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AI-Based Approaches for X-ray Image Interpretation

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ABSTRACT

Radiologists have a significant opportunity to raise the standard of care and highlight the importance of radiography in patient care and public health through the use of artificial intelligence. Given that radiographs are the most common imaging tests carried out in the majority of radiology departments, the potential for AI to assist in the triage and interpretation of conventional radiographs (X-ray images) is especially noteworthy. The development of AI algorithms for the interpretation of chest and musculoskeletal (MSK) radiographs has advanced significantly in recent years, with deep learning currently holding a leading position in picture analysis. Compiling large public and private image data sets has facilitated the development of AI algorithms for radiograph interpretation; many of these algorithms show accuracy comparable to radiologists for targeted, targeted tasks. The foundation for current AI solutions to support chest and MSK radiograph triage and interpretation; opportunities for AI to support non interpretive tasks related to radiographs; and considerations for radiology practices choosing AI solutions for radiograph analysis and integrating them into current IT systems. While all-encompassing AI solutions spanning modalities are still in the early stages of development, organizations may start choosing and implementing targeted solutions that boost productivity, improve quality and patient safety, and provide value for their patients.

Introduction

Around the world, the most widely used imaging modality in most practice settings is conventional radiography, sometimes known as x-ray imaging. The high amount of radiographs taken on a daily basis makes radiography an ideal candidate for the development and application of artificial intelligence technologies, which could boost productivity and enhance quality. Increased computer power, more data available for algorithm training, and the introduction of machine learning techniques like deep learning and representation learning have all contributed to significant advancements in AI. These developments have spurred corporate and university research teams to redouble their efforts in creating AI solutions. Conventional radiographs have been the subject of numerous attempts because of their significance in radiology practices, the abundance of image data that can be used to train algorithms, and their ease of use as a two-dimensional image to three-dimensional.

Conventional radiography practices now have more opportunities to use artificial intelligence to improve patient care and clinical workflow. AI for radiograph analysis has proven effective in a number of use cases, and more AI solutions are being commercialized. This article explains four things: (1) how AI solutions for radiograph analysis were developed; (2) which AI solutions are currently available to help with the triage and interpretation of chest and musculoskeletal (MSK) radiographs; (3) how AI can help with non interpretive tasks related to radiographs; and (4) how radiology practices should choose AI solutions and integrate them into their current IT systems.

Methodology

The first medical imaging modality for which computer-aided techniques were created was radiography. A coding scheme for a computer to later assess the importance of imaging features on radiographs for assessing the prognosis of lung cancer was described by Lodwick et al. in 1963.11 The technique of identifying certain features from every radiograph-such as the margin, density, and form of lesions—opened the door for more advanced computer-aided radiography diagnosis techniques. Two prominent methods for computer-aided diagnosis emerged over the next forty years: machine learning and rules-based approaches, which use precise, step-by-step coding to evaluate images. In machine learning, features from images are fed into classifiers, which then find feature combinations to produce a classification or prediction (e.g., whether pathology is present or not). While over the next few decades, the types of features that can be extracted from images using methods like Fourier analysis, co-occurrence matrices, and wavelet transforms have grown, traditional machine learning techniques have been dependent on engineering and extracting particular features from images.

Since 2013, deep learning, a machine learning method which often uses neural networks composed of multiple layers to transform input data to outputs, has become the dominant approach for medical image analysis, including analysis of radiographs. In contrast to earlier approaches, deep learning in radiographic analysis is often based on convolution neural networks which serve as both feature extractors and classifiers. Using images as input (without features defined a priori), intermediate layers in a convolution neural network extract salient features from the image. The final layer in the network performs classification. Popular convolution neural networks for image analysis include, for example, ResNet, DenseNet, AlexNet, and Google.

While deep learning techniques have proven to perform better for many image processing applications, large volumes of labeled data are needed for network training in order to maximize performance. One important prerequisite is thought to be the availability of high-quality labeled data from representative populations. The National Institutes of Health Clinical Center released a data collection of 112 120 radiography in 2017 called ChestX-ray14, which is one of the most well-known publicly available chest radiograph data sets. Eighteen Natural language processing (NLP) was used to extract the presence of 14 distinct pathologies from radiologists' reports, including atelectasis, cardiomegaly, effusion, infiltration, mass, nodule, pneumonia, pneumothorax, consolidation, edema, emphysema, fibrosis, pleural thickening, and hernia. This provided the ground truth for the data set.

Table 1. Large Radiograph Data Sets Available for Training AI Algorithms.

