

CHAPTER 5

Current Medical Imaging and Artificial Intelligence and its Future

Shigao Huang¹, Jie Yang^{2,3}, Lijian Tan³, Simon Fong^{2,4} and Qi Zhao¹

¹ Institute of Translational Medicine, Faculty of Health Sciences, University of Macau 999078, Macau SAR, China

² Department of Computer and Information Science, University of Macau, Macau, China

³ Chongqing Industry & Trade Polytechnic, Chongqing, China

⁴ Zhuhai Institutes of Advanced Technology of the Chinese Academy of Sciences, China

Abstract: “Artificial intelligence and medical image” is an auxiliary tool for the computer to complete image classification, target detection, image segmentation, and retrieval and assist doctors in diagnosing and treatment based on medical image through deep learning. This chapter includes the review of Artificial intelligence (AI) and its application in radiology, pathology, eye disease, deontology, dermatology, and ophthalmology, which we have benefited from the use of AI methods. Modern medicine is evidence-based medicine based on experiments. Doctors' diagnosis and treatment conclusions must be based on corresponding diagnostic data. Imaging is an important part of diagnosing, and 80% to 90% of data in the medical industry are derived from medical imaging. Therefore, clinicians have a strong demand for images, and they need to conduct a variety of quantitative analyses of medical images and comparison of historical images to complete a diagnosis. In contrast to this qualitative reasoning, AI is good at identifying complex patterns in the data and providing quantitative assessments in an automated manner. Integrating AI into clinical workflows as a tool to assist physicians allows for more accurate and repeatable radiological assessments.

Keywords: Artificial intelligence, Deontology, Eye disease, Medical imaging, Radiological assessments.

1. INTRODUCTION

Medical fields that rely on imaging data include radiology, pathology, dermatology, and ophthalmology [1], which have been benefited from the use of

* **Corresponding author Shigao Huang:** Institute of Translational Medicine, Faculty of Health Sciences, University of Macau 999078, Macau SAR, China; Tel: 853 88222953, Fax: 853 88222953; E-mail: huangshigao2010@aliyun.com

AI methods. In radiology, for example, experienced physicians evaluate medical images visually to detect, characterize, and monitor the disease [2]. This assessment is usually based on personal experience and is subjective. In contrast to this qualitative reasoning, AI is good at identifying complex patterns in the data and providing quantitative assessments in an automated manner [3]. Fig. (1) shows AI to screen the medical imaging quickly to find the lesions in the mammography radiation photograph, which is a combination of technology with AI and GSM. Integrating AI into clinical workflows as a tool to assist physicians allows for more accurate and repeatable radiological assessments.

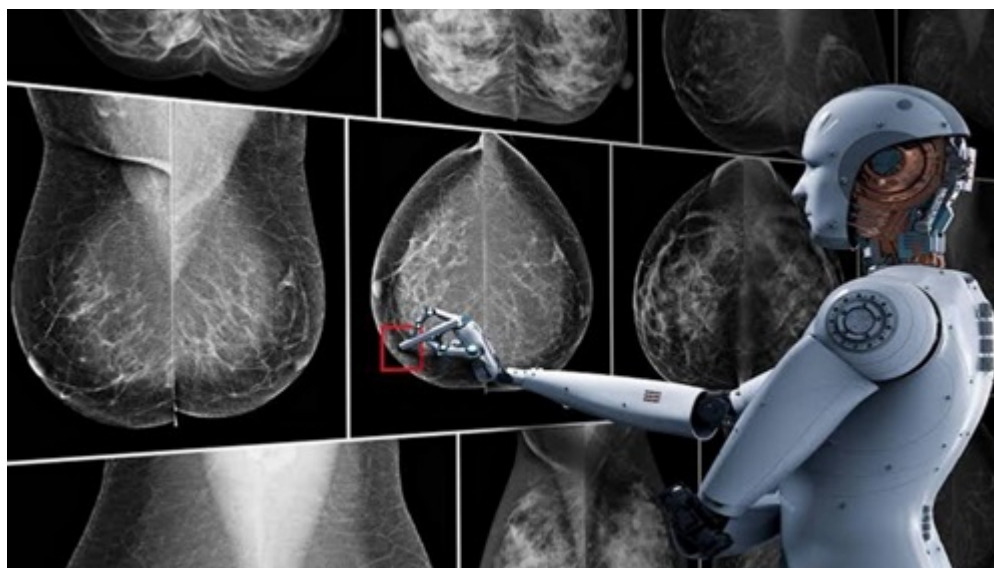


Fig. (1). National Cancer Institute sends AI to make smarter mammography. AI mammogram” is a combination of technology with AI and GSM. The purpose of the National Cancer Institute is to extend breast cancer prevention, help to speed up the service, reduce the workload of the staff, which can also help in reducing the costs and increasing the opportunities for Thais to access the service. (Source:<https://newsbeezer.com/thailandeng/national-cancer-institute-sends-ai-t-make-smarter-mammography/>).

