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Integrating Deep Learning in Musculoskeletal Radiology: Current Applications and Future Directions

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Abstract

Background: Artificial intelligence (AI), particularly through deep learning techniques, is transforming musculoskeletal radiology. The integration of convolutional neural networks (CNNs) enhances the detection and classification of musculoskeletal conditions, addressing the rising demands of radiologists.

Methods: This review synthesizes the current literature on the applications of deep learning in musculoskeletal imaging. A narrative approach was employed, analyzing data from the PubMed database using general and specific search terms related to deep learning in radiology. Key clinical studies were selected based on their relevance to everyday practice.

Results: Recent advancements demonstrate that deep learning algorithms can accurately identify fractures, cartilage lesions, and ligament injuries, often achieving performance levels comparable to expert radiologists. Notably, CNNs have reached high diagnostic accuracy in detecting upper and lower extremity fractures, with some models outperforming human specialists. The review highlights automated assessments of osteoarthritis, spinal stenosis, and skeletal maturity, showcasing the potential for AI to streamline workflow and improve diagnostic accuracy.

Conclusion: The rise of deep learning in musculoskeletal radiology presents significant opportunities for enhancing diagnostic processes. While many algorithms exhibit expert-level performance, the need for thorough interpretation of imaging studies remains. As AI technology evolves, it is poised to play a critical role in the future of musculoskeletal radiology, potentially reshaping clinical practices.

Keywords: Artificial Intelligence, Deep Learning, Musculoskeletal Radiology, Convolutional Neural Networks, Diagnostic Imaging

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1. Introduction

The most recent and significant technical improvement in radiology is the emergence of deep learning using convolutional neural networks (CNN), a swiftly evolving branch of artificial intelligence particularly adept at addressing image-related challenges [1-3]. The response of radiologists to this potentially revolutionary technology is evolving, including a spectrum of emotions including skepticism, curiosity, anxiety, and hope as the potential advantages and drawbacks become apparent [4]. Numerous recent advancements in deep learning pertain directly to musculoskeletal radiology, making it essential for musculoskeletal radiologists to comprehend the current landscape of deep learning research that could imminently influence their practice.

The clinical and non-clinical responsibilities of radiologists across all subspecialties are escalating, including heightened imaging volumes and complexity, quality and value incentives, as well as administrative, educational, and research commitments [5]. Optimists may perceive the potential of deep learning as a means to enhance a musculoskeletal radiologist's capacity to provide efficient, high-quality care in a high-volume clinical setting, enabling the radiologist to concentrate on more intellectually challenging tasks by delegating routine functions. Conversely, legitimate concerns have been expressed about the possible effects of deep learning on the radiology profession across all subspecialties [6]. This review aims to accomplish three objectives: to succinctly elucidate the principles of deep learning, to offer a narrative overview of the contemporary state-of-the-art applications of deep learning in musculoskeletal imaging for practicing musculoskeletal radiologists, and to explore prospective future trajectories of this technology and its implications for the field.

This study targets practicing musculoskeletal radiologists rather than research data scientists, thereby adopting a narrative structure that highlights the most therapeutically relevant applications. A formal systematic review was not conducted; instead, the PubMed database was queried using various general terms such as “deep learning radiology,” “artificial intelligence radiology,” and “deep learning musculoskeletal imaging,” along with more specific terms related to established applications of deep learning in musculoskeletal radiology, including “deep learning fracture,” “deep learning cartilage,” “deep learning orthopedics,” and “deep learning bone age,” among others. Manuscripts of significant clinical relevance to the everyday practice of musculoskeletal radiology were chosen for inclusion, with no stringent exclusion criteria based on publication year or topic matter.

2. Deep Learning: Technical Considerations and Historical Context

The technical theory and science of deep learning are intricate and may be challenging for a clinical radiologist without a background in data science to comprehend. It is beneficial for the practicing musculoskeletal radiologist interested in deep learning to possess a rudimentary comprehension of essential terminology and ideas. Numerous comprehensive reviews have recently been published, offering an in-depth exploration of the technical aspects of deep learning, which we recommend to technically inclined radiologists and clinical data scientists [2, 3, 7-10].

