AI-Based Solutions for Automating Radiology Workflow

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1. Introduction to AI in Radiology Workflow

Role of AI

In recent years, artificial intelligence (AI) has proven to be an important technology for enhancing the radiology workflow, leading to improvements in cutting-edge practices. Historically, AI has only been seen as a fully automatic Computer-Aided Diagnosis tool. Nowadays, its applications have significantly been extended from imaging interpretation to image quality control and image acquisition, effective medical big data mining and utilization, to study individual radiologist performance and automate the higher quality radiology workflow, making it an important part of the growing interest in the development of quality of care. Radiologist-driven automation (RDA) is defined as automated tools that are built to aid radiologists in their workflow, with such tools still requiring a report by the radiologist as the endpoint of care. Most, if not all, RDA tools can be classified as using AI.

Importance of AI

Automating the radiology workflow increases radiology throughput and helps to maintain efficient diagnostic processes, and can also help the radiologist interpret the report without having to spend a lot of time interpreting an image from normal data studies. For radiologists to use AI, they need to have an understanding of its principles. Automation can improve the interpretation of imaging data and report quality by reducing the impact of various time and cognitive biases. AI has the potential to provide various automation support for clinical decision-making in diagnostic imaging, including time efficiency, educational feedback, and quality enhancement. This support aims to reduce working and emotional burdens to ensure working pleasure. In terms of patient outcomes, AI can also assist in reducing missed pathological findings and guiding referring physicians' tests, thereby promoting improved final patient pathway outcomes.

Challenges

There are several critical issues associated with automating the radiology workflow using AI, such as high expenditure for vendors and a lack of evidence of additional patient outcome improvement. Another important issue is a lack of literature at the point of care to implement AI in the radiology departments. Regarding studies related to AI in radiology, widespread recognition of AI benefits is still needed. It is crucial for an AI RDA to reach the top tier levels of this informed implementation. AI, especially deep learning, is now rapidly being incorporated into various radiological applications. One of the major areas of interest is becoming our radiology workflow. This is an entirely different domain from previous fundamentals, even though basic machine learning diagnostics started most of the AI field; a few other radiological diagnostic applications have started to become interesting. We want to ensure that AI for our workflow is just as excellent; we can achieve a good ROI and make it transparent to us. What matters in using AI relates primarily to how well it helps radiologists work. It is still uncertain how to include these considerations in the application of commercial workflows.

2. Fundamentals of Machine Learning in Radiology

Radiological images are a data source that is easily available for scientific and clinical research, making knowledge from a wide range of institutions and sources publicly available for use. Hospital-based systems possess 98% of all images and have access to the patient's private medical record to correlate imaging data with patient outcomes. Computer-aided diagnosis and AI-based decision support systems do not replace radiologists but are used as a second reference to improve patient management. These are the logical propositions to be the future building blocks of modern radiology systems. AI characterization of the pulmonary, liver, spleen, and kidneys in chest CTs, abdomen CTs, MRIs, and specifically diabetic retinopathy screening from fundus images has shown the potential to transform the workflow in a radiology department.

Machine learning is the field of computer science encompassing computer programs with the ability to automatically improve and generalize performance according to a skill function and in total a "loss." A model that may be entirely determined by means of infinite data items will generalize if it can rigorously learn the training data properties. When a model applies generalization to applications beyond the training data, the model is identified as learnable.

Collecting high-quality data in quality and quantity is important since the learning method works only in practice. High-quality data in this circumstance may specify a radiological dataset with ground truths. For example, a dataset with MRI data slices in which label 1 and label 0 show the entire or a part of the meniscus is important, as the design of the model in some neural network designs will be performed automatically. We can use the same methods, even if the representations differ.

