A Systematic Literature Review of Medical Image Analysis Using Deep Learning

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***Abstract*—We review literature in top journals and conferences on the usage of deep learning for medical image analysis in modern healthcare. As a result it is shown that deep learning offers unique capabilities and breakthroughs in identifying, classifying and segmenting different kinds of medical images, especially related to cancer in the breast, lung, and brain.**

Keywords—data-driven medical diagnosis, medical image analysis, deep learning, literature review

I. INTRODUCTION

One of the key aspects in today's medical diagnosis process is the use of medical imaging (MI), as it is used in all fields of modern medicine [1]. Medical Image Analysis (MIA) is almost always a complex and time-consuming task which even professionals struggle with [2, 3]. Today's technological progress could make it possible to use new methods in the health domain. The use of Deep Learning (DL) could provide a wide variety of new possibilities for different medical fields, for example, it could be used to make faster and more accurate diagnoses which in turn would lead to better and more sophisticated personalized treatment [4].

The following paper will provide an overview of the current state of MIA using DL technology.

II. RESEARCH METHODOLOGY

We conducted a systematic literature search capturing deep learning-related work in the digital health domain until 09/12/2019, including four meta-databases (IEEE, ACM, AIS Basket of 8, SpringerLink/"Image Processing" and "Data Mining and Knowledge Discovery") that met the inclusion criteria of "deep learning" AND medical AND "image analysis". Only international peer-reviewed publications were considered.

III. RESULTS

A. Cancer Tissue Identification

The most commonly researched field of DL in MIA is *cancer* and *tumour* detection and classification. The accurate identification and categorization of cancer structures and sub-types plays a major role in histological images. Studies showed promising results for the automatic analysis of *cancer tissue* by using DL approaches. For example, with the use of FAST [5] it is possible to make volume segmentation in CTs. The image is passed to a patch generator and a volume renderer. This patch generator splits the volume into sub-volumes which in turn is passed onto the convolutional neural network (CNN). The segmentation network then processes the volume which is then stitched back together with the help of a patch stitcher. This processed volume is then rendered to highlight the segmented tumor [5]. In another example, CNNs were able to organize and extract the discriminative information from the data [6]. One of the most reliable cancer diagnosis methods is the histopathological examination. The main downside to it is that it is time consuming and prone to errors because it requires a detailed inspection by a pathologist. With the help of DL in MIA it is possible to make this process faster and more efficient since it wouldn't rely necessarily on human interference [7]. The use of CNNs makes it possible to segment cancerous tissue and to classify it in many cases [8].

B. Mammographic Applications

Another popular use for DL in MIA is *breast cancer* detection. Breast cancer is one of the main causes of death in females and there is a rise in the number of diagnoses, but there are not enough specialists to take care of the patients. The use of DL applications would be a possible solution to speed up the process and therefore offer the possibilty of earlier treatment [9]. In addition, Yunchao and Faqiang [10] presented an approach for predicting breast cancer with the help of DL in MIA, which is more reliable than before and thus is able to replace most of the pathologists' workload.

In the medical subdiscipilne of breast cancer detection, a fusion of a CNN and a Support Vector Machine (SVM) was able to detect cancerous tissue with an accuracy of 92% [11]. With the help of the CNN it was possible to narrow down the region of interest (ROI) in digital mammograms [12].

C. Medical Imaging of Lungs

Anthimopoulos et al. [14] described an approach to *lung* pattern classification using CNNs. They designed a network that captures low level textural features of the lung tissue. These image patches were generated through the annotations of a CT slice. In this example, the CNN processed the patches and assigned them to the proper area of unhealthy tissue. The patches have a 100% overlap with the lung, at least 80% with the ground-truth and 0% with each other [13].

In the past years, DL techniques in general became the state-of-art in the widespread field of image classification. For example, diffuse lung diseases are a challenge for medical doctors since the disease comes in many different forms. ML applications are able to help physicians with their work by drastically reducing the time needed to perform a MIA of the lung patterns [14]. Currently, CT and PET scans are used to detect lung cancer, as by combining the imagery it allows the detection of metabolically active lesions. With the use of CNNs it was possible to retrieve the information from the CTs only. This cuts the time of the analysis of the MI and thus make it more efficient while maintaining a high level of accuracy [15].