Chest radiographs

Name of data set	**Institution**	**Number and type of radiographs**	**Labels**	**Labeling method**
ChestX-ray14	National Institutes of Health Clinical Center (United States)	112 120 chest radiographs from 30 805 patients	Presence/absence of 14 pathologies, including atelectasis, cardiomegaly, effusion, infiltration, mass, nodule, pneumonia, pneumothorax, consolidation, edema, emphysema, fibrosis, pleural thickening, and hernia	Natural language processing from radiology reports
CheXpert	Stanford Hospital (United States)	224 316 chest radiographs from 65 240 patients	Presence/absence of 14 pathologies (as above)	Natural language processing from radiology reports; subset manually labeled by radiologists
MIMIC	Beth Israel Deaconess Medical Center (United States)	227 835 studies (including frontal and lateral radiographs for a total of 377 110 images) from 65 379 patients	Radiologist-generated free-text reports for each study	NA
PadChest	Hospital Universitario de San Juan, Alicante (Spain)	160 868 chest radiographs from 69 882 patients	174 different labels using Unified Medical Language System terminology; differential diagnoses annotated with 19 different labels	27% manually annotated by physicians; remainder labeled using a multilabel text classifier

Msk Radiographs

Name of data set	**Institution**	**Number and type of radiographs**	**Labels**	**Labeling method**
MURA[71]	Stanford University (United States)	14 863 studies of the upper extremities	Normal/abnormal	Manually labeled by radiologists
LERA[72]	Stanford University (United States)	182 studies of the lower extremities	Normal/abnormal	Manually labeled by radiologists
he Osteoarthritis Initiative[73]	Multicenter study sponsored by the National Institutes of Health (United States)	8892 knee radiographs	Kellgren and Lawrence	Manually labeled by radiologists

			osteoarthritis grades	
Digital Hand Atlas [74]	Children's Hospital of Los Angeles (United States)	1400 hand radiographs	Sex, ethnicity, and bone age	Based on radiology report
RSNA 2017 AI Challenge[44]	Stanford University and the University of Colorado (United States)	14 236 hand radiographs	Sex and bone age	Based on radiology

Which AI options are available now and in the future for the analysis of chest radiographs?

Large chest radiograph data sets have been developed, which has greatly benefited the development of AI algorithms for chest radiograph analysis. Although one of the first uses of AI for radiograph analysis was the detection of lung nodules, cases—such as pneumothorax detection, pleural effusion detection, tuberculosis screening, and more general algorithms detecting multiple pathologies on chest radiographs—have recently attracted the attention of research groups and vendors. Evaluation of catheters on radiographs is another new field of study. These algorithms typically produce a flag or "heat map" as their output, which shows potential pathologies or places the user may want to concentrate on. While fewer have been approved by Health Canada, an increasing number of AI products for radiograph analysis have been granted approval by the US Food and Drug Administration (FDA) under the 510(k) pathway and have been certified with the CE mark, which denotes compliance with EU standards. At this point, there is a lot of promise for using these solutions as a second reader when interpreting radiographs and for triaging imaging studies for urgent radiologist evaluation.

Pneumothorax detection

Systems and Zebra Medical Vision have created products for computer-aided triage and notification for pneumothoraces on frontal chest radiography. Although neither product has yet been approved by Health Canada, they have both been approved by the US FDA. These devices create a secondary capture image known as Digital Imaging and Communications in Medicine (DICOM) that displays the AI results, and they also give passive notifications of pathological discoveries during image transmission to the picture archiving and communication system (PACS). With sensitivity and specificity as high as 93.15% and 92.99%, early research indicates that AI systems that choose radiographs for immediate examination could speed up the interpretation of time-sensitive images. When the product was used to create a prioritized work list, it took an average of 8.05 minutes (95% CI: 5.93-10.16 minutes) for three US board-certified radiologists to interpret time-sensitive images, compared to 68.98 minutes (95% CI: 60.53-77.43 minutes) for the standard of care. Each radiology read 588 radiographs.8 The product's average performance time to analyze the radiograph and notify the PACS worklist was 22.1 seconds.8 The therapeutic impact of this method may differ greatly throughout clinical contexts and be contingent upon the frequency of radiographs with important findings, turnaround times, and current turnaround times, notwithstanding the outstanding results that were showed in lowering the time to interpretation for time-sensitive pictures.

Pleural effusion detection

The FDA has approved Zebra Medical Vision's targeted product for the identification of pleural effusions on chest radiographs; as of this writing, Health Canada had not granted approval. The product showed an area under the receiver operating characteristic curve (AUROC) of 0.9885, sensitivity of 96.74%, and specificity of 93.17% in a validation study involving 554 chest radiographs. Among other disorders, pleural effusions are detected by other, more general AI devices.