3. Image Analysis Techniques in Radiology

Radiology image analysis can be broadly divided into four categories: image segmentation, image classification, detection, and image reconstruction. Algorithms used to process images for extracting meaningful information differ according to specific problems. Convolutional neural networks (CNNs) are widely used for image recognition tasks in various domains and guarantee efficient performance. They perform learning on their own for detection, segmentation, labeling, and interpretation of medical imaging data. The evolution of CNNs has provided superior results over classical methods in almost all cases. Segmentation and classification are the two main problems that have been resolved through various methodologies and techniques to improve accuracy, which in turn improves the interpretation of outcomes from medical images. For both approaches, feature extraction is a crucial task that needs to be performed with utmost accuracy. In deep learning-based classification and segmentation models, feature extraction is performed during the training of the network. For both techniques, CNNs have shown tremendous success.

Segmentation divides an image based on pixel-level intensities and classifies them into categories accordingly. It has multiple applications, including dividing the brain into gray matter, white matter, and cerebrospinal fluid in MRI, or segmenting the whole lungs and their nodules in CT scans to detect lung cancer and any defects in organs. Segmentation can be done in two ways: region-based segmentation and edge-based segmentation. Classification, on the other hand, classifies the whole image into a label such as defect or non-defective. It is quite simple compared to segmentation techniques. Supervised learning, a machine learning technique, is widely used for both segmentation and classification tasks that require a labeled dataset for training the algorithm. The above techniques are integrated with the clinical workflow setup to make use of these methodologies in the deployment phase and analyze their performances in detail. Additionally, we present some critical findings in the integration of these techniques with radiology practices to validate the potential of these technologies in the future. A large amount of data is in the form of images. Analyzing this data manually is very time-consuming and prone to human error due to subjective decision-making. In light of advancements in the field of AI, accurate and consistent results, gained more promptly, are promised. Today, AI-based medical image analysis is at the forefront of new technologies. This area of radiology is concerned with radiomic and radiogenomic data. Researchers are developing decision-making systems, integrating high-throughput technologies for the opportunity to better help improve predictions of medical imaging findings. AI-based image analysis techniques are of newer origin, and their incorporation into everyday clinical practice is an active area of research.

3.1. Convolutional Neural Networks (CNNs)

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Convolutional Neural Networks (CNNs) have been a category of deep learning algorithms particularly powerful for analyzing spatial hierarchies in images. This subsection describes an issue of such CNNs for the task of radiology. With a particular design of the network's architecture and a training process adapted to radiological images, not only can the network accurately interpret these images, but it is also able to point to the parts of the images that are most informative for such interpretation. CNNs contain a unique architecture and training process that allows them to work with radiological data from CT, radiographs, MRI, and more as end-to-end systems or auto-encoders, meaning it requires no manual extraction of any features by domain experts. Specifically, CNNs are trained to make decisions about pathology or normality on the basis of features of spatial local parts of the images; then feature maps are extracted and concatenated across the volume of the image to classify. Unlike other computational intelligence strategies, CNNs empower a network to learn in both supervised and unsupervised settings.

The underlying principle of CNNs is representation learning, as the features in the high layers represent complex structures in the images by aggregating the features learned in the lower layers. DNNs that use this technique can be conceptually thought of as learning the sum of multiple inference functions of different spans, from pixels to textures, from features to parts, to objects, to scenes, to patient cultures, to syndromes, and to diseases. This ability to automate intrinsic structure prediction, such as texture on a superficial level, is one potential as-yetunexploited power of CNNs in imaging. No other computational intelligence strategy currently offers both the effectiveness and tasks learned by CNNs, so there is enormous interest in radiology in developing this recent innovation in computational intelligence.

3.2. Segmentation and Classification Methods

Segmentation is the process of delineating structures or regions of interest within images. It is a fundamental step in medical image analysis, and the accuracy of diagnostic and therapeutic decisions is highly dependent on accurate segmentation of abnormalities. Various segmentation methods, including contour or edge-based, region-based, hybrid, and atlas-based methods, have been proposed. Simple thresholding is one of the basic techniques used to segment anatomical organs with a considerable difference in density compared to the surrounding tissues. Other widely used methods that are relatively simple yet powerful include intensity-based methods, regional histogram methods, clustering methods, and region-growing methods. Multiregion-growing methods and region-growing methods based on seed point determination explore the image from a holistic point of view, and they ignore the boundary conditions between lesions and blood vessels, which can cause prominent lesions.

