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Artificial Intelligence In Medical Imaging

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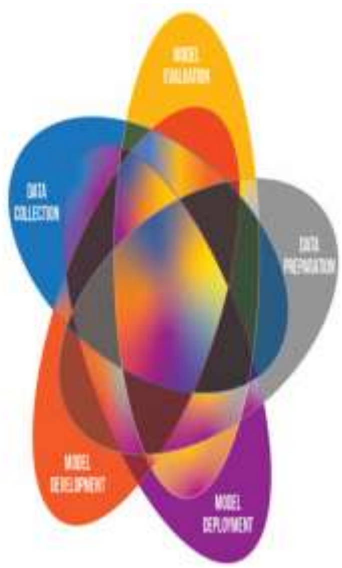
Abstract

With rapid advancements in data capture, data storage, and computer processing capabilities, it is now possible to consider "real-world" medical imaging data and the associated clinical information in the development of artificial systems that support clinical decision-making. As a predictive tool, the focus of AI (and AI research) is to provide prediction to support the most effective patient management. Ideally, in the future, there is the possibility that decisions to treat could be supported by a more precise prediction of outcomes. For example, modern imaging can detect subtle abnormalities in the brain and label patients with the potential for mild cognitive impairment. However, the rate of progression to dementia varies considerably in this group. AI methods could be used to define those patients at highest risk of progressive disease (using changes in serial imaging and clinical monitoring) and thus inform decisions about early intervention tailored for this risk group. This broad scope could be used to tailor prediction models for individual disease processes that define the likelihood of specific diagnoses or outcomes and potential responses to treatments. In defining any of these decision tasks, AI requires vast data knowledge of the disease process in question. Prediction today in most clinical conditions

is based on expert opinion, often using simple probability estimation without reference to specific patient variables. Thus, there is an opportunity for a knowledge discovery step using existing health datasets to define the decision task and enable a model that predicts individual patient risk and potential expected treatment responses.

1. Introduction

Medical imaging is essential for identifying and diagnosing a variety of diseases. Over the last decade, integrating artificial intelligence (AI) technology with medical imaging has brought major advancements to the field. The notable growth of AI in medicine has demonstrated remarkable potential for the development of innovative applications, which could enable earlier and more accurate disease detection, improve treatment protocols, and enhance patient outcomes. In particular, medical imaging is considered to be one of the most promising areas in medicine for the implementation of AI. This is due to the large quantity of image data, recent advances in image analysis and computer vision, and the increasing clinical demands for effective solutions to problems in image analysis. In this short article, we examine the role of AI in medical imaging and discuss the opportunities and challenges associated with the technology. (Zhou et al.2021)



1.1. Role of Artificial Intelligence in Medical Imaging

AI programs aim to replicate human cognitive functions. Pattern recognition is a cognitive function that is integral to the interpretationthe interpretation of medical imaging studies and is a primary means by which diagnostic radiology adds value to patient care. Most obviously, radiologists identify in radiographs the anatomic abnormalities and variants that underlie the signs and symptoms of disease. But beyond this, pattern recognition includes recognition of the imaging appearances that are associated with various diseases (e.g.,(e.g., lung cancer staging) and recognition of when and how to apply specific imaging modalities to optimize diagnostic yield in a cost-effective manner. Pattern recognition,recognition, notably,notably, also includes the detection of changes in disease appearance over time. In so doing, radiologists may make complex probabilistic inferences. For example, a pediatric radiologist interpreting a series of abdominal ultrasounds in a child with known Crohn disease may seek to correlate the clinical symptoms of the child with changes in the distribution and appearance of bowel wall thickening. A change to a more advanced AI--supported practice of medical imaging would ideally shift pattern recognition tasks from radiologists to computers with AI programs. This could in principle be achieved by programming computers to extract the patterns that radiologists recognize and more directly, by training computers to recognize the patterns themselves. High-level pattern recognition tasks have historically been beyond the capability of AI programs, but rapid advances in machine learning and image analysis suggest that this is likely to change. Pattern recognition tasks are especially amenable to automation and should AI tools can be developed to carry these tasks reliably, they stand to provide huge productivity gains for radiologists and major cost savings in the provision of diagnostic imaging. An improvement in the cost effectiveness of diagnostic imaging would facilitate an increase in imaging usage when it is clinically indicated and would ideally lead to better global health outcomes. (Wang et al.2023)

