Artificial intelligence in musculoskeletal imaging: review of current literature, challenges and trends*

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Abstract

Artificial intelligence (AI) has gained major attention with a rapid increase in the number of published articles, mostly recently. This review aims at providing a general understanding of how AI can or will be useful to the musculoskeletal radiologist. After a brief technical background on AI, machine learning and deep learning, we will illustrate, through examples from the literature, potential AI applications in the various steps of musculoskeletal radiology workflows, from managing the request to communication of results. The implementation of AI solutions does not go without challenges and limitations, these will be also discussed, as well as the trends and perspectives.

Keywords

Machine learning; Artificial intelligence; Deep Learning; Automatic; Musculoskeletal imaging

Introduction

Artificial intelligence (AI) was introduced with the early advances of computer technologies in the 1950s and has gained tremendous popularity in the past half-decade, springing to public attention with some recent advances resulting in above-human performance, in particular with the AI algorithm AlphaGo, developed by Google DeepMind, which defeated the world Go champion in 2016 and garnered much attention in the popular press.[1-3] Using sophisticated or deceptively simple AI algorithms, machines are now able to mimic human intelligence and cognitive functions in some areas.[4] AI is used as an umbrella term including machine learning, which itself comprises deep learning. Machine learning, a branch of mathematics and computer science, is based on letting algorithms learn from data without the exact relationship between input data and output predictions being explicitly programmed.[5] Machine learning includes *supervised* learning problems, as well as *unsupervised* learning problems. In *supervised* classification, the algorithm is given labeled data (for example the diagnosis of osteoporosis attached to each patient in the database), based on which it predicts the presence or absence of osteoporosis in a new patient. In *unsupervised* learning techniques, labels are not available. Unsupervised learning includes clustering, in which case the algorithm learns the inherent structure of the data, by searching for common characteristics among them. For example, it is possible to group patients in a dataset with the same bone density and cartilage volume. Unsupervised techniques can be used for instance for subtyping patients.

Machine learning algorithms are categorized as either *classical* (or *shallow*) or *deep* (Figure 1). In *classical* machine learning, features of interest are defined by the practitioner, and are referred to as “handcrafted features”.

In contrast, deep learning, a subset of machine learning, relies on *end-to-end learning*, meaning that the features of interest (the data *representation*) are computed automatically by the algorithm, for instance from a magnetic resonance (MR) image. Deep learning algorithms are implemented as neural networks, which can learn highly non-linear functions of the input data. Convolutional neural networks are a type of neural network used for image recognition and classification. This type of model has gained enormous popularity in the engineering community due to record-setting performance in open competitions on large-scale natural image recognition, which quickly outperformed human level.[6,7] "Deep" in this context does not directly imply a "deeper understanding", but means that the input data goes through several steps (*layers*) of non-linear transformations, giving the network very high expressive power.[8,9] The notion of depth therefore refers to the succession of the different layers. To illustrate, a deep network using radiographs of the ankle for fracture detection will be trained on a large number of images, which have been labeled by radiologists as being normal or as having a fracture, and automatically learn data representations which allow it to minimize the error on the task of classifying an ankle image into these two categories.

Although the applications of deep learning in medical imaging are growing exponentially, the applications of AI to musculoskeletal imaging specifically are still limited.[10] A search in PubMed of original papers in the English literature including the search items ("artificial intelligence" OR "machine learning" OR "deep learning") AND "musculoskeletal" AND ("imaging" OR "radiology"), published until December 31st 2018 retrieved 64 entries, of which 30 pertained to the practice of radiology. This paper will focus on these specific applications of AI to musculoskeletal radiology. Applications of AI in research in the field of musculoskeletal disorders is beyond the scope of this review.

In musculoskeletal imaging, just as in any other imaging subspecialty, AI may assist the radiologist in every step of the workflow, from receiving the request to communication of results. In this paper, we will illustrate applications of the many tools and models offered by AI to these different steps in the process of the musculoskeletal radiologist's workflow. Based on examples taken from the musculoskeletal literature, we will illustrate how different AI models can be applied to the management of the radiological request, the protocoling and production of images, their interpretation, as well as the communication of the results to the referring clinician (Table 1).