At present, two kinds of AI methods are widely used in medical images. The first is artificial feature engineering, in which features are defined by mathematical equations, such as tumor textures, and can be quantified by a computer program. These artificial features serve as inputs to machine learning models trained to classify patients using clinical decision-making [4]. Although these characteristics are different, they rely on expert definitions and are therefore not necessarily the best quantification of the characteristics currently being used to identify tasks. Besides, predefined features are generally not applicable to imaging model changes, such as computed tomography (CT), positron emission tomography (PET) [5], and magnetic resonance imaging (MRI), and their associated signal-to-

noise ratio characteristics. The second approach, a deep learning algorithm, automatically learns feature representations from the data without intervention by human experts. This data-driven approach allows for more abstract feature definitions, making them more informative and generalizable. Therefore, deep learning can automatically quantify the phenotypic characteristics of human tissues and can make substantial progress in diagnosis and clinical care [6].

Another benefit of deep learning is that it reduces the need for artificial preprocessing. Like a trained radiologist, deep learning can identify image parameters and weigh their importance against other factors to make clinical decisions [7].

2. PROCESS OF AI IN MEDICAL IMAGING

At present, more than 90% of medical data is obtained from medical imaging, and medical imaging data has become one of the essential “pieces of evidence” for doctors in diagnosis. AI can be used to help doctors make an accurate diagnosis. In that case, it is the current direction of efforts of many imaging AI explorers, which is of great help to widely improve the accuracy of disease diagnosis and treatment [8]. The following are four steps to achieve AI application in medical imaging.

2.1. Develop Standardized Use Cases

According to a study, the cases of AI used in medical imaging lack the standard inputs and outputs as compared to the algorithms already in use. As the algorithm may need to run on a local server or cloud service, a standard method needs to be developed to accept the input and output processed by the algorithm. Moreover, without the standardized inputs and outputs for AI cases, training and testing to develop standard data sets become more challenging, thus resulting in the output algorithm showing different results for the same case [9].

Ideally, AI cases need to be developed in the same format that can translate human narrative descriptions of what an algorithm should do into machine-readable languages, such as extensible Markup Language (extensible Markup Language) or JavaScript object representation using well-defined data elements. According to a study, structured used cases can help AI algorithms create validation standards before they are ready for clinical use, and applications in medical imaging can help achieve those standards. Medical professionals, academic institutions, and radiologists in medical imaging have a positive impact on AI development, and they all need to be involved in this structured

development used cases to create common standards and structures and build specific AI used cases [10]. These cases can help AI algorithms establish the same definitions and develop practicable clinical approaches [8].

2.2. Establish a Data Sharing Method

To develop high-performance AI algorithms, models will need to learn from high-quality data sets that contain appropriate annotations or rich metadata. While there has been a lot of innovation around the topic, according to the study, it was mainly available in data-rich organizations only and these issues could limit the wide availability of information. Privacy concerns will limit the disclosure of patient data by such institutions, and these conditions will hinder the development of AI. Expediting the release of publicly available data sets and helping AI to be applied more quickly in clinical practice, and ensuring that patient data is used in a way that ensures its safety so that more diverse data are available, is critical.

2.3. Assess Clinical Practice and Infrastructure Needs

As per the report, the current lack of user interfaces in AI algorithms in clinical workflows limits the widespread use of AI models in clinical settings. IT developers need to create an efficient user interface and user experience design so that AI can be integrated with existing clinical workflow tools to accelerate the use of AI. Besides, developers need to establish vendor-neutral interoperability standards for communications between healthy IT systems. Understanding infrastructure needs, including qualitative and quantitative analysis of how AI will be deployed in clinical practice - whether local or cloud-based - will be key for the thousands of AI algorithms that can be used in real clinical practice. The medical imaging community must involve in assessing clinical practice and infrastructure needs and work with existing standards bodies, such as the National Science Foundation and the NIH Connected Health Initiative, to find solutions that can contribute to the adoption of AI in clinical practice.

2.4. Ensure Technical Safety and Accuracy

According to the study healthcare, stakeholders should work with IT developers, government agencies, and public organizations to ensure the accuracy of AI algorithms, reduce unconscious bias, and keep patients safe. To do this, stakeholders need to use data sets that contain demographic and technological diversity to validate AI algorithms. Federal agencies, such as the FDA need to play a key role in validating AI models to ensure patient safety. According to the

report, FDA supervises a wide range of medical imaging devices, computer-aided diagnostic software, and other algorithms to support decision making for healthcare practitioners. The agency has long recognized the rapid growth of digitization across the health care sector, as well as the importance of regulating computer software that can detect and classify disease processes. Since 2012, It has been issuing regulatory guidance for software computer-aided testing and computer-aided diagnosis. Clinicians in the field of medical imaging will be the key to advancing cross-industry cooperation. Creating models for the validation and monitoring of AI algorithms and minimizing unconscious bias will require collaboration between researchers, industry developers, and government agencies. The medical imaging community should play a leading role in promoting these collaborations.

Although there are many obstacles to overcome, the application of AI in medical imaging is promising. In the future, industry stakeholders will need to work together to ensure that technology is safe, effective, and efficient. There are great prospects for AI applications in improving diagnosis and image-based diagnosis. The opportunities and challenges summarized here can serve as a roadmap for future development.