The aim of the development of artificial intelligence (AI) is to produce computer systems that can execute tasks thatthat would normally require human intelligence. AI has developed swiftly over the past decade,decade, and AI tools are progressively embedded in the practice of medicine. Research into AI programs intended to undertake sophisticated reasoning has been around since the 1970s. AI has much to offer in the healthcare domain. Yet the results of research in AI have not resulted in robust tools that can outperform clinicians in the day-to-day reasoning that underpins medical practice. Meanwhile, AI tools that can automate complex and routine tasks have been more successfully developed and deployed. Medical imaging is the use of electromagnetic radiation (e.g.,(e.g., X-rays, CT scans), radioactive substances (radiopharmaceuticals), and magnetic fields,, a field thatthat is especially rich in routine tasks thatthat could be effectively automated using AI. As such, the application of AI in medical imaging is an exciting proposition with the potential for a great deal of benefit to patients.

2. Image Analysis in Medical Imaging

The eventual goal of AI in medical imaging is to extract the maximum possible information from images to enable earlier and more accurate diagnosis and treatment of disease. Two particular areas of interest are using AI methods to recognize patterns in images and to improve the accuracy of diagnosis. An example of the former would be the detection of micro-calcifications in mammograms, which can be early indicators of breast cancer. These are often only visible as faint white specks on the mammogram image and can be easy to miss. Researchers at the University of Castilla-La Mancha in Spain have developed a system that can automatically search for such patterns on mammograms, decide which areas are suspicious, extract them for further computer processing, and highlight them on a display for the radiologists to review. In a test on a database of 83 mammograms, the system achieved 83% sensitivity in the detection of micro-calcifications, with 1.07 false positives per image. This compared favorably with a performance of around 80% sensitivity and 5 false positives per image for radiologists. As micro-calcifications are often difficult to detect and easy to misinterpret, a more accurate automatic system could be of great use to radiologists, as it could reduce the number of unnecessary breast biopsies prompted by false-positive results. In another example, an international team of researchers have developed a fully-automatic computer algorithm for diagnosing malaria from Giemsa-stained blood smears. This is based on an artificial neural network that has been trained using a database of images of infected blood cells, to automatically segment and analyze the cells and detect and identify any infected cells present. The results of a study on 1000 infected and uninfected cells demonstrated the potential of such an image analysis methodology for the diagnosis of human malaria. High levels of diagnostic accuracy were achieved, with over 90% sensitivity and specificity for detecting infected cells and a similar performance for distinguishing the cell infection status. Automatic methods like this can be a useful alternative to current practices, which often involve manual examination of the blood smear and can be time-consuming and of questionable accuracy. (Loizidou et al., 2023)

2.1. Recognizing Patterns in Medical Images

The most important of these is recognizing and detecting the patterns and features thatthat are indicative of some abnormality, which is a key stage in the diagnosis of many diseases. There is a vast array of potential patterns and abnormalities, which makes this a daunting task. For some diseases, for example,example, Alzheimer's, it can involve recognizing subtle differences in the size, shape, and texture of particular parts of an image, such as the image of a particular part of the brain as seen on an MRI scan. For others, it may involve comparing the relative positions of features, for example,example, in identifying a hip fracture from an X-ray by assessing the displacementthe displacement of the bone. Accurate diagnosis of such abnormalities is often very difficult. This is particularly the case with invasive procedures,procedures, which carry a risk to the patient, and so a less invasive but reliable diagnosis is highly desirable. An example is a study by Cosio et al., which investigatedinvestigated using ultrasound imagesimages to diagnose stress from anfrom an injury to the Achilles tendon. The use of the automaticthe automatic analysis method here successfully avoided thethe need for histological assessment of the tissue to confirm the presence of the injury. For these reasons, it's increasingly common for pattern recognition to be the primary target of medical image analysis. (Stolte & Fang, 2020)

Recognizing patterns in medical images. Medical image analysis is concerned with the extraction of information from visual representations of the interior of the human body. The interpretationThe interpretation of the data is done with the help of various diagnostic methods. It can be donebe done by simple direct observation,observation, often involving the unaided human eye. At eminent places,places, it may include techniques like enhancing image quality, drawing inferences using image data, and performing expert-like reasoning. Due to the complexity and volume of data, this is increasingly being performed with the help of automated methods.