Digital media, especially medical images, contain a huge amount of information. Therefore, image classification, which is based on their content, eases storing, searching, and retrieving such a large number of images. Radiological documents store large amounts of data, thus making it difficult for a radiologist to decide on the most appropriate diagnosis. Deep learning algorithms for image classification have shown to be promising. In fact, a CNN architecture named AlexNet, which consists of a composition of eight processing layers, was implemented for the first time in 2012. A few months later, another type of neural network architecture was developed that has contributed to major advances in computer-aided diagnostic radiology. This approach is based on the research of convolutional neural network algorithms. Since tissue region extraction and image detection are closely related, a survey of image processing algorithms and the optimal region extraction methods is important. The accuracy of certain algorithms in the classification of medical images can help in qualitative and diagnostic radiological evaluations. In such diagnostic evaluations in relevant anatomy regions, tumors can be predicted, and the spatial concentration thereof corresponds to the blood flow.

4. Automated Report Generation in Radiology

Many radiological exams conclude with a radiological report containing an official statement about the findings and a final conclusion. Historically, these radiological reports were created solely by human readers. After each examination, radiologists were responsible for processing images and determining their opinion on potential findings that the referring treating physician should be aware of. Automated report generation could liberate radiologists from the overwhelming administrative work that has intensified over the years, transforming radiologists into primarily medical consultants. Automating the reporting process is no longer an if, rather a when. Integration of advanced research in the field of artificial intelligence, combined with decades of experience using procedural automation in radiology information systems, machine learning prediction models, and natural language processing to aid in the interpretation of information for the final radiological diagnosis, has brought us to the brink of a new era of streamlined, efficient, next-level reporting facilities. For the most part, automated reporting is perceived positively across the board by the radiological community. Overall, improved report efficiency, accuracy, readability, and concerning patient outcomes are issues that garner the most excitement from those interested in AI-based reporting. Natural language processing has shown to improve the accuracy and readability of generated reports. While technology does seem to approach human performance in some ways, there are many significant hurdles that remain before automated report generation is reliable and can be adopted into a clinical workflow. Automated reporting has been piloted and broadly implemented across several domains. Regulation and compliance have not been explicitly studied, but are at the forefront of radiologists' minds. To our knowledge, there are no public domain investigations on AI-based reporting systems that are clear of methodological bias, harming the widespread utility of these systems.

4.1. Natural Language Processing (NLP) Applications

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NLP is a definitive application of AI and is crucial in transforming unstructured information into more accurate and structured data in medical imaging. In the radiology field, NLP can be used to extract key findings or information about the patient image report. In addition, NLP can be integrated to support healthcare systems or to be used by radiologists or clinicians for simplifying clinical documentation. In medical workflows, NLP technology is used to improve efficiency and save time. NLP technology itself is fundamentally used for handling the complexity of natural language text processing. In AI-assisted workflows, NLP offers potential help in analyzing or extracting radiologists' image findings. Furthermore, NLP is also recommended to be integrated with other applications, like computer-assisted diagnosis, machine learning, and other classifiers.

Many challenges are encountered when transforming unstructured radiological image data into structured ones, especially in NLP technology. Many different medical terminologies are still required or created for encoding similar medical expressions, which results in ambiguity in automated text analysis. Extracting information at a sentence or word level should be implemented accordingly to ensure that it corresponds with the actual contextual meanings. NLP aims to provide additional clarity and insights in radiological reports, with an end goal of better collaboration between radiologists and referring physicians. Several use cases for the use of NLP to support radiologists are cited.

Another group implemented NLP in radiology to parse radiology reports in an imaging archive and automatically create a structured database of diagnoses for use in mining operations. The use of NLP with reports made by different reporters enabled quicker identification of cohorts in population studies. A study on cases focused on the concept of manageably correct synonymy. In another study, NLP was used to generate a structured database of diseases from patient records from a medical center. Demonstrated more accurate clinician completion of the BIRADS scores when using NLP-assisted reporting techniques. An NLP engine was implemented using a different approach, which selected the paragraphs within a report that contain image findings. Implementers noted the ability for an image management system to highlight areas of the report usually handwritten by the radiologist.

