surgeons can carry out an independent clinical process seamlessly with cheaper cost. Every human can be able to re-grow their heart, liver, lung whenever they require it, instead of waiting for the donor.

The main leading possibilities in healthcare using AI are drug discovery and biomarker expansion. Even though, the huge amount of data associated to huge number of chemical objects, which are toxicity and many hostile effects together with other clinical data, predicting the accurate drug for particular disease is always difficult. The collective human province in drug discovery and intelligent deep learned markers can change the pharmaceutical field. In near future AI will make remarkable in drug discovery and bring new players in new dimensions to the market. In future, deep learning is going to replace the radiologist, which perhaps could be mitigated as virtual radiologist assistant.

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