2.2. Improving Diagnosis Accuracy

Although initially founded as a method to integrate physiological data with an image, a more recent aim in diagnostic accuracy is to compare two images directly using computer image processing, effectively treating one image as a model for the real patient and the other image as a model for the diseased patient. This is most true for monitoring the progressionthe progression of a disease or response to treatment. An early but interesting study used a simple subtraction method for comparing chest radiographs by subtracting the pixelthe pixel values of a normal image from thosethose of a diseased image to show the differences. Unfortunately,Unfortunately, this method was not successful due to differences in the way a radiograph is exposed and differences in scanner and film characteristics. More modern image comparison methods endeavour to register (mathematically match) two images together and compare them at the level of corresponding anatomical features. The outcomeThe outcome of these methods is highly dependent on the type and quality of the imagethe image as well as the disease being studied. A very recent study is that of Yang et al.,al., who used computer image analysis to compare CT images of the same patient to quantify if the change in mass and density of early--stage lung cancer correlated withwith survival rate.

Adverse events can have significant financial implications for healthcare providers and patients. Automated classification of lesions and other abnormalities has been widely regarded as a key aim for improving diagnostic accuracy. The use of CAD to classify lesion malignancy in breast and lung imaging modalities has been extensive. Early research has been promising, suggesting that CAD provides a useful aid for clinicians and,, in some cases,, has improved patient outcomess. A study by Pesce et al.. compared the accuracy of inexperienced and experienced radiologists in interpreting mammograms with and without a decision aid from CAD. Findings indicated that inexperienced radiologists significantly increased their accuracy using CAD,, whereas experienced radiologists showed no significant improvement. The latter result was somewhat unexpected,, but it was suggested that experienced radiologists had already formed diagnostic habits, making it difficult to change. This provides evidence that CAD can be particularly useful for training clinicians and also for providing a useful second opinion. However, there is still a long way to go before CAD is reliable enough to replace the human eye and the decision to depend on CAD suggestions will be largely based on the risk and benefit for each patient. (Li et al.2021)

Diagnostic accuracy in medical imaging is vital because high error rates are no longer tolerable as clinicians have significant societal responsibilities to minimize false negative results and thereby also minimize adverse events. Many medical decisions are based on imaging results and an incorrect interpretation can result in suboptimal treatment for a patient.

3. Applications of Artificial Intelligence in Medical Imaging

Medical artificial intelligence (AI) has modified the medical arena by giving a brand new era of probability for improved identification, remedy, and monitoring of patients. The growth of AI inside the discipline of medical image analysis has the capacity of not only detecting sickness but predicting the development through quantifying the changes over time. This can be carried out by observing the changes in the structures of human anatomy and pathology through imaging modalities. A major increase is the advent of AI in radiology where diagnosed imaging data of a patient may be analyzed and considered in comparison to present and former imaging data. This notion is supported by the arena of PACS (picture archiving and communication system) where all radiological images are stored, attended to, and diagnosed. AI can thus be utilized in a way in which it always and repetitively monitors the patient's imaging data to locate any abnormalities. AI has been shown to be highly successful in helping to systematize and interpret the massive amount of data being produced by imaging research that would not otherwise be possible using traditional methods. An example is a study by Huo, Xu, Li, and Ogunyemi in which the usage of AI they developed a computer-aided diagnostic system for automatic detection of chronic liver disease using ultrasound images. This system, which is based on an algorithm that focuses on texture analysis, has demonstrated to be very sensitive and specific in detecting mild to moderate chronic liver disease in ultrasound images and has the potential to provide immediate diagnosed results. This example shows a direct approach to evaluating specific changes that occur in a single organ or structure over time by detecting the change in the attributes of that form, with the advantage of being able to provide replicated measurements. (Jiang et al.2020)

3.1. Disease Detection and Diagnosis

Disease detection and diagnosis are two of the most important aspects of medical imaging. Artificial intelligence techniques have been used to attempt to automate the diagnosis of a wide spectrum of diseases and conditions. One such disease is schizophrenia, which affects about one percent of the world's population. Using an MRI environment to scan subjects, AI was used to test for differences in brain activities between those diagnosed with schizophrenia and those who were not. What the AI technique discovered was that there was abnormal brain activity in those who had the disease. The AI then created a spatial map and time series of brain activity, achieving a classification of 74% between schizophrenia patients and the healthy control group.