5. Clinical Decision Support Systems (CDSS) in Radiology

Clinical Decision Support Systems (CDSS) are based on electronic tools designed to assist in clinical judgments using a combination of patient data and algorithms. Many hospitals and clinics have already implemented or are working to implement some form of CDSS. They are considered a valuable tool, especially in radiology, where radiologists and physicians are overwhelmed by the increasing number of imaging studies. CDSS can have a significant clinical impact when it comes to radiology, as workflow automation supports accurate and evidence-based assistance in clinical management using imaging and improves the quality of patient care. Clinical workflows in healthcare, especially in radiology, can face different setbacks. Thus, tools such as CDSS that can be integrated into the radiology workflow and incorporate clinical information related to the management of patients and evidence-based information with access to full diagnostic information could be of utmost importance in order to get consistent and optimal information about the patient.

CDSS that have been successful contain a vast amount of knowledge about the procedures and decisions made. Often, they provide valuable aid in highly complex decisions and are the result of years of accumulated knowledge. CDSS are divided into many types: those that alert you, those that provide reminders, those that allow you to look at specific patient data, and those that may provide an instant recommendation. The priority for these systems is to adapt well to the current clinical workflow and integrate well with clinical pathway rules and guidelines. A key requirement for these systems to be truly useful is the seamless availability of patient data, which entails integration with the hospital's Electronic Health Records.

Even in developed countries, diagnostic errors are very common. It is estimated that the error rate is 10%, and the majority of these occur in primary care and the emergency department. Radiology contributes greatly to this problem, as it is ultimately a data-driven final step. The increasing number of imaging studies in recent years and the increasing complexity of imaging are some of the reasons for the miss rate. The incorporation of CDSS in radiology can help substantially reduce the error rates, especially as it provides comprehensive solutions for decision support covering the entire patient journey inside the hospital. The issues of handling big data, both structured and otherwise, the quality of the data, the type of algorithms to intervene for processing and handling of big data to improve processing times, and the role of input quality contribute to the accuracy of diagnosis that CDSS should inculcate.

Therefore, Japan and many other countries have been struggling with this burning issue. Apart from the growing workforce challenges, the evolving field of CDSS is in response to the growing demands and challenges of modern radiology. They are in a unique position to access both radiology images and various clinical algorithms and are at the forefront of the efforts to use AI to improve the quality and efficiency of patient care. Unlike traditional CDSS algorithms, which work as if a patient ID is given as input and go straight to display what is already decided, AI-based CDSS works with a combination of medical records as input and reports accuracy, narrowing down the focused information based on its algorithm. AI-based CDSS could work with improved accuracy when combining data, different from the method used in traditional image characteristics of a single hospital, which originates from big data in real-world cases because of its shared data creation. This in itself represents the challenge in the handling of big data.

5.1. Integration with Electronic Health Records (EHRs)

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Radiologists frequently produce reports that are directly relevant for clinical patient management, and as such, their reports are expected to contain specific observations, interpretations, and recommendations. By integrating a Clinical Decision Support System (CDSS) directly with an EHR, patient data and models more easily become accessible to the decision support system. The improved mode of access to data through EHR improves workflow and efficiency and enables real-time display of relevant data and patterns. CDSSs can be integrated with EHRs in a variety of ways, either through linkage at the database or application level; however, these approaches can be challenging. Invariably, the greatest challenge is the processing framework or software that is relatively independent of the EHR's makeup and, as a result, can offer its outputs to a variety of EHRs with relatively minor alterations.