Artificial intelligence encompasses the discipline of programming computers to acquire the ability to execute complex tasks. In the first stages of artificial intelligence, meticulously crafted rules were developed to enable computers to achieve certain objectives; however, this methodology has intrinsic limits due to the escalating time and effort necessary to define and implement the rules. Conversely, machine learning is a subset of artificial intelligence that automates the development of analytical models and decision rules to a certain extent using statistical approaches, enabling computers to "learn" from data to recognize patterns. Nonetheless, image-based machine learning often needs the involvement of human image-processing specialists to identify the most significant imaging elements, such as textures, areas, edges, patterns, or intensity values. Deep learning is a subset of machine learning in which the algorithm autonomously identifies the ideal imaging characteristics necessary to address the model's specific clinical inquiry, features that may not be easily recognizable to human specialists. The predominant architecture for deep learning in medical imaging is convolutional neural networks (CNNs).

Convolutional Neural Networks (CNNs) achieved a crucial milestone when CNN secured victory in the 2012 ImageNet picture categorization competition. The victorious CNN, known as AlexNet, attained a top 5 error rate of under 15% in image classification tasks, a remarkable accomplishment for the computer vision world since no algorithm had ever reached such a high degree of accuracy [11-13]. Following this pivotal moment, the rapid advancement of graphics processing units (GPUs), optimally designed for the intricate parallel processing necessary for operating a CNN, with several open-source frameworks, has facilitated a surge in deep learning research. Libraries of this kind include TensorFlow, Keras, and Caffe2/PyTorch [14-17].

3. Training a Convolutional Neural Network model

A convolutional neural network is termed as such because it simulates the functions of the human brain. Although a young kid may easily differentiate between images of a cat and a dog, articulating the precise morphological characteristics that facilitate this discrimination proves to be somewhat challenging. Both creatures possess fangs, tongues, whiskers, eyes, ears, and hair. A trained CNN can consistently recognize objects (or lesions) or categorize abnormalities without necessitating specific morphological parameters; it merely requires numerous images labeled as either “cat” or “dog,” or correspondingly, “fracture” or “no fracture.” Typically, images used for training a CNN do not demand manual preprocessing, feature extraction, or segmentation of regions of interest [18]. The CNN model is frequently characterized as a "black box" that identifies salient features from images and generates weighted probabilities for the specifically trained query, without requiring the user to specify any morphological characteristics to differentiate among the various output options. The CNN executes this intricate process by extracting both basic and complicated characteristics via many layers of convolutional kernels, which are then flattened into a vector and input into the neural network. The neural network employs forward and backward propagation to determine a weighted probability for the outputs of the training task (e.g., "fracture" or "no fracture").

To develop an effective CNN model, a substantial quantity of pictures is required for training. As previously stated, it is unnecessary to annotate or delineate certain imaging characteristics. For example, if the objective of the CNN model is to identify distal radius fractures, it is unnecessary to emphasize the exact areas of the pictures containing the fracture, nor is it essential to indicate the location of the distal radius. The greater the number of photos supplied, the more precise the model will become. The number of pictures used for diverse musculoskeletal CNN models might vary from hundreds to tens of thousands of training images. A model trained on an inadequate number of photos may experience overfitting, rendering it inapplicable to clinical images outside the training dataset. After the CNN model has been trained on an adequate quantity of pictures, its diagnostic performance may be evaluated using a distinct dataset known as the validation set.

4. Summary of clinical uses of deep learning in musculoskeletal radiology

Identification of clinically significant anomalies in radiographs and cross-sectional imaging constitutes around twenty-five percent of musculoskeletal deep learning applications. The most prevalent is the automated identification of fractures, meniscal tears, and cartilage lesions [18-33]. Additional applications in this area include cartilage T2 mapping for osteoarthritis diagnosis, ACL tear identification, and the identification of degenerative and metastatic spinal lesions [30,34-37].