Another important part of detection and diagnosis is the early onset of disease. If disease is found early before major symptoms develop, this can increase the chances of treatment or cure. An example of this is the detection and diagnosis of knee osteoarthritis through x-ray images. A new AI technique has been developed for the detection of osteoarthritis. This technique compares x-ray images of a knee joint with medically accepted standards to determine the likelihood of a patient developing osteoarthritis in the future. Tests have shown 66-75% sensitivity and 68-72% specificity, and once osteoarthritis is present, it can determine the severity of the disease. This technique is preferable to a blood test as it offers a non-invasive and relatively inexpensive method of testing. (Korda et al.2022)

3.2. Tumor Detection and Classification

In medical diagnostic imaging, the detection and classification of tumors demands extensive clinical analysis and can be time-consuming and subject to inter- and intra-observer variability. Typically, tumors must be detected and their malignancy or benignity determined based on their shape, size, and textural features. Artificial neural network (ANN) paradigms have been widely used for the detection and diagnosis of cancer on a variety of medical imaging modalities. ANN-based approaches have shown good discrimination between benign and malignant lesions, leading to a reduced number of unnecessary biopsies in cases of false-positive diagnosis. Shape analysis of tumors has also proved to be an important feature for diagnosis, has been shown to be useful in automated histological analysis, and has great prognostic significance. Conventional computerized methods to extract shape features are usually complex, involving pre-processing, segmentation, and mathematical morphology operations. Oliveira et al. have proposed a method for automatic extraction of shape and margin characteristics of masses in mammography using an artificial neural network technique to classify one type of malignant cancer. This approach eliminates the need for explicit segmentation and achieves discrimination rates that are competitive with top-tier CAD methods for mammography. Pattern recognition is a field within the area of machine learning that focuses on applying automatic methods to analyze data for the purpose of extracting patterns that can be used to classify the data. Pattern recognition methods have been widely used to provide automated diagnosis and prognosis of various cancers on medical imaging, with success in the classification of different tumor grades and predicting patient outcomes. Textural analysis, which is an important part of pattern recognition, has been used to characterize tissue structure, has provided useful information for tumor classification, and has been shown to be of prognostic significance. Specific applications of texture analysis methods include the classification of different types of brain tumors and the differentiation between radiation-induced necrosis and recurrent tumors in patients with treated brain tumors. Success in textural analysis methods has led to a large number of studies regarding automated grading and classification of gliomas. A recent task involving radiogenomic analysis with the aim of linking imaging phenotypes with gene expression has led to work using machine learning methods to predict the genetic information of tumors using MRI data. (Cortes-Briones et al.2022)

3.3. Image Segmentation and Registration

The above-described processes can enable the discovery of new knowledge of interactions between diseases and the anatomic and functional changes they incur. Image segmentation and registration play an extremely important role in understanding disease and are at the center of much current research in medical image computing. With the advent of such new technologies as MRI and fMRI, understanding disease processes and making decisions in the treatment of disease more and more involve understanding the changes that occur at a functional level. Image segmentation and registration are directed at just that and are becoming indispensable in the study of the disease process.

The process of image segmentation involves decomposing an image into different segments or isolating certain objects, possibly with the intent of changing pixel attributes, such as color or texture. The goal of registration is to bring two images of the same object into the same spatial coordinate system. Two images are being obtained from different machines or at different times. Image registration enables us to compare images and analyze the changes that have occurred since image acquisition. These changes can be of several different types, such as a change in size, shape, location, or even a change in pixel intensity or the presence of new lesions. Identification of these changes can be an extremely difficult and time-consuming task. By utilizing our knowledge of the changes that have occurred during image acquisition, we can do a great many things, such as predict the efficacy of a chosen therapy or decide on the best possible treatment for a patient.

4. Machine Learning Techniques in Medical Image Analysis

In supervised and unsupervised learning, features have to be extracted from the image data to allow the algorithm to learn and make decisions. With traditional feature extraction methods, a priori knowledge from a radiologist is used to determine the important characteristics of the image and provide a set of rules for detecting a certain abnormality. Features can then be applied locally across the image. An example of a feature for a mammogram could be to look at a cluster of micro-calcifications and their distribution across the cluster. These traditional methods of feature extraction have been successful; however, they take much time and effort to develop.