It goes without saying that the implementation of AI faces numerous challenges and limitations that we will describe. Finally, we will briefly present the trends and future perspectives of the application of AI.

Radiological Request and scheduling

A large number of requests limits the ability to directly communicate with each and every referring physician. The ordered modality may not be the most appropriate for the specific clinical condition, or the clinical information given on the request may be insufficient to make a specific diagnosis. AI may support in ordering decisions by retrieving pertinent patient information including allergies to contrast media, MRI-sensitive devices or implants, which are ideally automatically gathered from an electronic radiological request or the digital medical record, and by alerting the system to schedule the exam in the best conditions.[11-14]

In musculoskeletal radiology, investigations for computed tomography (CT) or magnetic resonance imaging (MRI) in patients with metal hardware in the requested anatomic area should be ideally filtered by an electronic system, obtaining pertinent information from the request, from the latest radiograph or from previous reports to automatically schedule the patient at dedicated scanners, e.g. dual-energy CT or 1.5 T MRI. Ideally, automated procedure selection algorithms are based on established guidelines such as American College of Radiology (ACR) appropriateness criteria or European Society of Radiology (ESR) iGuide considering efficiency, costs and risks of various possible procedures.[15,16]

Appointments could be given according to the severity of the indication and in arrangement with the follow-up appointment at the referring physician. Information documents could be sent electronically to the patient and returned before the radiological investigation to ensure any constraint or contraindication, such as claustrophobia, and are taken care before the scheduled appointment. Automated text messages could remind patients about their pending appointment.

For these applications, natural language classification algorithms could have many applications. Promising results were shown for example to automatically determine whether intravenous contrast was required in musculoskeletal MR investigations using IBM Watson natural language classifier on the free text clinical indication of the study, reaching an accuracy of 83%.[13] This clinical decision support tool could help to improve efficiency and to decrease scheduling errors among other advantages.

Protocoling and Image Production

Radiology scanner hardware has greatly improved in the past 25 years, whereas software-related algorithms have been slower to develop. If algorithms can capture information on patients and prior imaging studies, this gap may be bridged for several applications including protocoling, image acquisition and postprocessing.

With this, scan protocols for radiographs, CT and MRI, embedded in the electronic scheduling system, may be automatically proposed based on the clinical information and indication given in the request. Lee recently demonstrated the benefit of a deep-learning convolutional neural network for automatically choosing between routine or tumor musculoskeletal MRI protocols.[14] Accuracy of automated MRI protocoling reached 94%, enabling the radiologists to easily confirm the recommendation.[14] Using these techniques, scan protocols could be automatically tailored to each individual patient. Image quality checks, especially important for MRI, may be performed by technical quality assurance programs identifying severe artefacts, such as inadequate fat saturation, motion or pulsation artefacts, and propose protocol modifications. Additional sequences may be proposed by the machine based on certain pathological findings, such as contrast-enhanced sequences in case of an incidental bone lesion.

AI can potentially increase the speed of reconstruction and be used for automated reconstruction algorithm, whether in CT or high-resolution three-dimensional (3D) MRI to reduce repetitive, time-consuming, strenuous work for the technicians providing more time for patient care. Chaudhari et al. developed a deep learning-based super-resolution method generating thin-sliced MR images of the knee from thicker slices.[17] With this DeepResolve technique, image acquisition time can be decreased, motion artifacts reduced by the acquisition of fast low-resolution images with increased image resolution, and finally a higher throughput per scanner could be obtained. Others have investigated the potential of such generative models (algorithms able to generate new data, as opposed to the classical models of deep learning that process or classify data) to generate new sequence weightings based on another, or even to generate MR images based on radiographs.[18] Although preliminary, these works could lead to interesting applications in the future.

Ideally, image reconstruction of 3D MRI sequences or CT should be performed automatically by the system to accelerate the time to finalize the report and decrease the waiting time for patients at the emergency department or the outpatient clinic.

