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Deep learning methods and corresponding applications in medical imaging

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Abstract. Deep learning is a subfield of artificial intelligence and machine learning, and it is becoming a popular topic in recent years. It is a powerful tool in solving complex tasks and achieve state-of-the-art results in many areas, including language processing, computer vision, and more. This paper briefly introduced two main deep learning models, Convolutional Neural Networks (CNNs) and Generative Adversary Networks (GANs) and their applications in medical imaging. CNNs are often used in image recognition tasks, like separating different organs in one medical image. While GANs are better doing medical image generation tasks, like creating an X-ray image of chest. This study introduced some deep learning methods for image segmentation, image classification and image generation. Not only are the basic CNNs and GANs architectures used, but also some improvements and modification involved. These methods greatly expand the existing medical image datasets. They also save lots of time for doctors and radiologists from labeling and recognizing those medical images. Deep learning methods are super strong in processing complex and numerous medical images. However, there are still some limitations caused by the lack of training datasets and learning models.

Keywords: Deep Learning, Neural Networks, Medical Imaging.

1. Introduction

In the medical field, Computed Tomography (CT), X-ray, ultrasound, Magnetic Positron Emission Tomography (PET), and Resonance Imaging (MRI) are commonly used to obtain medical images from patients. Medical imaging facilitates doctors in better detecting and understanding the conditions of the patients. Its significance is particularly evident when doctors encounter situations involving asymptomatic patients. In such cases, the precision and accuracy of medical images play a pivotal role. The process of studying and scrutinizing these images necessitates substantial datasets and properly annotated samples for effective analysis. However, studying and analyzing images requires large datasets and annotated samples. Many datasets are not big enough and limited to some specific conditions due to the cost and complexity of the task. Due to the lack of data, doctors spend more time specifying the problems. Sometimes, the image has never been seen, doctors cannot justify the issue. Therefore, it is urgent to find a method to solve this issue.

Artificial Intelligence (AI) has become popular in recent years. Computers have high computational ability; however, they cannot think as human. So that they cannot deal with complex tasks. But an increasing number of algorithms are created to help computers to think about more difficult problems

[1, 2]. Computers start to have intelligence; it can help people to study and analyze the data. A particular deep neural network architecture known as Convolutional Neural Networks (CNN) is designed to handle data having a grid-like structure, such as photos and videos. CNNs are successful in doing computer vision tasks and are widely used in tasks like image segmentation, image classification, and object detection. CNNs led revolutions in many fields, and it showed remarkable performance in various applications. Besides CNNs, A group of deep learning models called Generative Adversary Networks (GANs) were created by Ian Goodfellow in 2014 [3]. The techniques can generate new data with the same characteristics as the training datasets. Hence, it is known as a tool to synthesize images. Generating medical images for training and analyzing purposes is possible with GANs. With the improved techniques of training GANs, the visual Turing test has proven that it can produce images of excellent quality. With human eyes, the fake image has no difference with the real one [4]. GANs can highly improve the accuracy and efficiency of the diagnosis, as well as reduce the cost of collecting and labeling the images. With the development of GANs, the interconnection between medical science and computer science has become inseparable. Some medical imaging applications have already applied GAN models. Dai et al. [5] used GANs to train models to make correct organ segmentation between lung and heart in chest X-ray. This algorithm significantly reduces the workloads of the radiologists 3. Frid-Adar et al. [6] improved the performance of medical images by synthesis data from a limited CT dataset. To improve CNN performance, they use their synthetic data augmentation methods. In medical research, deep learning techniques are important. They help to enlarge the medical image datasets and reduce the time cost on analyzing medical images. So, this study would like to summarize several deep learning methods and applications, and their current development.

The rest of this paper is organized as follows: Section 2 provides information of some existing deep learning methods in medical studies. The use of deep learning algorithms in many medical disciplines, such as picture segmentation and image production, will be covered in Section 3. Section 4 will make a conclusion of the whole paper and discuss some future developments in this area.

2. Method

2.1. Medical image classification

2.1.1. CNN. To identify lung images that contained interstitial lung disease, Li et al. [7] created a customized CNN with shallow convolution layers. Given the absence of well-defined structures in the lung image's texture, employing deep layers of a CNN would not yield optimal results in this scenario. During the process of training CNN, image pixels were directly used as input which will result in forming complex systems. By using kernel filters, the CNN model is faster than the traditional fully connected network. Rectified Linear Unit (ReLU) activation function was used in the method, it slightly improved the performance of the network. CNN network training is computationally intensive task, especially for medical images. Advanced Vector Extensions (AVX) were used by this study during the training to accelerate the process.

2.1.2. Synergic Deep Learning (SDL). Zhang et al. [8] proposed an SDL model which includes several pairs of deep CNNs. Whether a given pair of input photos belongs to the same class can be detected by this fully connected model. All pairs of DCNNs collaborate, meaning that if one pair fails to provide the correct classification, the model will undergo an update. The SDL model is formed by an image pair input layer, n DCNN components and synergic networks. This method has shown great performance in ImageCLEF-2015 and 2016 as well as ISIC-2016 and 2017 datasets.