Unsupervised learning does not use training data, and the algorithm learns from the structure in the input using probability to make decisions. This is done by modeling the higher-level structure in the data, and the learning can be used to automatically label the input, extract examples for supervised learning, and categorize the data. This has been used by radiologists to label reports and images and group them according to the similarity in the data. Groups can then be used as examples to train a supervised learning algorithm. The use of unsupervised learning is often a stage before supervised learning to better understand and represent the data for later learning. An example of unsupervised learning can be seen in the study done by Liu et al. They used the hierarchical mixture model to look at the whole brain to detect subtle structural changes in patients with Alzheimer's disease.

Supervised learning uses known data or training data to make an informed decision. It can be a regression model used for measuring future end results and making a decision, or a classification model used when decisions have a yes/no output. An example would be detecting a certain pathology in an image, and another classification whether a tumor is malignant or benign. An example of supervised learning in radiology can be done using the Naive Bayesian Classifier. Wang et al. utilized this algorithm to train a computer to detect micro-calcifications in mammograms. With supervised learning, the algorithm requires a representative example, which is used classification would be to the actual output to modify the algorithm and improve the result.

4.1. Supervised Learning

Supervised learning involves learning a mapping from inputs x to outputs y using input-output examples, with the aim of generalizing the mapping to new examples. A supervised learning algorithm analyzes the training data and produces an inferred function, which can be used for mapping new examples. There are two types of supervised learning: classification, which maps inputs to a finite set of outputs, and regression, which maps inputs to a continuous output. In the context of medical image analysis, supervised learning has been used for a diverse array of tasks. For detection of anatomic or pathologic structures in an image, the task is often to classify an individual pixel as either belonging to the structure or not. This can be framed as a pixel-wise classification problem, where features that describe the intensity and texture around a pixel are used to classify that pixel. Local features and classifiers have been used for detection of microcalcifications in mammograms, where features from a small neighborhood around a point are used to determine whether the point is a microcalcification. Supervised learning has also been applied to learning a mapping from raw image data to a clinical variable. For example, Motwani et al. presented a method for predicting future cardiovascular events in asymptomatic patients from the feature set of carotid MRI using supervised learning. In this case the task is regression, and the function maps the image data to a prediction of the clinical variable. Supervised learning methods can be effective for these tasks, when a representative and discriminative set of features can be defined and extracted from the image data. The quality of the learned function is highly dependent on the quality of the input features and the availability of a large and accurately labeled training set. (Alabdali, 2023)

4.2. Unsupervised Learning

Unsupervised learning shows promise in medical image analysis tasks, most of which are currently still performed by visual inspection of the image by a qualified professional, with no analysis of the structures present being performed aside from what the professional knows from previous experience. An application that can draw structures present on an image, such as anomalies, when given a database of what classifies an anomaly, would be equivalent to a clustering task, where the drawn structures are the clusters. Structure can also be in terms of finding a compact representation of the data. For example, an eigenface is a compact way of representing a face, where a task can be performed to find a grouping of similar images to become an equivalent of finding a class of data. This should lead to a stage where image analysis can begin to take place automatically and current techniques begin to be surpassed.

Unsupervised learning is the training of a machine using information that is neither classified nor labeled, allowing the algorithm to act on that information without guidance. Here, the algorithm is given the data and asked to perform some task. Usually, the task is to cluster the data, which is a finding task in that it finds groupings or clusters that the data can be split into. This is a useful exercise, as different or similar instances of grouping data can prove useful in itself or for a follow-on task. Another method of training can be to find the structure of the input data. This can be useful when the explicit results of the task are not known. For example, in finding interesting ways of grouping data together, it may be found that an actual task performed with guidance can benefit from this result.

4.3. Deep Learning

Deep learning algorithms have been applied to biomedical image analysis in order to automate feature construction [19]. Vercauteren et al. [49] presented a method to identify radiological sub-types in brain image data to study Alzheimer's. They used a layer of principal component analysis for feature reduction before applying a deep Boltzmann machine to learn features and a classifier to separate the sub-types. Palangi et al. [50] used a similar method to predict MCI and Alzheimer's from brain image data. These machine learning models have shown excellent classification results, but can only be as good as the data on which they are trained.

Deep learning algorithms are based on the neural network model in the human brain [48]. These can be very effective for classifying, detecting, and predicting various medical outcomes from multi-faceted data sources such as images. Classical machine learning methods can be applied to one specific task by manually extracting features, whereas deep learning algorithms can simultaneously build the features and the classification/prediction models directly from the data. They do not require the same expert domain knowledge for feature selection and are more flexible. Deep learning has shown to be useful in learning from image data.