3. APPLICATION OF AI + MEDICAL IMAGING IN VARIOUS FIELDS

There are three main applications of AI in the field of medical imaging, namely disease screening, lesion delineation, and three-dimensional imaging of viscera.

We summarized the main coverage methods and types of medical images used by AI in medical imaging. Next, we will introduce the application of AI in lung screening, sugar mesh screening, lesion delineation, three-dimensional imaging of viscera, and pathological analysis, which are the most popular at present.

3.1. Lung Screening

The steps for AI to perform lung screening are as follows: image segmentation algorithm is used to process the lung scan sequence, generate the lung area map, and then generate the lung image based on the lung area map. The pulmonary region image generated by the pulmonary segmentation and the nodule labeling information was used to generate the nodule region image. The pulmonary nodule segmenting device based on the convolutional neural network was trained, and then the pulmonary nodules were segmented from the image to obtain the suspected pulmonary nodules. After the suspected pulmonary nodules are found, the 3D convolutional neural network is used to classify the pulmonary nodules, to obtain the location and confidence of the real pulmonary nodules.

3.2. Screening for Radiculopathy

Sugar mesh disease is the abbreviation of “diabetic retinopathy”. It is a common retinal vascular disease and the main cause of blindness in diabetic patients. As sugar mesh disease does not have any clinical symptoms very often, but once symptoms start to appear, the disease becomes severe, and the best time for treatment is already missed. Therefore, the therapeutic effect of sugar mesh disease depends upon whether the treatment is timely or not. However, due to the shortage of ophthalmologists in China and the low attention of residents, the proportion of screening for sugar grid disease in China is less than 10% at present.

3.3. Target Outline

Target delineation and treatment plan design occupy a lot of time for oncologists. When patients are diagnosed with tumors, they tend to be panic and ask the doctor if there is any slightest movement in the body. However, the oncology department of the famous Grade three to Grae one hospitals is usually overcrowded. Besides visiting doctors, doctors are also involved in other tasks such as scientific research, *etc.* When they face endless questions from patients, they get irritated [11]. Oncologists in primary medical institutions are inexperienced, and in many cases, they are afraid to make treatment plans for patients, so they can only refer patients, which exacerbates the contradiction between doctors and patients in grade three hospitals. Therefore, it is of great concern for hospitals to use new technologies to improve the efficiency of doctors, improve the treatment level and confidence of primary doctors. In the process of tumor treatment, two tasks occupy a lot of doctors' time and energy. They are target area delineation and treatment plan design, respectively.

3.4. Three-dimensional Imaging of Viscera

Three-dimensional (3-D) imaging of Viscera is an AI-based data of medical images, such as MRI and CT, to locate and segment the target viscera and display the internal situation of the patient on the computer. The patient's MRI, CT, and other disease image data on the computer, display the patient's internal situation [12]. The probe in the doctor's hand points to the system updates and displays in real-time, allowing the doctor to have a clear understanding of the patient's anatomical location, making the surgical operation faster, more accurate, and safer.

3.5. Pathological Analysis

Even highly trained pathologists have different diagnoses for the same patient, and this difference is an important cause of misdiagnosis. For example, doctors' diagnoses of some forms of breast and prostate cancer were as low as 48 percent consistent. The lack of consistency shown by the doctors is not surprising. To make an accurate diagnosis, doctors must judge the amount of information available. Normally, the pathologist is responsible for reviewing all the biological tissue visible on the biopsy, but each patient has many biopsies, each of which has over 10 billion pixels (10+gigapixels) after 40 times magnification.

We reviewed the literature on the application of AI to the prognosis of various cancers in different research populations by scientists around the world (Table 1). In the past decade, the number of such studies has increased rapidly in China, the United States, and Europe. Generally, medical statistics covers methods such as the area under the curve (AUC). Cancer prognosis involves the recurrence of the disease and the survival of the patient, and its purpose is to improve patient management. Bychkov *et al.* [41] trained a classifier based on deep learning to predict the five-year survival rate for specific diseases in a series of digitized tumor tissue samples stained for CRC, which require basic morphological staining, and the level of TMA points and the entire slide was performed by human experts. Compared with experienced human observers, b) Haenssle *et al.* [62] aims to promote the detection of melanoma. These levels are divided into the following categories: Level I only involves dermoscopy. Therefore, doctors with different levels of training and experience can benefit by using CNN's image classification capabilities.

Table 1. AI applied to various kinds of cancer prognosis by the global scientist in the different study population.

Type of Cancer	Authors	Year	Country/Region	Number of Patients in Study	Study Population	Methods	Results
Breast Cancer	Sun <i>et al</i> [24]	2018	China	1980		Multimodal DNN	/
	Park <i>et al</i> [25]	2013	USA	162500	SEER	Semi-supervised Learning Model	/
	Delen <i>et al</i> [26]	2005	USA	433272	SEER	ANN and DT	Accuracy: DT (93.6%), ANN (91.2%)
	Lu <i>et al</i> [27]	2019	USA	82707	SEER	Dynamic Gradient Boosting Machine with GA	Accuracy Improved (28%)
	Samala <i>et al</i> [28]	2018	USA	2566	Both	DCNN	AUC(0.85±0.05)

(Table 3) cont....