Tuberculosis screening

Significant advancements have also been achieved in the creation of AI algorithms specifically designed for tuberculosis screening, which may find use in environments with limited resources. An ensemble of deep convolutional neural networks, including AlexNet and GoogLeNet, was reported by Lakhani and Sundaram to reach an AUROC of 0.99 when classifying photos as either normal or showing pulmonary signs of tuberculosis.5. An overall sensitivity of 97.3% and specificity of 100% were achieved by having a radiologist assess only the cases where outputs from the two deep convolution neural networks differed. This suggests a place for a "radiologist-augmented approach," in which a radiologist reviews only a subset of all images. AUROC values ranging from 0.92 to 0.94 were obtained from a multisite study of three commercially developed systems for the categorization of chest radiographs with anomalies associated to tuberculosis. Two of the three deep learning systems had specificities that were much greater than those of the two radiologists at a sensitivity that matched theirs. This could potentially reduce the number of referrals for nucleic acid amplification testing. Commercially available products have been used for tuberculosis screening, such as Qure's qXR, a CE-mark certified tool for detecting multiple abnormalities on chest radiographs, including cardiomegaly, consolidation, and pleural effusions. Performance metrics specific to tuberculosis have not been published, though. To guarantee enough specificity for screening and diagnosis, artificial intelligence algorithms that are trained on data sets containing radiographs with a tuberculosis label will be essential.

Multiple diseases identified on chest radiographs

Pneumothorax and pleural effusion detection are two examples of the limited use cases for many of the products that have gained regulatory approval to date. However, artificial intelligence (AI) algorithms that can detect many pathologies using a single network are becoming more and more developed and commercialized. With AUROC scores ranging from 0.73 to 0.94.4, the convolution neural network CheXNet, created by Stanford University's Andrew Ng's lab, obtained state-of-the-art outcomes for 14 diseases on chest radiographs. The network was trained using the ChestX-ray14 data set. The ChestX-ray8 data set was used to train and internally validate CheXNeXt, another algorithm. Three senior radiology residents and six board-certified radiologists from three academic institutions were used to compare the algorithm's performance. The model outperformed radiologists for the identification of one pathology (atelectasis), three pathologies (radiologists outperformed the model) and the remaining ten (model AUROC values ranged from 0.70 to 0.94) were of similar performance. Similar high AUROC values have generally been attained by other studies.

Park et al. used a data set with groundtruth defined with reference to recent computed tomography when available to assess the possibility of AI to demonstrate performance superior to radiologists' interpretation of chest radiographs. The model fared better in lesion-wise detection than all nine readers. If artificial intelligence (AI) systems are trained on data sets containing cross-sectional imaging correlation and pathological diagnoses, it is predicted that these algorithms will eventually outperform radiologists in terms of diagnosis accuracy for targeted, focused jobs.

Which artificial intelligence (AI) uses for MSK radiograph analysis are available now and in the future?

Among other uses, musculoskeletal radiographs are effective first-line investigations for skeletal dysplasia’s, bone malignancies, and trauma. There are several use cases for AI to help with the interpretation of MSK radiographs. These include automating measurements like the Insall-Salvati ratio or femoral neck-shaft angle, identifying fractures, determining skeletal maturity (bone age), and estimating the likelihood that a bone lesion is benign or malignant. Some of the most common use cases investigated in the literature and for which AI solutions have just been commercialized are determining bone age, identifying fractures, grading osteoarthritis, and automating measures.

The Radiological Society of North America Machine Learning Challenge 2017 featured the development of algorithms to assess bone age, which attracted a lot of interest. For the challenge, a data set of 14,236 hand radiographs was made available. Four independent radiologists used the Greulich and Pyle standard to determine the ground truth ages, which were also derived from the corresponding clinical radiology reports.44 The mean absolute difference (MAD) between the model and the ground truth was used to gauge overall performance. The best 5 entries, out of 105 total, obtained MAD values that ranged from 4.2 to 4.5 months from the ground truth ages.

Identification of fractures AI Promising for fracture identification With an AUROC of 0.967, Lindsey et al employed a data set of 135 845 MSK radiographs from various anatomic locations, with ground truth determined by one or more orthopedic surgeons. A statistically significant improvement in both sensitivity and specificity for fracture detection was observed when emergency medicine physicians were assisted by the algorithm compared to when they were not, according to a study that evaluated how the algorithm may change fracture detection performance among emergency physicians interpreting posterior-anterior and lateral-view wrist radiographs.

Conclusion

Triage and automated interpretation of radiographs are particularly attractive use cases for AI to boost the value that radiology gives to patient care because of the volume of radiographs performed every day across radiology clinics. While focused tasks related to radiograph interpretation have seen high diagnostic performance from artificial intelligence solutions, more research, including clinical effectiveness studies, is required to fully understand the clinical impact of AI in radiology departments and healthcare systems. It is projected that future development work will broaden the scope of use cases for AI for radiograph analysis across interpretive and non interpretive tasks; increase the availability of labeled radiograph data sets for training and testing AI algorithms; increase the use of AI across patient populations, including pediatrics; and facilitate easy, vendor-neutral integration of AI solutions into legacy IT systems. Institutions can start integrating targeted AI solutions that improve their practices from an expanding number of FDA- and CE-approved solutions, as well as from a currently smaller number of Health Canada approved solutions, even though full AI solutions across modalities have not yet been established.

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