5. Challenges and Limitations in AI-based Medical Image Analysis

Data is the "fuel" on which AI algorithms run, and it is widely recognized that one of the most significant barriers to the development and deployment of decision support systems in medical imaging is the difficulty in accessing data. Traditionally, medical images are stored in a wide variety of different formats within hospital Picture Archiving and Communication Systems (PACS), and in many instances, the images are not in a format from which they can be readily analyzed (e.g., the images may be digitized X-ray films). Even when the images are in a suitable format, they are usually accompanied by only limited, often text-based, metadata. This makes it very difficult to retrieve images that are suitable for algorithm training or testing and to associate the images with a ground truth (e.g., a diagnosis and/or patient outcome). An obvious potential solution is to create new image databases with structured data and annotations. However, this is a resource-intensive task, and there is currently a lack of funding to support this type of initiative. (Sadeghi et al.2022)

The potential benefits and rapid advances in AI-based image analysis have not been matched with the deployment and acceptance of these tools in real-world clinical applications. Several major challenges and limitations must be addressed to enable the successful deployment of AI-based image analysis in medical imaging. These include the need to improve the quality and increase the quantity of the image databases used to develop and validate the algorithms, the need to interact with our clinician colleagues to understand and address their uncertainties when making diagnoses, and to ensure that the methods we develop are acceptable and integratable into the clinical workflow.

5.1. Data Quality and Quantity

The performance of any AI system is largely determined by the quality of data on which it is trained and tested. A fundamental assumption in supervised learning based medical image analysis is that the labelled data used in the training phase and the cost function used to learn the model provide an accurate reflection of the target task. However, in medical imaging this assumption is frequently violated, and the consequences of this carry over into the use of AI systems trained on this data. Commonly there is a lack of consensus in the labelling of medical image data, and label noise can occur due to inter-observer variability. Furthermore, the full extent of information in an image may not be fully revealed by the available labels. For example, an image may be labelled with a binary outcome such as 'cancer' or 'no cancer', but the image may contain information on the cancer's stage and its optimal treatment may depend upon this. In this case, the image has limited usefulness for learning to make a treatment decision. An AI system trained on such data may still be used for decision support and would be making predictions that appear to be optimal given the data, but these may not be clinically useful.

5.2. Interpretability and Explainability

The need to understand or interpret the decision made on medical image analysis is more important than accurately discriminating shape and intensity of the disease. In clinical practice, often decisions made from imaging are the basis for making important and complex clinical decisions. It is often the case that the decision was wrong and the patient deteriorated. It may be difficult to retrieve decision-making processes for the clinician. A system that is able to simulate the decision-making process may help both the development and testing of medical image analysis technology, and it may help to explain the diagnoses to clinicians. This promotes higher confidence in AI decisions and avoids the well-known AI winters where retraction of AI systems occurs due to a lack of confidence and a poor match with user requirements. (Ayesha et al.2021)

Interpretability refers to the ability to understand or interpret the system. On a secondary level, interpretability refers to understanding the learned models of the AI system or the decision-making rationale. Most machine learning algorithms are so-called "black box" systems. No model explicitly states why a particular instance is classified in the way it is. Much of the future work in AI would benefit from the understandability of the models and higher-level decisions made from the AI system. This is especially desirable in medical AI technologies, which are not only expected to explain decisions to expect patients but also to contribute to existing medical knowledge.

5.3. Ethical Considerations

The use of AI in medical imaging comes with its own set of ethical considerations. Most of the medical data contains sensitive patient information, and this would also be the case with medical image data. Despite data being anonymized, re-identification of patients has been shown to be possible, meaning that it could be traced back to a patient. Leakage of this sensitive data could have serious consequences on an individual's life with respect to their insurability, employment, and discrimination. There's also the risk of harm to patients through usage of AI systems that have not been properly clinically validated. A developer would be held responsible if it was proven that an injury to a patient could have been avoided if an AI system had made a different decision that was considered but not acted upon. An extreme case would be assigning blame to an AI system for a decision that resulted in a fatality. Adequate testing and post-market surveillance of AI systems is needed, and there should be transparency of an AI system's performance measures.

Other considerations include the impact of AI on the workforce, with automation leading to job losses for some healthcare professionals, and a change in the job content for others. While some welcome automation in hope to improve productivity and shift focus to higher-value tasks, others are wary of the impact on patient care and the consequences of removing the human element from certain tasks. Steps should be taken to ensure that the implementation of AI is safe and monitored, and to evaluate its impact on the quality and efficacy of healthcare.