Type of Cancer	Authors	Year	Country/Region	Number of Patients in Study	Study Population	Methods	Results
Gastric Cancer	Biglarian <i>et al</i> [29]	2011	Iran	436	Hospital	Cox Proportional Hazard, ANN	TP(83.1%),
	Zhu <i>et al</i> [30]	2013	China	289	Hospital	ANN	TP: ANN(85.3%)
	Zhu <i>et al</i> [31]	2019	China	203	Hospital	CNN	Sensitivity(76.47%), and Specificity(95.56%), Overall Accuracy(89.16%),CI(95%,90-97)
Glioblastoma	Vasudevan <i>et al</i> [32]	2018	India	215	TCGA	Neural Network	Accuracy: DT (89.2%)
Bladder Cancer	Tian <i>et al</i> [33]	2019	China	115	Hospital	Statistical Analysis	NEDD8: Poor Prognosis Found
	Hasnain <i>et al</i> [34]	2019	USA	3503	Hospital	KNN, RF, <i>etc</i>	Sensitivity& Specificity (>70%)
Nasopharyngeal Carcinoma	Zhang <i>et al</i> [35]	2019	China	3269	Hospital	Large Scale, Big Data Intelligence Platform	EBV DNA: a Robust Biomarker for NPC Prognosis
Prostate Cancer	Kuo <i>et al</i> [36]	2015	Taiwan	100	Hospital	Fuzzy Neural Network	/
	Zhang <i>et al</i> [37]	2017	USA	/	TCGA	SVM model	Average Accuracy (66%)
	Stephan <i>et al</i> [38]	2002	Germany	928	Hospital	ANN	Specificity Level(90%)
Colorectal Cancer	Bottaci <i>et al</i> [39]	1997	UK	334	Hospital	Six Neural Networks	Accuracy(>80%), mean Sensitivity(60%), mean Specificity(88%)
	Wang <i>et al</i> [40]	2019	China	1568	SEER	Semi-random Regression Tree	/
	Bychkov <i>et al</i> [41]	2018	Finland	641	Hospital	LSTM, Naïve Bayes, SVM	Hazard Ratio(2.3); CI(95%,1.79–3.03), AUC(0.69)
Oral Cancer	Chang <i>et al</i> [42]	2013	Malaysia	156	MOCDBS	Hybrid model of ReliefF-GA-ANFIS	Accuracy (93.81%), AUC (0.9)
Lung Cancer	Lynch <i>et al</i> [43]	2017	USA	10442	SEER	GBM, SVM	RMSE(32,15.05) for GBM, SVM
	Sepehri <i>et al</i> [44]	2018	France	101	Hospital	SVM with RFE and RF	Accuracy(71%, 59%)
	Yu <i>et al</i> [45]	2016	Italy	168	Hospital	Naive Bayes, SVM with Gaussian, <i>etc</i>	/
Ovarian Cancer	Lu <i>et al</i> [46]	2019	Taiwan	84	Both	SVM	HR(0.644), CI(95%,0.436-0.952)
	Lu <i>et al</i> [47]	2019	UK	364	Both	Unsupervised Hierarchical Clustering	RPV: A Novel Prognostic Signature Discovered
	Acharya <i>et al</i> [48]	2018	Singapore& Malaysia	469	Hospital	Fuzzy Forest	Accuracy(80.60 ± 0.5%), Sensitivity(81.40%), Specificity (76.30%)

(Table 3) cont....

Type of Cancer	Authors	Year	Country/Region	Number of Patients in Study	Study Population	Methods	Results
Glioma	Lu <i>et al</i> [49]	2018	Taiwan	456	TCGA	Improved SVM	Accuracy(81.8%), ROC(0.922)
	Papp <i>et al</i> [50]	2018	Austria	70	Hospital	GA and Nelder–Mead ML methods	Sensitivity (86%-98%), Specificity (92%-95%)
Spinal Chordoma	Karhade <i>et al</i> [51]	2018	USA	265	SEER	Boosted DT, SVM, ANN	5-year Survival (67.5%)
Long Bone Metastases	Stein <i>et al</i> [52]	2015	USA	927	Hospital	Multiple Additive Regression Trees	/
Oral Cavity Squamous Cell	Lu <i>et al</i> [53]	2017	USA	115	Hospital	RF, SVM	AUC(0.72), Accuracy(70.77), Specificity(73.08), Sensitivity(61.54)
Pancreatic Neuroendocrine	Song <i>et al</i> [54]	2018	China	8422	SEER	SVM, RF, DL	Accuracy(81.6%±1.9%),curve(0.87)
Thyroid cancer	Li <i>et al</i> [55]	2019	China	17627	Both	DCNN	Sensitivity (93.4%), CI (95%,89.6-96.1) Specificity (86.1%,p<0.0001)
Skin cancer	Esteve <i>et al</i> [56]	2017	USA	2032	Both	Inception v3 CNN	AUC(over 91%)
Non-small cell lung cancer	Coudray <i>et al</i> [57]	2018	USA	137	TCGA, NCI Genomic Data Commons	DCNN(inception v3)	AUC(0.733-0.856)
Non-small cell lung cancer	Wu <i>et al</i> [58]	2018	Italy	1034	Hospital	Bayesian network	/
Non-Hodgkin's lymphomas	Lorenzo <i>et al</i> [59]	1999	Italy	98	Hospital	Multivariate Cluster Analysis	/
Breast Invasive Ductal Carcinoma	Nadia <i>et al</i> [60]	2019	Italy	374	Lymphoma and IDC Datasets	Convolutional Autoencoder, Supervised Encoder FusionNet	F-measure Score Improved(5.06%), Accuracy Improved(5.06%)
Pan-Renal Cell Carcinoma	Tabibu <i>et al</i> [61]	2019	India	Ensemble	TCGA	CNN	Accuracy(92.61%)
Dermoscopic melanoma	Haenssle <i>et al</i> [62]	2018	International Skin Imaging Collaboration (ISIC)	100	International Skin Imaging Collaboration (ISIC)	Google's Inception v4 CNN architecture	Sensitivities(86.6%-88.9%, ROC AUC(>0.86,P < 0.01)