Image Interpretation

In terms of image analysis and interpretation, the most common benefits of AI that come to mind comprise the detection of abnormalities (e.g. a fracture) and the diagnosis of abnormalities (e.g. a tumor) (Table 2).[19,20] Rather than a pure replacement of the radiologist, the use of AI for these applications should instead help the radiologist optimize its workflow. By prompting prescreened images or flagged critical findings, AI should help us increase our speed to provide a report for the most urgent cases, improve our diagnostic accuracy, prevent errors and observer fatigue (e.g. in reading large numbers of postoperative radiographs), and improve the quality of the image interpretation task. Additionally, AI may be beneficial as a decision support system for studies performed after office-hours, in remote areas or in teleradiological services, where radiologists are not attending in person.

But image interpretation by a radiologist is not limited to the act of making a diagnosis based on the images being viewed. It also consists of other actions, such as prompt and easy access to relevant clinical data, comparison to previous studies, production of a report comprising the relevant information. Many AI application may help optimize these tasks. For example, by uploading the relevant previous exams, and by automatically synchronizing these using registration tools.[21] The analysis of clinical data could also be greatly improved by natural language processing algorithms.[13]

Finally, AI should help us in the task of providing semi-quantitative (i.e. the grading of certain pathological findings such as lumbar canal stenosis, disc pathology, Kellgren-Lawrence grades on knee radiographs or semi-quantitative grading systems on knee MRIs, etc) as well as quantitative analyses in our reports. These can be quite cumbersome to perform and their automatization should allow the growth of this valuable type of information.

Following are examples of AI applications to the interpretation of images (Table 2).

Automatic Lesion Detection

Fracture Detection

The increasing number of skeletal radiographs in high-level trauma units as well as remote hospitals without 24/7-radiological services necessitate automated fracture detection to accelerate diagnosis and treatment decisions. Several research groups addressed automated fracture detection using deep learning algorithms.[22-25] Accuracies reached up to 83% for a variety of peripheral fracture detection with equal results as compared to orthopedic readers.[23] Similar results were presented by Lindsey et al. in a similar study including over 130000 peripheral annotated radiographs.[22] Machine-assisted fracture detection was most helpful for emergency medicine clinicians, which are typically less exposed to radiographic readings compared to specialized orthopedic surgeons. A deep learning algorithm specifically designed for distal radius fractures tested on 695 positive radiographs showed an even higher detection rate with a sensitivity of 90% and specificity of 88%.[24] One limitation of the applied open-source machine-learning algorithms in the study by Olczak et al. was that only one image of a whole series of radiographs could be analyzed, even though the fracture may not be visible on that particular image orientation.[23] Utilizing all available radiographic projections could potentially further increase the accuracy of fracture detection.

Knee Pathology Detection

AI may assist in diagnosing abnormal findings of the knee joint as shown by Bien et al.[26] Their algorithm was able to accurately detect abnormalities, meniscal tears and anterior cruciate ligament (ACL) tears achieving an area under the curve of 0.937, 0.965 and 0.847, respectively on 1370 knee MRI. Accuracies were comparable to radiologists for detection of abnormalities and ACL tears, however, was slightly inferior for the detection of meniscal tears. Similar results were obtained by Stajduhar et al. on MRI diagnosed partial and complete ACL tears with an area under the curve of 0.894 for partial tears and 0.943 for complete tears.[27]

Automatic Diagnosis

Bone Tumor Diagnosis

Bone tumors are rare and typically present with a variety of morphological imaging characteristics, thereby posing difficulties in image interpretation among general radiologists. In 1980 Lodwick published a landmark paper on determining computed-based radiographic bone tumor destruction.[28] Based on his work, following researchers developed computed models to aid in diagnosing bone tumors.[29-31] However, attempts were limited to 10 bone tumor entities, although the World Health Organization defines more than 20.[32] To overcome this, a Bayesian model was developed to predict bone tumor diagnosis and differentials on 710 annotated pathological radiographs.[33] The accuracy in predicting the correct diagnosis reached up to 62% and the accuracy for a correct diagnosis out of three differentials reached up to 80%. The system has the potential benefit to aid non-musculoskeletal radiologists, since bone tumors are frequently detected as incidental findings.