The majority of EHRs are based on technologies developed and deployed years prior to the development of advanced learning and imaging models. It is often necessary to develop the output of the AI/ML tool into codes that can be uploaded to the EHR. Current outputting approaches for text-based reports include copying text into an EHR note, using an Application Programming Interface to upload the information to the EHR, or copying the AI/ML output directly into dictation and then having that dictation uploaded to the EHR. An EHR may also handle structured data differently—such as regarding coded values or screening results—and how snapshots or images, particularly moving images, are currently handled or worked into system boundaries. It should be recognized that data privacy regulations demand that the patient must have control or consent for the process of sharing a patient’s medical data for AI and CDSS. CDSS can potentially provide a clearer understanding and more depth of patient condition or care, but such data sharing has to be compliant with these standards. By offering quick access to patient-related, updated, real-time AI, machine learning, or predictive models based on historical data, a clinical decision support system integrated directly with an EHR can better inform clinical decision-making and reduce the chance of errors. Some EHR platforms have the capabilities to support such integration or linkage already.

6. Future Direction

In the years to come, we anticipate that advancements in algorithm design and machine learning techniques will continue to electrify the field of AI-based solutions in radiology. Fundamentally novel visions of diagnostic processes in radiology can be created by future algorithms that go beyond simple feature engineering and rather plunge into breaking down the processes of medical image diagnosis. These algorithms are adept at retrieving favorable salient and diagnostic patterns of disease from large-scale, extrinsic emergent networks modeling image data. As we move increasingly into personalized medicine, AI solutions will need to be integrated with a suite of other technologies such as remote monitoring and augmented reality.

One of the trending concepts of AI-based solutions in radiology is interpretability; beyond mere interpretability, we aim to integrate interpretability into the domain of medical reasoning. As the demands for integrated care delivery grow, the same data that enables the practice of radiology is in turn useful to optimize the operational workflow of health systems. As AI-based solutions penetrate the radiology landscape, they will provide a comprehensive approach to the optimization of both patient care and hospital operations. In such an environment, the workflow between patients, their diseases, and advanced technologies can be algorithmically re-envisioned and precision-targeted. As AI applications of the future succeed in enhancing clinical viability, there are significant potential regulatory challenges that could slow their implementation. Possible concerns include the justification of added value, procedure optimization and safety, validation and quality control, ethics, patient privacy, and liability.

The lack of a skilled workforce and ethical considerations were common discussion points centered on opacity and trust issues related to AI solutions. Incorporating the patient perspective into established frameworks for performance evaluation would enhance the transparency of AI in this classification. Trust calibration can be performed by running the developed visual saliency prediction module and ultimately boost the trust of the patient in the image classification system. Despite challenges, participants often cited a significant potential for the use of AI in triaging and detection in radiography, limiting human resource burden, promoting operational efficiency, and delivering higher quality outputs consistently. AI is found at every stage of the patient pathway, from consultation triage, radiography interpretation, and reporting, to be beneficial. In the near future, we can expect great work in the field of deep learning, algorithmic interpretation, macro-managing AI, and adaptive systems. Furthermore, the discussion has led to workflows that may be influenced by the integration of AI solutions into the workflow of radiology. Regulatory compliance is seen to be beneficial at large to ensure safety. The most crucial entailment needed is a workforce that is equipped with advanced training in both AI and clinical components.

7. Conclusion

The use of artificial intelligence for automating radiology workflows can lead to several benefits, including increased efficiency, accuracy, and patient care. The technology is, however, still in a very early stage of development, and many technical, ethical, and regulatory challenges need to be addressed. Solutions to these challenges require further research and development work in collaboration with radiologists, technologists, and regulatory bodies, as well as expanded educational initiatives for the radiological community. There is reason to believe that AI, if properly developed and deployed, could have a transformative effect on radiology practice in the coming years. There are challenges in improving the performance of AI solutions, designing technologies to work seamlessly within clinical environments, and guaranteeing that predominantly technical systems are transparent, interpretable, ethical, and robust. The increasing use of AI solutions within society at large and the healthcare system is also likely to have an impact on the work radiologists do within care pathways, which will need to be studied as practice develops. Optimally, AI solutions will leverage the complementary strengths of machine and human intelligence. While AI is likely to contribute significantly to radiology practice in the coming years, it will not replace human interpretation and clinical judgement within radiology expertise. In this, as in many other areas, optimal outcomes will be served by smart collaboration between human and computational resources.

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