6. Future Directions and Opportunities

Second, our work suggests that AI methods will someday make it possible, either through image acquisition or later processing, to provide new kinds of information to the clinician based on imaging data. A simple example is a direct mathematical estimate of the likelihood of a particular diagnosis, used to guide clinical workup and to decide whether treatment would be more harmful than helpful. More complex and powerful methods are also possible. In a study of CT screening for lung cancer, our model, based on a 3D analysis of nodule clusters, estimated future volume doubling times of nodules and identified feature characteristics strongly associated with doubling times of less than one month, an aggressive form of lung cancer. Another possibility is a simulation based on a patient's imaging data, which could predict the consequences of alternative treatment strategies and thus help in medical decision making. Yet another promising application is quantitative disease tracking in clinical trials, which can increase efficiency and reduce necessary sample sizes in trials of new treatments. Any or all of these methods could prove to be important new tools for improving patient care. (Zhou et al.2021)

First, AI methods are likely to increase the quality of imaging analysis. As we have seen, imaging is crucial in many areas of medicine, but quality interpretation is often difficult due to the subtlety of findings and the need to integrate information from many sources. In some cases, imaging results are equivocal and a definitive diagnosis can only be made with time. Improved analysis methods hold the promise of increased detection accuracy in the initial study. AI methods may also increase cost-effectiveness in imaging: Simultaneous improvement in sensitivity and specificity may lead to fewer unnecessary diagnostic and therapeutic interventions for false positive results and increased accuracy of results for true positive findings.

We have reached a key and timely area within the growing field of AI in medical imaging. The rapid advances in machine learning research and large healthcare investments in information technology have created a window of opportunity in the years ahead. Work that is currently in its early stages has the potential to result in substantial changes in medical imaging in the relatively near future. There are a number of broad areas of opportunity that deserve special mention.

Conclusion

The above aspirations can only be met if there is significant out-of-sample performance in clinical data not typically demonstrated by publications featuring small academic datasets. This is an acute issue for supervised deep learning methods which can fail to replicate the same performance when tested on other image equipment using different image acquisition settings or even on data from a different site. This has led to a reluctance on the part of medical industry to widely adopt AI technologies. Unequivocal standards of performance and validation with clinical end-points are needed if wider clinical adoption of AI methods is to be realised. There remain many challenging methodological issues in seeking to maximise the benefits and minimise risks in using AI technologies for health improvement. This is still a novel area for health research and it closely aligns to the concept and practice of precision medicine where tailored interventions and patient care are informed by data uniquely relevant to the individual. AI methods also have the potential to deliver rich decision-support in the many areas of health maintenance and disease treatment where imaging is not the primary modality. Although AI methods are quite adept at unsupervised discovery of primary imaging features relevant to disease, feature extraction and representation learning are still a solving process in capturing high-level human disease concepts and prior knowledge on what is clinically relevant for a particular pathology. Getting this right is pivotal to delivering useful secondary analyses that will complement established trial and error treatment approaches and augment healthcare knowledge relevant to individualised patient care.

This chapter has set out the case that AI-based image analysis has now reached a tipping point and is ready for wider clinical adoption. It has done so by showcasing how modern AI methods can encapsulate human perceptual expertise to deliver quantitative measures from images that are at least as good as, and often better than, the best attainable by human measurements and that these increasingly encompass and at times surpass human diagnostic and predictive performance. This represents a game changer for the health sector even in nations with well-developed healthcare systems. The drivers are the urgency to cope with the rising tsunami of chronic diseases for which current diagnostic and prognostic methods are inadequate and frequently deliver diagnoses which are only verified at a late stage often when the optimal opportunity for treatment has been missed, the escalating technical and pharmacological therapies which require more precise and more granular disease identification and quantification of treatment effects and the need to leverage efficiency in the face of escalating numbers of images required to effectively monitor a given disease process. Cost and efficiency demands will be the prime drivers of change in the health sector in the developing world. AI presents the only realistic means of delivering affordable and scalable high quality imaging services for countries currently facing a crisis in the acute shortage of human expertise. AI can also potentially be applied to automate scanning and diagnostic triage procedures thus releasing funds and human expertise for care of the actual patients identified with significant disease.

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