Automatic Classification of Images

Semi-quantitative Analysis of Cartilage and Osteoarthritis Imaging

AI has potentially very interesting applications in the field of OA. Indeed, research in this field is mainly based on the assessment and follow-up of large cohorts of patients. The availability of these repositories opens the opportunity to perform descriptive analyses, with the hope of developing predictive and prescriptive models in the future, which motivates the development of AI-based algorithms to achieve these tasks. Although the imaging modality of reference for the assessment of OA has for long been radiography, MRI is currently the imaging technique of reference for all articular components involved in the development of OA. MRI provides morphological datasets as well as compositional techniques, in particular T2 mapping, allowing the assessment of tissue structure, both of which can now be achieved at high-resolution in 3D.[34-37] Currently, the analysis of MRI examinations is mainly based on semi-quantitative assessments of morphological sequences. These semi-quantitative scoring systems are extremely time-consuming, and therefore costly, which also limits their use in clinical practice. Having a tool to automatize these analyses and integrate the data provided by compositional imaging techniques would be quite beneficial to the field. In this context, machine learning represents a great opportunity to improve our understanding of this disease, and the assessment of new therapeutic options.

Usually, the image interpretation algorithms contain a segmentation step followed by a second classification network to detect lesions. Using a deep convolutional neural network, Tiulpin et al. have reached a quadratic kappa coefficient of 0.83 compared to clinical experts in grading the severity of OA based on 3000 randomly selected radiographs from the Osteoarthritis Initiative (OAI) cohort.[38] Besides, the algorithms present attention maps highlighting the radiological features leading to the decision. A similar study by Norman et al. on grading the severity of OA on knee radiographs have led to similar results.[39] Xue et al. investigated the presence of OA on 420 pelvic radiographs, achieving sensitivity/specificity of 95%/91% and an accuracy of 93%.[40] Their model showed comparable results to a senior radiologist.

Liu et al. showed that 2D convolutional neural networks could achieve high sensitivities and specificities of about 81 to 88% in automatically detection of femorotibial cartilage lesions.[41] 3D convolutional neural networks were also able to detect meniscus and patellofemoral cartilage lesions on 3D MRI datasets, with a sensitivity/specificity of 90/82% and 80/80%, respectively, compared to clinical experts. The algorithm could also grade the severity of the lesions with accuracies above 75%.

All of these studies compare the diagnostic ability of AI algorithms to expert radiologists, which most of the time provide the closest evaluation of the truth available. Considering the low interobserver agreement and moderate diagnostic performance of clinical radiologists to perform some of these tasks, it would be interesting to compare AI techniques to a validated gold-standard such arthroscopic results, whenever available.[42,43]

Semi-quantitative Analysis of the Spine

The imaging of spine MRI may be cumbersome for radiologists due to the number of levels to be analyzed, as well as the number of parameters (e.g. disc pathology, foraminal or central canal stenosis, etc.). Jamaludin et al. have shown that AI can help automate the grading of disc pathology on MRI using various classifications with an accuracy of 95.6% in terms of disc detection and labeling.[44] This system would be of much help to alleviate the radiologist workload considering the number of spine MRIs performed.

Automatic Determination of Bone Age

Estimating bone age of pediatric hand radiographs is cumbersome and time-consuming. A study by Tajmir et al. on 280 hand radiographs showed that AI improves bone age interpretation compared to radiologists alone. Best values were reached when AI complemented the radiologist with an accuracy of 68% to improve performance.[45]

The RSNA Pediatric Bone Age Machine Learning Challenge consisted of more than 14000 hand radiographs from 48 different users utilizing different machine learning algorithms to determine bone age.[46] The five best algorithms showed similar results in age determination with a mean absolute distance to the reference standards of 4.2-4.5 months.

Automatic Quantitative Analysis of Images

Analysis of Spinal Deformity

Any type of quantitative analysis, although essential to clinical routine or research, is both time-consuming for the radiologist, and subject to interobserver variability. Having a reliable tool to automatize these analyses would be highly beneficial. Many applications are possible, one of which is the automatic measurement of spinal deformity that could be achieved with high accuracy using artificial neural network.[47]

Peripheral Nerve Segmentation

Quantitative analysis of any structure requires prior segmentation. Manual segmentation of peripheral nerves for quantitative analysis can be particularly time-consuming due to the extensive scan size. Deep learning methods were shown to segment peripheral nerves much faster, and with similar accuracy than manual segmentation.[48] The ischial nerve in 42 patients with sciatic neuropathy and 10 healthy volunteers on non-fat suppressed T2-weighted MR images could be fully automated segmented in less than 1 second as compared to a time-consuming manual segmentation of 19 minutes. With this method, the deep neural network separated the nerve from background tissue. This AI-based automated postprocessing allows quantitative imaging such as diffusion weighted-imaging and magnetization transfer imaging to further assess the extent. Non-standardized imaging protocols, restricted contrast between the nerve and the surrounding soft tissue and motion artefacts limit the ability of automatic segmentation.