2.2. Medical image segmentation

2.2.1. Dense-Res-Inception Net (DRINet). Chen et al. [9] proposed a novel CNN structure called DRINet, which is improved from U-Net architecture. U-Net architecture is a well-known semantic segmentation in CNN. It has difficulties when learning data that has subtle differences in terms of intensity, position, structure, and size among different categories. The improved one, DRINet, was meant to solve this problem. DRINet includes analysis path and synthesis path, and it is fully connected. This method is efficient when facing 3D CT images, which are stacks of 2D images with large thickness. Furthermore, it also increases the segmentation accuracy for smaller organs, like pancreas.

2.2.2. 3D convolutional architecture. Lai et al. [10] did experiments on several methods and got a 3D convolutional architecture that gives better classifications with higher requirement of computation. They first tried to use a stack of 2D patches to surround each pixel, in this way, they can use a relatively low space to represent the data. Then they tried tri-planar method developed by Prasoon et al and Roth et al. This method extracts 3 patches around the voxel along the vertical axis, and feeds those into the fully connected layer to finish classification. Finally, combining the idea of the tri-planar method, they used a 3D patch instead of planar patch. Tri-planar approach provides better results than the 2D approaches. And their 3D convolution provides slightly better results than the tri-planar approach but causes a significant increase in the computational power requirement.

2.3. Medical image generation

2.3.1. Generating brain PET images. Islam et al. [11] proposed a model which can generate brain PET images for Alzheimer’s disease. This new model used Deep Convolutional Generative Adversary Networks. The inputs are 128×128×3 PET images of brain, and they follow the guide of Redford et al. [12] to build the generator and discriminator for the training model. Random noise was used in the generator to generate fake images which would be used to update the model. The test result of the generate images has Peak Signal to Noise Ratio (PSNR) of 32.83 and Structural Similarity Iniex (SSIM) of 77.48. PSNR measures the error between the generated images and real images, SSIM defines the similarity of pixels between synthetic and real images. This model generates high quality PET images which can be used to enlarge the annotated dataset.

2.3.2. Synthetic brain MR image. Han et al. [13] provided a realistic generation approach which can generate brain MR images that cannot be distinguished by expert physicians. They compared two models Deep Convolutional GAN (DCGAN) and Wasserstein GAN (WGAN) to see which model can avoid model collapse during the training. DCGAN here was implemented by removing tanh in the generator and use Exponential Linear Unit (ELU) as discriminator. With some changes in the batch size and optimizer, the model was completed. WGAN has the same architecture as DCGAN, but the learning rate was reduced. In comparison to DCGAN, WGAN performs better since it preserves the realistic appearance of the brain MR images while capturing the texture and appearance of the tumor.

3. Applications and discussion

3.1. Hospitals
Medical images can be generated by the GANs methods, which provide much more data than the existing annotated datasets. Doctors can increase their knowledge of rare conditions by studying and analyzing the generated images. As a result, hospitals can save large amounts of money and they can use the funds to improve the environment or update medical devices. However, it is not so practical in the real world. There are many limitations with the GANs methods. GANs need to be trained with large dataset to keep accuracy and realism, which is usually expensive and time-consuming. Also, GANs may struggle to generate diverse and meaningful data when trained with complex datasets. Even though there are many existing GAN methods that can be used to synthetic images, hospitals can not apply the methods easily. As the development of deep learning and AI technology, GAN models and new models can lower the requirements of the training data and generate more realistic images.

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3.2. Remote medication

Usually, doctors cannot determine the exact disease on the remote medication. With the help of GANs methods, doctors now can give more accurate diagnosis from a medical image of the patient. GANs model trained with large amount of data, such that it can analyze the symptom and give some advice to the doctor while doing remote medication. Remote medication can greatly reduce the stress of the compacity of the hospital, and reduce the time that patients need to spend on waiting. However, the advice may be inaccurate depending on the rarity of the medical image. As a result, doctors may be misled by the advice and give wrong diagnoses. This is unacceptable in medication. But, with increasing datasets, the model will give more accurate responses to the medical image. Doctors can trust it more.

4. Conclusion

This paper provides a general overview of various deep learning techniques and their applications within the field of medicine. Notably, CNNs and GANs play pivotal roles in the generation and analysis of medical images. These techniques contribute significantly to the expansion of medical image datasets by generating high-quality medical images, facilitating research into rare disease cases. Furthermore, they alleviate the burden of recognition and labeling for radiologists and medical professionals, resulting in substantial time and cost savings. The utilization of deep learning methods enhances the efficiency of hospitals in symptom analysis for patients. Remote medication is more reliable, and it is much more convenient for the patients compared to clinical diagnosis. Even though the development of deep learning methods is super advanced, they still cannot generate authentic and varied images due to the lack of training datasets. In the future, with more intelligent neural network architectures and expended training data, these problems will no longer exist.

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