*SVM: Support Vector Machine, DNN: Deep Neural Network, ANN: Artificial Neural Network, DT: Decision Tree, GA: Genetic Algorithm Optimizer, KNN: K-Nearest Neighbor, RF: Random Forest, LSTM: Long Short-Term Memory Network, GBM: Gradient Boosting Machines, RFE: Recursive Feature Elimination, TP: True Prediction; AUC: Area Under the Curve, Ensemble:1027 (KIRC), 303 (KIRP), and 254 (KICH) tumor slide image. (Table 1 was cited and merged from my previous study and obtained approval. Huang *et al.* 2019).

4. AI AND ITS APPLICATIONS IN EYE DISEASE

Blood vessel segmentation techniques in fundus image analysis and computer-aided diagnosis in various eye diseases play an important role in the current medical practice. It is the foundation of medical diagnosis, surgery-aided design,

and for early detection and treatment of various cardiovascular diseases and eye diseases [13] which include stroke, venous congestion, diabetes retinopathy, and hardening of the arteries.

In recent years, vascular segmentation has become one of the hot issues in the field of medical imaging. Many automatic segmentation techniques have been proposed and these have achieved good results (Fig. 2). AI diagnosis system for eye diseases has been established *via* Ultra-wide-angle. However, as an auxiliary technology, the image matting model is rarely applied in vascular segmentation. So far, we have only found one patent, which performs vascular segmentation by invariant moment feature and KNN matting technology. However, since generating Trimap is a tedious and time-consuming task in the process of vascular segmentation, it is necessary to design an appropriate image matting algorithm to segment vessels as efficiently as possible.

The process of vascular segmentation algorithm based on the hierarchical Matting model consists of Trimap Generation and Matting. In the generation of trisomy, to improve the contrast of blood vessels, we use wavelet transform and morphological processing to enhance the overall features of blood vessels, and then combine threshold processing and shape features of blood vessels to realize image segmentation and arterial trunk extraction, to obtain trisomy of fundus images.

5. AI IN DENTISTRY

5.1. The Rise of Machine Learning

Big data sets are needed to train smart systems [14]. The project uses deep learning to extract meaning from 10m YouTube video images. Amazingly, Machine learning is the most advanced technology in the field of AI. Dentists now have an in-depth learning AI platform to detect cavities. AI, in the later stages of clinical evaluation, allows any licensed dentist to register as an investigator and use the system.

5.2. The Future of AI in Dentistry

When you hear about AI, you might think of science fiction and imagination, but the future of AI in dentistry is bright [15]. Some of us remember Will Robinson's loyal robot friend from the *Lost In Space* series of the 1960s. Others will trace the sci-fi vision of intelligent autonomous robots back to the day in the *Terminator* films when Skynet's sense of self and humanity began. The term AI and the

scientific community's official pursuit of intelligent machines dates back to the Dartmouth and IBM conference of researchers in 1956. The use of AI in the dental field has emerged! It was easy for the dentist to check for cavities with an X-ray. We have read radiology in practice for thousands of years. Even so, it is estimated that x-rays may misdiagnose cavities. Radiologists must be “trained” to recognize meaningful patterns. They must be able to understand new information in the form of spoken, written text, or images, with appropriate context and nuance.

Finally, they must be able to make decisions based on new information and then learn from their mistakes to improve their decision-making process. For AI systems to have any real benefit in the real world, all of this must happen at the same time that humans perform the same tasks. Until recently, large-scale adoption of AI was not technically feasible or cost-effective, so the reality of AI has not matched the possibilities. Whatever the technical challenges may be, machines do offer some clear advantages. Computers are not biased. As human beings, we are naturally biased and we may make judgments too early. The computer considers only the data provided. Machines don't get tired. We can work for four or five hours without getting tired; the machine works 24 hours a day with no breaks. Another advantage is that machines don't get bored. The tasks we are happy to unload are monotonous and repetitive. Finally, the machine is fast. While current AI systems are primarily based on training and programming for specific tasks (for example, reading radiological images and predicting the location of cavities), they are generally much faster than humans.

