Application Of Ai-Assisted Medical Imaging

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Abstract. Artificial Intelligence (AI) has rapidly gained widespread attention and has made unprecedented strides in recent years, significantly influencing various sectors, especially the medical field. Its applications have revolutionized healthcare by assisting doctors in making faster, more accurate, and data-driven decisions. This paper aims to provide an in-depth analysis of AI's role in medical imaging, focusing on its applications in interpreting X-rays, CT scans, and MRIs. These imaging techniques utilize cutting-edge image recognition algorithms, with Generative Adversarial Networks (GANs) and Convolutional Neural Networks (CNNs) being the most prominent. AI not only improves diagnostic precision but also reduces human error, leading to better patient outcomes. Furthermore, the paper discusses current trends in AI-driven medical imaging and explores potential future directions, emphasizing how AI could continue to advance medical diagnostics and treatment planning, paving the way for more personalized and effective healthcare solutions.

Keywords: medical imaging, Artificial Intelligence, X-rays, CTs, MRIs.

1. Introduction

Artificial Intelligence (AI) has gained great attention in recent years, and at the same time AI has been greatly developed since the 21st century. Currently human research and development of AI has covered the fields of medicine [1], natural language processing [2], image recognition, handwriting recognition and so on. Artificial Intelligence (AI) is the intelligence exhibited by machines. In computer science, the field of AI research defines itself as the study of "intelligent agents": any device that senses its environment and takes action to maximize its chances of success at a given goal. In layman's terms, the term "artificial intelligence" is applied when a machine mimics the "cognitive" functions associated with human and other human minds, such as "learning" and "problem solving".

As early as the 1980s, it was envisioned that AI could be combined with biomedicine [3]. However, this kind of AI is quite different from the modern AI, people first collect a large amount of data, and then use computers to find the laws of data, and then finally adjust and improve the performance of the machine to achieve the optimal purpose by virtue of the perceived experience, this kind of AI can help human beings to carry out simple data processing and logisic regression analysis, with the purpose of obtaining more accurate results. However, this kind of AI relies too much on human control, does not have the autonomous ability to fight against risks, and at the same time is not completely automatic, and is still not essentially out of the human category.

With the continuous development of artificial intelligence, machine systems have been able to simulate human learning, build neural networks, and realize deep learning models for prediction and classification of practical problems. Currently, with the rapid advancement of machine learning and neural networks, AI has made significant progress in areas such as medical robotics, AI-driven medical imaging, and AI-assisted diagnosis and treatment.With the invention of these systems combining AI and medicine, it greatly improves the accuracy and efficiency of doctors' diagnosis and treatment. This paper mainly summarizes the research of AI in ultrasound, X-ray film, magnetic resonance imaging (MRI), and points out the shortcomings of the current research and possible future research directions.

2. Application of AI in X-ray film

Digital X-ray film imaging system has been the most commonly used examination method, which can quickly and efficiently check out the chest and abdomen and other related diseases. However, the diagnostic standard is the consensus of domestic and foreign experts after long-term clinical experience, which is more comprehensive and reasonable, but due to the large workload, it is easy to have errors. Through AI algorithms and image recognition related technologies, the efficiency of diagnostic assistance can be greatly improved.

In order to provide sufficient training data for the research community, the U.S. National Library of Medicine provides two publicly available Postero-anterior (PA) chest radiograph datasets [5]: the MC (Montgomery County chest X-ray) set and the Shenzhen set, to promote the research of computer-aided diagnosis of lung diseases. The images in the two datasets were obtained from the Montgomery County Health Department, Maryland, USA, and the Third People's Hospital, Shenzhen, China, respectively, and both datasets contain normal and abnormal chest X-rays with tuberculosis manifestations. Both datasets contain normal and abnormal chest X-rays with TB manifestations, and these two datasets have been used in automatic TB screening and lung segmentation in publications [6-7]. In the automated TB screening experiments, the accuracy of these two datasets reached 87% and 90% of the area under the curve, respectively, which is still lower than that of humans, but is close to the performance of radiologists [7]. Although these two datasets can achieve good results for automatic TB screening, they are not sufficient for detecting abnormal chest X-rays.

In addition, Prof. Wu Enda's team open-sourced the MURA dataset [8] for detecting abnormal skeletal muscles and used it to train a convolutional neural network to find and localize the

abnormal parts of the radiographs.MURA is one of the largest datasets of radiographs, containing 40,895 musculoskeletal radiographs originating from 14,982 cases. Based on this dataset, the team developed a model that effectively predicts musculoskeletal abnormalities, as shown in Figure 1.