Several studies concentrated on identifying fractures in radiographs, and the diagnostic efficacy of several algorithms is progressively reaching or surpassing expert levels. In 2017, Rajpurkar et al. trained a convolutional neural network (CNN) to identify upper-extremity fractures using a training dataset of 11,184 patients, 13,457 studies, and 36,808 pictures, which is among the biggest publicly accessible labeled datasets [38]. In a test set including 207 examples, the deep learning model attained an average AUC of 0.929. The model's performance was comparable to that of the top three radiologists on finger radiographs (Cohen's kappa value, κ of 0.389 compared to κ 0.410) and wrist radiographs (κ 0.931 vs κ 0.931), indicating agreement relative to the gold standard. The average κ for the 169-layer CNN was somewhat worse (0.705 compared to 0.778) than the optimal performance of radiologists when considering all extremities radiographs [39,40]. Since its publication, the extensive dataset known as MURA (musculoskeletal radiographs) has been made publicly available to foster competition and advancement in automated fracture identification. Subsequently, public contributions have shown superior performance compared to the first deep learning model. As of April 2019, the live competition scoreboard for the top 8 models indicates κ values between 0.795 and 0.843, surpassing the performance of the best radiologist in the original research (0.778) [41].

Subsequent research has shown expert-level proficiency in identifying fractures of the upper extremities, lower extremities, and spine [18-20, 24-26]. Recent articles highlight hip fractures as a major contributor to long-term impairment [21, 38]. In 2019, Cheng et al. reported an accuracy of 91%, an AUC of 0.98, a sensitivity of 98%, and a false-negative rate of 2% for diagnosing hip fractures on frontal radiographs, based on a test set of 100 patients. This performance level was attained with a deep convolutional neural network pre-trained on 25,505 limb radiographs and then refined on 3,605 frontal pelvic radiographs.

A significant constraint of this research is that CNN models must be trained on the particular body region being assessed, necessitating a substantial quantity of accurately labeled radiographs for each training batch, sometimes amounting to tens of thousands. Unlike humans, a convolutional neural network's capacity to identify a fracture in one body part does not transfer to another body part. Furthermore, the results of all documented fracture detection investigations are binary: fracture present or absent. Descriptions of fracture morphology or particular imaging results to inform therapy are now sparse.

The identification of cartilage anomalies is relevant to musculoskeletal radiologists, orthopedic surgeons, and arthritis researchers. Liu et al. presented a very efficient automated deep-learning approach for cartilage identification [32]. The CNN model, trained on a dataset of 660 picture patches from 175 patients and evaluated on a test set of 1320 image patches, had a sensitivity of up to 88% and an AUC of 0.917, comparable to that of experienced radiologists. Pedoia et al. created a CNN-based deep neural network (DenseNet) that achieved an AUC of 0.83 for identifying cartilage defects and diagnosing osteoarthritis using T2 voxel-based relaxometry data [34]. It is essential to recognize that these cartilage-detection CNN models consist of two distinct CNNs: Initially, the first CNN segments the image regions containing cartilage, followed by the second CNN, which identifies cartilage anomalies.

Bien et al. obtained an area under the receiver operating characteristic curve (AUC) of 0.847 for identifying meniscal tears using their CNN model (MRNet; 1130 training and 120 validation examinations) [30]. The network was further trained to identify ACL rips, with an AUC of 0.937 on the internal validation set. When evaluated on an external validation set of 183 examinations sourced from a public dataset of 917 tests from Croatia, the AUC for detecting ACL tears was somewhat lower at 0.824. Nevertheless, when MRNet was trained on the external dataset, the AUC increased to 0.911 on the external validation set. Couteaux et al. (AUC 0.906), Roblot et al. (AUC 0.906), and Lassau et al. (AUC 0.91) showed comparable results for meniscal tear detection in 2019 [27-29].