Overall, the US Food and Drug Administration started making developments began two years ago. However, significant progress has been made in providing predictive assistants [16]. AI evaluated systems outperform dentists in “sensitivity” by accurately predicting the proportion of cavities that, in reality, the total number of caries is real. Although the machine matched the accuracy of one of the three dentists, the dentist won the title for “accuracy” -In the next 12 to 24 months, AI may emerge, as an application to detect periodontal disease and bone loss associated with periodontal disease [17].

The use of AI in dentistry will spread rapidly in the next years to come. In the next 10 to 15 years, the use of AI-based technologies in practice will be as common and pervasive as practice management and imaging systems are today.

6. EFFECTS OF AI ON TUMOR IMAGE WORKFLOW

There are three main clinical, radiographic tasks in oncology: anomaly detection, characterization, and change monitoring. In the workflow of manual anomaly

detection, radiologists can identify possible anomalies based on personal experience. Dependence on computers or computer-aided detection (CAD) can misguide physicians to make abnormal detection (Fig. 2) [18 - 19]; For example, the traditional image of PET-CT and AI platform to diagnose disease is shown in Fig. (3). Recent studies have shown that CAD based on deep learning is superior to CAD systems with traditional artificial features and that human performance is similar [10]. Characterization is a general term covering disease segmentation, diagnosis, and staging. The most recent deep learning architecture used for segmentation includes the fully convolutional network, which only includes the convolutional layer and the output in the segmentation probability graph of the whole image. Other architectures, such as U-NET, are specifically designed for medical imaging.



Fig. (2). Ultra-wide-angle AI diagnosis system for eye diseases.

Tumor radiation image feature including size, maximum diameter, the spherical degree, internal texture and edge definition of information, *etc.*, are the characteristics to determine the diagnosis of a benign and malignant tumor, which is often subjective, but architecture like CNN, due to the automatic feature extraction, is very suitable for supervision and diagnosis. The staging system divides patients into predefined categories by segmenting and diagnosing before information gathering. Disease surveillance is essential for diagnosis and evaluation of treatment response. The workflow involves image registration

processing, first aligning images from multiple scans of diseased tissue and then evaluating them using predefined metrics.