Communication of Results

Algorithms integrated in image interpretation that quickly identify negative and positive examinations may enable prompt communication of critical findings to the referring physician after being reviewed by the radiologist. Communication of imaging results, especially in a hospital environment, needs to be prompt to ensure an adequate and efficient patient management.[8] Radiology reports are usually communicated via phone, however, reaching the responsible physician can sometimes be challenging. An electronic system, connecting the radiological report and medical record would allow flagging patients charts to prompt urgent attendance. Audio alerts automatically sent out to the referring physician could help reduce repetitive distracting phone calls. This would leave more valuable time to focus on reporting or to communicate with the relevant corresponding physicians and the patient.

Structured reports could automatically be generated and include semi-quantitative and quantitative data.

Limitations and Challenges of AI

Despite the implementation of various useful AI algorithms, several limitations must be acknowledged. First, AI algorithms need to be integrated seamlessly into clinical workflow and need to be able to interface with varying current information technology environments as well as Picture Archiving and Communications Systems (PACS) and Radiological Information System (RIS). Only very few reports have been published on how AI actually affects the workflow of a radiologist in daily practice.[13,14] Second, reproducing results of recently published studies is challenging, mainly because a) training data, and b) the code to reproduce the investigation are rarely released. However, improvements have already been achieved in medical publications, and code release is now standard in engineering publications. Third, future AI research investigations require anonymized data exchange between large radiology institutions to gain high volume image databases, which need to be standardized, annotated and of high-quality, although methods to deal with multi-site imaging data are increasingly being developed.[49] All of these developments require careful consideration of major privacy and ethical issues. Fourth, with the increasing amount of radiological investigations witnessed over the past decade, one may assume that a sufficient amount of data is available to train algorithms. However, in reality, this data is not prepared for training. Data cleaning and image selection with equivalent image kernel or contrast, and consistent annotations are a prerequisite to training algorithms, although much work is currently focusing on making algorithms more resilient to unwanted variations in images.

Lastly, sufficient computational power is needed to run the most complex algorithms. If no special processor (graphics processing unit (GPU)) is available, it may require several tens of seconds to process and analyze an image. Without a special GPU, algorithm training is unfeasible in practice.

Along with these obstacles, several unsolved challenges inherent to AI have to be mentioned. First, current machine learning systems have no means of understanding what they are seeing. If fed with the wrong images, they still try to find patterns they are trained on. Users need to be aware of the limitations of these systems. Second, machine learning algorithms lack common sense. The algorithm should be comprehensive enough to deal with failures and uncertain cases. This also entails that legal liability is ultimately assigned to a human authority, and the radiologist should take full responsibility. Third, machine learning algorithms are typically unable to address more than one task at a time. That is, an algorithm for fracture identification will not be usable for bone age estimation. Thus, hospitals face the prospect of having to deal with a zoo of algorithms, each with their specific performance limits and failure modes. How to train radiologists to use these tools appropriately and calibrate their expectation is an open issue. Fourth, different readers may have different opinions of an image, and the algorithms will reflect the opinion of the annotations provided by the reader it is trained from. Tentative solutions include requiring several readers for annotations, but this is expensive. Finally, and most importantly, patients may want to have an image interpreted and a diagnosis made by a human expert rather than a machine. In other words, patient may be comforted by the presence of a pilot in the plane. How to produce trustable and fair machine learning results is an area of active investigation in the machine learning community, but recurring scandals involving data usage and sale on web platforms such as social media giants may, by association, undermine patients trust in machine learning techniques.