D. Brain Tissue Segmentation

4D CT imaging could be essential in the future for workups after a stroke [16]. One major breakthrough was made in *dementia* diagnosis. With the help of DL applications in MIA it was possible to detect early signs of dementia in testing samples [17]. These predictions of *Alzheimers disease* would help enable earlier treatment and therefore slow down the degenerative process and provide support in sustaining patients' quality of life for as long as possible [17].

E. Miscellaneous Applications

Another medical field in which the pattern of the images is diverse and subtle is *fetal anatomy* assessment. DL applications in MIA are able to detect the organs of the yet unborn fetus [18]. In clinical routines, it is common to use a 2D Ultrasound (US) for check-ups during pregnancy but some monitoring tasks can not be done properly because of multiple factors including, for example, the orientation of the fetus. One possible solution would be the use of a 3D US, but to fully check on the fetus, prior organ localization is needed. This information is difficult to obtain since every fetus varies in size and orientation. Raynaud et al. [18] propose the use of DL applications in the analysis of the 3D US imagery as a solution to accommodate for this problem. One of their examples is a combined spine detector. With the use of DL and morphological filter responses is it possible to combine the two outputs and obtain a more robust spine binary mask.

For *Cervical Histopathology Image Classification* (CHIC), many ML methods were developed and applied to image segmentation, feature extraction or classification tasks. So, the ML methods are constantly updated with the current state-of-art of technology in CHIC [19].

Gastrointestinal (GI) disease is a widely occurring illness which is examined by GI endoscopy. With the help of CNNs it is possible to detect, classify and segment GI diseases [20].

Stacked Sparse Autoencoder (SSAE) is a DL application which allows high level features to be captured through learning processing from low level features (pixel). In *nucleus and cytoplasm morphology* analysis, SSAE helps the physicians to indicate if the cells are normal or abnormal [21]. Methods for *thoracic aorta calcifications* (TAC) or *coronary artery calcification* (CAC) also rely on segmentation to seperate the ROIs in the images [22].

DL approaches are also widely used in *cardiac image segmentation* were the high accuracy of those methods have made them the state-of-the-art in this field. For example, the CNNs used by Duan et al. [23] were able to localize landmarks and segment the CMRs simultaneously. The network combined the computational advantage of a 2D network with the capability of addressing 3D spatial consistency issues without a loss of precision [23].

Another use of the automatic segmentation ability of CNNs is the field of *retinal vessel segmentation*. The retinal vessel segmentation is a fundamental part in the diagnosis of eye-related diseases. Both the thick and the thin vessels are important for symptom detection. With the help of DL models it is possible to automate this process. Usually an attempt is made to segment both vessel types simultaneously. For example, Yan et al. [24] proposed a method in which they segment thick and thin vessels seperatly. Zang et al. [25] proposed an accelerated matrix for the same task.

IV. Discussion

In summary we found that deep learning offers unique capabilities and breakthroughs in identifying, classifying and segmenting different kinds of medical images, especially related to cancer in the breast, lung, and brain.

V. Limitations and Future Work

A. Limitations

Some research publications with interesting material is potentially excluded because the analysis was limited to peer-reviewed publications with completed research work. This excluded material could potentially lead to a publication bias.

B. Future Work

In future work we will systematically compare ML methods in experimental laboraty settings, including the evaluation of mental concepts such as cognitive workload [26, 27], concentration [28], and personality [29, 30] in multi-agent-settings [31-34]. We will therefore triangulate objective and perceived user-oriented concepts [35-37] using physiological data (i.e., electroencephalographic data and spectra [38-39], electrocardiographic data [40], electrodermal activity [41], eye fixation [42, 43], eye pupil diameter [44-46], facial data [47]), and evaluate user acceptance [48-52], trust [53, 54] in multi-agent settings [55-62].

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