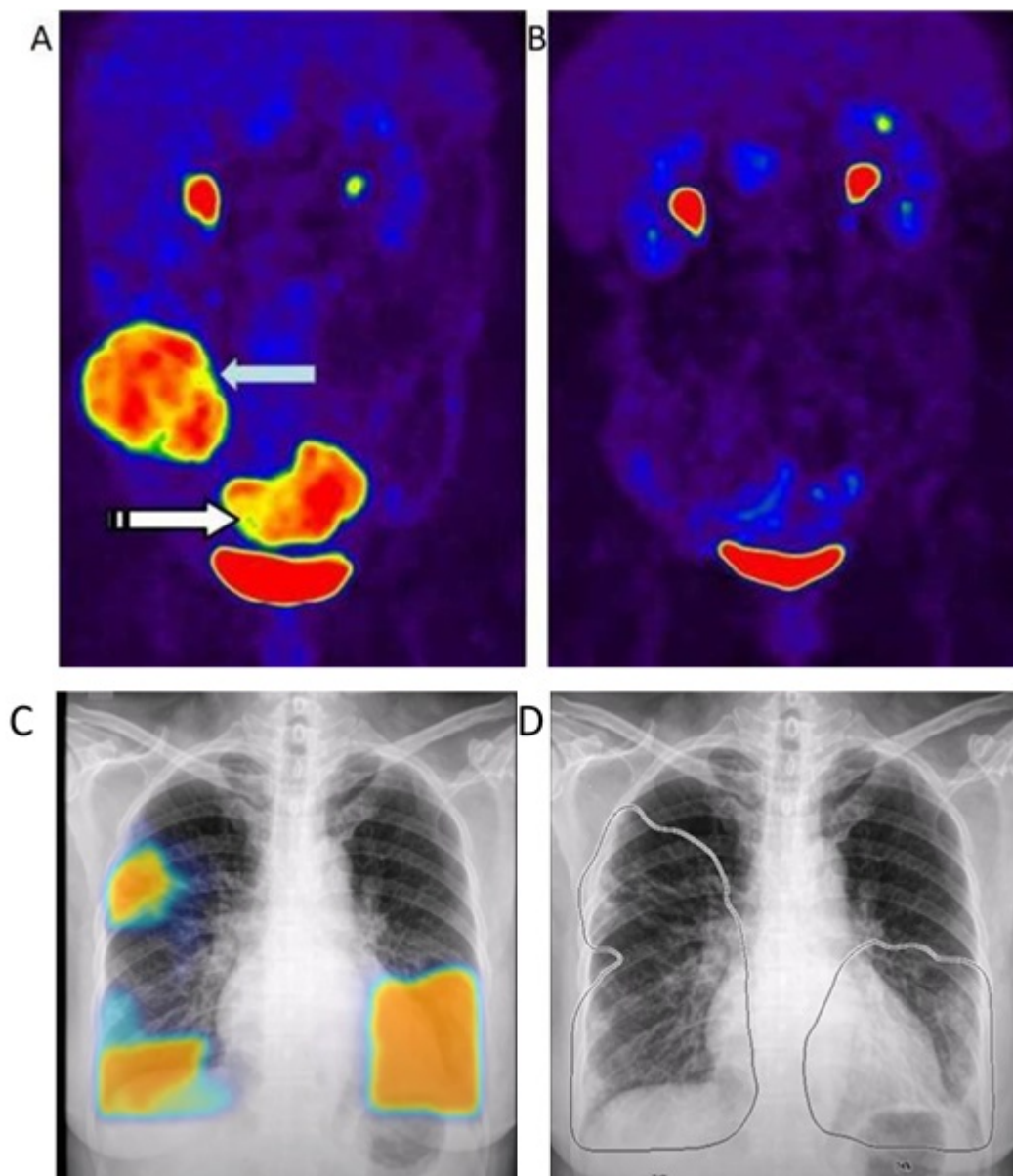


Fig. (3). Traditional image of PET-CT and AI platform to diagnose disease (A and B were cited from my previous study. Dang *et al.* 2018).

7. THE EXPLORATION AND DEVELOPMENT OF AI IMAGE

The following are summarized fourteen kinds of AI platform applications in medical imaging.

7.1. Philips

Intelligent tumor interventional treatment applied Onco Suite is the industry's first tumor comprehensive plan, tumor embolism, and percutaneous ablation to provide a one-stop solution. It can optimize the tumor lesion, guide catheter in place, curative effect evaluation, and so on, making the treatment of big tumor treatment more thorough. At the same time, it helps in avoiding similar healthy tissue damage.

7.2. Ali Health

The “Doctor You” AI system of intelligent image diagnosis jointly developed by Ali Health and Wanliyun includes a scientific research diagnosis platform, medically assisted detection engine, physician ability training system, *etc.* Doctor, You's CT lung nodule intelligent detection engine is jointly built by Ali Health's algorithm engine team and Alibaba iDST's vision computing team. It combines medical knowledge and AI technology to automatically identify and mark suspicious nodules, improve doctors' efficiency, and reduce the rate of misdiagnosis.

7.3. Tencent Miying

Tencent Miying AI medical imaging connects medical experts, AI, and product support teams. It also integrates leading technologies in image recognition and deep learning with medicine to assist doctors in early cancer screening.

At present, Tencent Miying's AI auxiliary diagnostic ability mainly includes diagnosis, treatment risk monitoring system, and intelligent medical record management system: diagnosis and treatment risk monitoring system is designed to help reduce doctors' diagnosis and treatment risk.

The structural output of medical records can free doctors from the tedious superficial work of medical records and effectively improve the efficiency of diagnosis, treatment, and scientific research.

7.4. Hainer Medical Trust

Susquehanna medical aortic dissection and complete quantitative analysis system, for the blood vessels image segmentation algorithm, were based on AI and the automation of quantitative modeling algorithm. By employing this, in 5 minutes, the clinicians can establish the precise aortic vascular quantitative model for critical patients with aortic dissection. Thus it greatly improves the efficiency of disease diagnosis and interventional treatment of aortic dissection.

7.5. Deduce Technology

It is assumed that technological intelligent CT-assisted screening products not only improve the efficiency of lung cancer screening but also show superior sensitivity to semi-solid and ground glass nodules and other signs of early lung cancer, which can help radiologists to improve the accuracy of diagnosis and achieve technical breakthroughs in early diagnosis and treatment of lung cancer.

Its intelligent X-ray-assisted screening product can judge more than 20 different lesions in the thoracic region, which can not only help the doctor to quickly screen out the image of existing lesions but also can quickly identify the location of lesions in the diagnosis process of outpatient and inpatient cases.

7.6. Yassen Technologies

Using the original patent mathematical model, Yassen has carried out scientific research cooperation projects of quantitative analysis of brain, heart, lung, thyroid, and other organs with several key hospitals in China developed and verified the biological and mathematical analysis of specific diseases, and continuously established the database of normal people of China. Yassen's product is developed based on the SPM Statistical Parametric Mapping theory. SPM theory is mainly applied to the quantitative analysis of brain images, and the application of this theory is extended to the lungs, thyroid, and so on by Jason technology.

7.7. Hui-Yi Hui Ying

Hui-Yi huiying used AI to build a smart image cloud platform, aiming to improve the efficiency and accuracy of doctors' diagnosis and treatment and solve the problem of mismatch of doctor-patient resources in some regions. The accuracy of the automatic diagnosis of pneumothorax, tuberculosis, and mass on a chest X-ray has reached 95%. The automatic recognition rate of the tumor was over 85%. The recognition rate of pulmonary nodules in chest CT is over 85%.