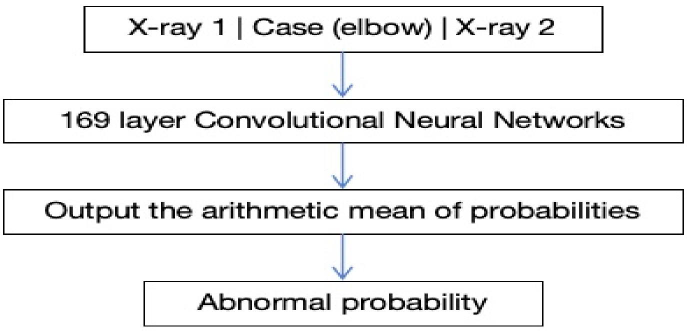

Fig. 1 Workflow of the model

After sufficient training, the performance ability of the model was compared with that of a professional radiologist. It was found that the model performed better than radiologists in diagnosing finger and wrist radiograph abnormalities, but worse than radiologists for other parts of the body (e.g., shoulder, elbow, forearm, palm). Notably, the 40,000 sheets in the MURA dataset came from nearly 15,000 papers, of which 9,067 were studies of normal upper-extremity musculoskeletal radiographs and 5,915 were studies of abnormalities. In other words, the team obtained the samples from open sources. The great advantage of this method is that it is less restrictive, the disadvantage is that it requires a lot of information to be collected and read, and the quality of the samples obtained is of varying levels. The following table lists some of the publicly available medical radiology image datasets.

Table 1. Publicly available medical radiology image dataset

database	field of research	label	Number of images
MURA dataset	Musculoskeletal (upper limbs)	Abnormality	41299
Pediatric Bone Age dataset	Musculoskeletal (hand)	Bone Age	14236
O.E.1 dataset	Musculoskeletal (knee)	K&L Grade	8892
Digital Hand Atlas dataset	Musculoskeletal (left hand)	Bone Age	1390
ChestX-ray14 dataset	chest	Multiple Pathologies	112120
Open I dataset	chest	Multiple Pathologies	7470
MC dataset	chest	Abnormality	138
Shenzhen dataset	chest	Tuberculosis	662
Digital image database of pulmonary nodules	chest	Pulmonary Nodule	247
Mammography screening digital database	breast	Breast Cancer	10239

In summary, it can be seen that in the field of deep learning, the known dataset is still very limited, and if it is used to train the machine learning model, it is not able to guarantee its effectiveness, so in the future research in the field of X-ray film, it is still necessary for the researchers to obtain more data from the clinic, in order to satisfy the AI's research related to clinical diseases.

3. Application of AI in CT images

As a common diagnostic method, CT technology not only has a clear image of high-density tissues, but also has a greater advantage in the diagnosis of bone structure diseases. By combining AI deep learning technology with CT, the site, size, nature and relationship with surrounding tissues can be quickly identified, which can greatly shorten the diagnostic time and improve the diagnostic efficiency.

Frid-Adar et al[9] used GAN to automatically generate synthetic medical images and used them for the classification task of liver lesions.Figure 2[9] shows three tumor lesion images.

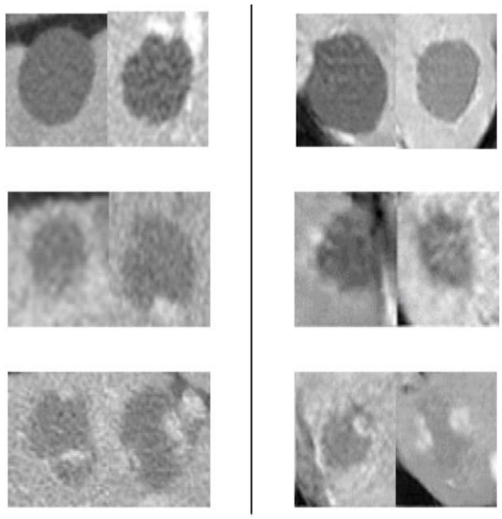

Fig. 2 Lesion ROI examples of Cysts (top row), Metastases (middle row) and Hemangiomas (bottom row). Left side: Real lesions; Right side: Synthetic lesions

The specific training process is as follows: 1) create a larger dataset with traditional augmentation methods (e.g., pan, rotate, flip, and scale), and then use it to train the GAN; 2) use the GAN to generate a synthetic image as an additional resource for data augmentation; and 3) combine the image obtained by the traditional augmentation methods with the synthetic image generated by the GAN, and use it to train the lesion classifiers.

Fig. 3 [9] shows the variation of liver lesion classification accuracy with respect to the training set. As can be seen from the figure, augmenting the training set with synthetic images shows a 7% improvement in performance over augmenting the training set using only the traditional method, which further demonstrates the effectiveness and feasibility of augmenting the training set with synthetic images generated by GAN.