Future Perspectives

With high-volume digitalized radiological data, AI is having a transformational impact on radiology departments and with the integration of further information technology services of the entire healthcare system. The few musculoskeletal publications illustrate first descriptive and diagnostic models which, as soon as they are ready to be incorporated into clinical practice, will support work efficiency, productivity and optimize cumbersome workflows. AI will increase the quality of our work and value and ensures that radiologists are able to focus on meaningful tasks. These include verifying reports, making decisions and managing multidisciplinary board meetings, tasks that increase radiologists' value. In this regard, AI should increase our personal satisfaction.

As of today, it is not clear how AI will eventually aid in our daily workflow, as current technology is still a few steps away from being successfully implemented into practice. However, there is room for optimism and confidence, as shown by a recent analysis of the trends in social media, or by the fact that Facebook received 1 million knee MRIs from the Radiology Department of New York University.[50,51] Indeed, constantly dealing with new challenges is part of the radiologist`s DNA. Over the last 40 years or so, we have had to adopt new imaging modalities in our practice (e.g. ultrasonography, CT, MRI) or technology that has revolutionized our workflow (e.g. PACS and RIS).

Based on existing publications in musculoskeletal imaging, present-day AI algorithms have not yet been able of performing the complex tasks a human is able to accomplish. Therefore, we believe that AI will not replace radiologists, but that in the near future it will rather help radiologists augment their performance and keep up with their ever-increasing workflow.

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Table 1: List of AI techniques and how they might impact the radiologist workflow, which consists of management of the radiological request, the protocoling and production of images, their interpretation, as well as communication of results to the referring clinician. Models that are not included in this table are those used in research, in the analysis of large cohorts of patients (i.e. in the field of OA). These consist of descriptive models (analyzing what has happened, such as correlations between factors and disease progression), predictive models (predicting what could happen, such as evolution of disease based on the presence of risk factors) and prescriptive models (optimizing parameters to obtain an outcome, such as what actions to take in order to prevent a disease from developing). All these techniques have seen significant advances in the past decade with the advent of deep learning.

AI techniques	**Examples taken from literature**	**Radiologist task that it might impact**
Natural language processing algorithms	Analysis of requests, digital medical data, including previous reports, etc.	Protocoling, image interpretation, communication of results
Generative models	Super-resolution MRI, sequence generation	Production of images
Segmentation algorithms	Automatic segmentation of cartilage, menisci, bone (bone mineral density), peripheral nerves, etc. for image diagnosis and quantitative analysis	Image interpretation
Classification models	Bone tumors	Image interpretation
Regression models	Automatic grading of the severity of OA on knee radiographs or MRI Determination of bone age	Image interpretation

Table 2: Examples of artificial intelligence applications to the interpretation of musculoskeletal images, taken from the literature (papers published until 31st of December 2018):

Authors	Organ structure	Task assisted by artificial intelligence
Lindsey R et al. 2018[22]	Wrist radiographs	Distal radius fracture detection
Olczak J et al. 2017[23]	Hand, wrist and ankle radiographs	Fracture detection
Kim DH, Mac Kinnon T 2018[24]	Wrist radiographs	Distal radius fracture detection
Urakawa T et al. 2019[25]	Hip radiographs	Intertrochanteric fracture detection
Do BH et al. 2017[31]	Skeletal radiographs	Predicting bone tumor diagnosis
Bien N et al. 2018[26]	Knee MRI	Detection of pathologies with emphasis on meniscal and anterior cruciate ligament tears
Stajduhar I et al. 2017[27]	Knee MRI	Detection of anterior cruciate ligament tears
Xue Y et al. 2017[40]	Pelvic radiographs	Grading hip osteoarthritis
Tiulpin A et al. 2018[38]	Knee radiographs	Grading osteoarthritis
Norman B et al. 2018[39]	Knee radiographs	Grading osteoarthritis
Liu F et al. 2018[41]	Knee MRI	Detection of cartilage lesions
Jamaludin A et al. 2017[44]	Lumbar spine MRI	Detection and labeling of vertebral bodies; Grading of segmental pathologies
Tajmir SH et al. 2019[45]	Hand radiographs	Estimating bone age
Halabi SS et al. 2019[46]	Hand radiographs	Estimating bone age
Lin H 2008[47]	Spine radiographs	Analysis of spinal deformity
Balsiger F et al. 2018[48]	Sciatic nerve MRI	Nerve segmentation

Figure 1: Diagram showing the difference between classical machine learning and deep learning techniques.