7.8. Tuma Depth

Based on the deep learning technology, Tuma Depth's "Lung nodules Detection and Analysis System" can analyze chest CT thin-layer scan images, to help doctors examine and mark patients' lung nodules. Besides, it can also make benign and malignant judgments and automatically generate structured reports.

Compared with traditional artificial screening, this analysis system has great advantages in intelligence and efficiency. With the deep learning analysis system, the machine can automatically detect nodules, calculate various relevant parameters, automatically generate monitoring reports, and provide a reference for doctors.

7.9. Diyinjia

Inga team specializes in providing AI-based medical image big data analysis solutions for precision medicine, such as cancer diagnosis and classification based on pathological image analysis. Its main products include AI-assisted diagnosis systems and digital pathological remote consultation systems, *etc.*, which can process and analyze full-field scanning digital pathological images with data size over 1G in 5-10 seconds on ordinary computers. Meanwhile, the accuracy rate of benign and malignant discrimination of several kinds of cancers is up to over 98%. The model and algorithm developed by the Yinga team can accurately, quickly, and intelligently analyze the various medical images, calculate key index parameters, generate automatic data analysis and reports, and provide pathologists with intelligent diagnostic systems for 7 types of cancer, such as breast cancer, gastric cancer, and prostate cancer.

7.10. Heart Link Medical

Defiled the remote medical care, tumor treatment platform can be seamlessly connected to the existing commercial linear accelerators, for cancer patients to provide more accurate, more automatic, more rapid personalized clinical radiotherapy plan, to improve the cure rate of radiotherapy for cancer, reduce the radiation injury of normal tissue, ultimately prolong the life of cancer patients, and improve the quality of life of cancer patients. The system provides functions including target area delineation, data storage, and backup, cloud computing and sharing, image deformation registration, workflow management, and remote consultation.

7.11. DeepCare

Taking a page out of the SaaS playbook, DeepCare puts the developed smart modules for different diseases on the cloud platform, allowing device manufacturers and telemedicine providers to choose and pay for them according to their needs.

As it is in the early stages of data accumulation, DeepCare is willing to pay for the service by providing images.

7.12. Peptide Building Blocks

Starting from medical image-assisted reading, the research field of fundus lesions was first selected to carry out the screening and diagnosis of sugar mesh disease by analyzing fundus color photos.

The assistant diagnosis of glaucoma and other eye diseases is also continuously advancing. Peptide Blocks is cooperating with Zhong Shan Ophthalmology Department in Guangzhou to carry out research and development.

This AI application can mark the focus, auxiliary diagnosis, and generate medical records. It will mark the focus point, inform the doctor what the probability of a certain disease is, and provide treatment strategies, disease development prediction, *etc.* Treatment strategies may be either further review or direct intervention, such as drug therapy.

7.13. Smart Shadow Medical

The first phase of Smart medical products, based on radiological imaging and pathological imaging, provides two auxiliary diagnostic solutions, including the intelligent diagnostic system for early lung cancer, tuberculosis, and silicosis, and the cardiopulmonary health index analysis and management system for the general examination.

Based on intelligent diagnostic pathology image solutions, it has now launched automatically based on sputum microscopy imaging of pulmonary tuberculosis disease diagnosis system; it is using dyeing pathological picture image, combined with the depth study of the artificial neural network, cluster analysis, multi-resolution, boundary identification and fuzzy logic algorithm for cell pathological condition of regional image segmentation, image feature extraction and use of multi-stage classification treatment to accurately identify the pathological cells number and level.

7.14. Imagemesh Laboratory

Through computer vision technology and deep learning algorithms, the ImageBiopsy will help doctors to make accurate diagnoses based on the radiographs. Based on the NVIDIA GPU, the company trains its algorithm with more than 150,000 radiological images so that doctors can get accurate measurements of the knee circumference. Doctors can determine the severity of osteoarthritis based on the measurements without further diagnosis.

8. THE NEXT FRONTIER

As technological barriers fall and research shifts, we are certainly close to the threshold of providing a range of AI tools to dentistry. We have seen recent product introductions incorporating elements of AI and machine learning (AI/ML). A device, launched at the Midwinter Conference in Chicago, is an amazing technology supported by Natural Language Processing (NLP) [20]. Simplifier's digital assistant, developed with Simplifier, replaces the traditional point-to-point interface with simple, fast voice commands, scheduling optimization project called MMG Chair Fill [21] was also recently announced. The project treatments initiate new profit-maximizing algorithm-based patient marketing campaigns.

We will continue to see the rapid adoption of AI in areas of practice management and growth. With the latest capabilities of deep learning technology, AI will begin to affect dentistry on a clinical level. The first-hand experience of the technology at the development stage, for example, has demonstrated the potential value of AI [22].

We can foresee images from deep learning analysis tools to assist in the diagnosis. The detection and early intervention of implant periodontitis is a possible benefit of implant dentistry [22, 23]. It certainly will, in the future, provide more clinical decisions, making a better dentist. Here there is a long way to go to popularise this technology.

CONSENT FOR PUBLICATION

Not Applicable.

CONFLICT OF INTEREST

The author confirms that this chapter contents have no conflict of interest.

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