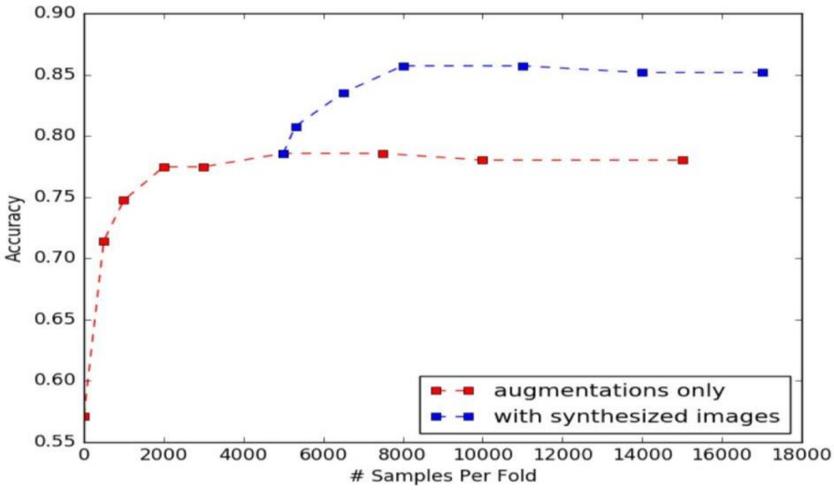

Fig. 3 Accuracy results for liver lesion classification with increase of training

GAN was originally proposed as a generative model by Goodfellow [10] et al. The first application of it in the field of synthetic medical image generation was by Nie et al [11], who used GAN for training in order to generate a more realistic CT image from a given MRI image.GAN can generate visually realistic images, as can be seen in Fig. 2, the synthesized lesion images are not very different from real lesion images are not very different visually and the method can be very effective for data augmentation.

4. Sample augmentation methods for MRI images

The characteristics of MRI images determine that they have special characteristics that are different from other medical images, and the diversity of MRI images determines that AI research on the effects of nuclear magnetic influence is more sparse and more difficult to develop. But there are also researchers who have used convolutional neural networks [12] for Alzheimer's disease recognition studies, using the augmentation method of image transformation used by Krizhevsky's group [13].

In view of the unbalanced nature of medical imaging datasets, literature [14] utilizes GAN to synthesize abnormal MRI images for data augmentation. The basic idea is: using two publicly available MRI datasets (ADNI and BRATS), a GAN network is trained to generate and then synthesize abnormal MRI images with brain tumors. They used the synthetic images as a form of data augmentation, demonstrated its effectiveness in improving tumor segmentation performance, and proved that similar tumor segmentation results can be obtained when training on both synthetic and real subject data. This method provides a potential solution to two of the biggest challenges facing deep learning in medical imaging (low incidence of pathology findings and limitations in sharing patient data).

While the above methods are effective in solving the sample size problem, the results achieved in solving the sample diversity are not very satisfactory. Literature [15] introduces a software platform for automatic broadening and batch labeling of MRI image samples (DMRIAtlas), which can solve the sample number problem as well as increase the sample diversity, and works on the following principle: the physical information of normal volunteers and a small number of positive cases focusing on focal areas is acquired by quantitative MRI imaging, and then virtual MRI imaging is used to perform virtual data acquisition and imaging of the normal or focal area information. Then virtual MRI imaging technology is used to acquire and image virtual data of normal or lesion areas, and output a large number of MRI images of different types and manifestations based on different imaging sequences and parameters. The images generated by this software can be MRI images with different resolutions, signal-to-noise ratios, weights and b-values, which can greatly expand the variety and number of training samples. Figure 4 shows the T1WI, T2WI, T1-FLAIR, T2-FLAIR, and STIR images of the same level of normal brain tissue using different sequences of virtual scanning with this software [15].

Fig. 4 The images of a normal brain model for the same slice acquired by virtual MRI scanning using different sequences (a) T1WI; (b) T2WI; (c) T1-Flair; (d) T2-Flair; (e) STIR

5. Summary

AI technology has made notable advancements in medical imaging diagnostics, enabling the development of fast and effective diagnostic methods. Through AI platforms that collect large volumes of clinical data and extract patient-specific features, the process of classification and image processing has been enhanced. This reduces the errors associated with manual recognition and improves detection accuracy. Deep learning, especially convolutional neural networks (CNNs), plays a key role in accurately segmenting medical images, which has found widespread application in medical technology and helps address various practical issues.

However, several challenges remain in AI-based image recognition. Although experimental research has shown that AI detection accuracy can match or even surpass that of professional doctors, the limitations of research databases, as well as the complexity and timeliness of real-world clinical cases, hinder AI's application in imaging clinics. To bridge this gap, stronger collaboration between software developers and clinicians is needed. Incorporating clinical needs into AI development programs can help ensure diagnostic processes are more aligned with clinical practices.

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