5. Classification

Classification is the procedure by which an algorithm generates the likelihood of a label for a certain input picture. The process of identifying a previously stated abnormality is the most basic kind of categorization, since an abnormality may either be present or absent. Applications related to musculoskeletal conditions include automated assessment of osteoarthritis by radiography [42,43], evaluation of degenerative lumbar spinal canal and neuroforaminal stenosis [44], classification of intervertebral disc degeneration, and determination of skeletal age [46-52]. Additional musculoskeletal-specific applications include an algorithm that assesses the healing progression of torn Achilles tendons and the determination of patient sex from hand and wrist radiographs, subsequently noted as an instance of AI exceeding human capability [45,53,54].

6. Automated assessment of osteoarthritis

A prevalent job in musculoskeletal radiograph interpretation is the assessment of osteoarthritis severity. In 2016, Antony et al. used transfer learning methodologies to leverage existing CNN characteristics for the development of an automated system for quantifying knee osteoarthritis, which classifies the condition into "mild," "moderate," or "severe" categories [42]. Utilizing images from the publicly accessible Osteoarthritis Initiative (OAI) dataset, which comprises 4476 patients, their algorithm attained superior accuracies in Kellgren–Lawrence osteoarthritis classification, with an average mean squared error (MSE) of 0.504, surpassing Wndchrm, a contemporary state-of-the-art open-source image classifier, which recorded an MSE of 2.459 [57]. In 2018, Tiulpin et al. exhibited human-level performance in the Kellgren–Lawrence classification, achieving an AUC of 0.93. This was accomplished using the Multicenter Osteoarthritis Study (MOST) dataset, including 18,376 photos, and evaluated on the OAI dataset, which has 5,960 images; both datasets are extensive and publicly accessible. Their publication also included class activation maps, which are color-coded regions in the picture that emphasize the visual attributes used by the model to reach its findings, providing insight into the model's automated decision-making process [43].

7. Automated assessment of spinal and neuroforaminal stenosis in degenerative spinal imaging

An often executed, time-consuming activity in everyday musculoskeletal imaging is the detailed, level-by-level analysis of degenerative alterations in spine MRI interpretation. This may be particularly time-intensive in individuals with severe, multilayer disco vertebral degeneration. Furthermore, inter-reader dependability often exhibits poor levels [58].

The first AI model exhibiting human-level proficiency in lumbar spinal stenosis grading was released in 2017 by Jamaludin et al. [56]. A training dataset of 12,018 hand-annotated disc levels from 2009 patients, derived from the Genodisc clinical dataset, was used to train a CNN. In a test cohort of 203 patients, the model attained a class average accuracy of 95.6% for disc identification and labeling. The model's capabilities included spinal canal stenosis grading, Pfirrmann grading of disc desiccation, assessment of disc space narrowing, evaluation of spondylolisthesis, identification of endplate defects, and detection of aberrant marrow signal alterations. Consequently, our algorithm can provide numerous reportable gradings, equivalent to the proficiency of a single radiologist, but requires just 1–2 minutes to process each lumbar MRI.

Recently, Lu et al. at the MGH & BWH Center for Clinical Data Science created an automated model for grading spinal and foraminal stenosis, utilizing a U-net convolutional neural network for vertebral body and disc-level image segmentation. This model was developed using a dataset from 4,075 patients, comprising a training set of 15,957-disc levels and a test set of 3,420 levels. Notably, they employed natural language processing to extract ground-truth labels from existing radiology reports, thereby circumventing the labor-intensive process of manual annotation. The class attained an average accuracy of 80% for spinal stenosis grading and 78% for neural foraminal stenosis grading. Nonetheless, a significant limitation of this method is the lack of a dependable gold standard, given that individual radiologists may exhibit considerable variability in grading degenerative spine conditions [59].

8. Evaluation of skeletal maturity

Radiographic skeletal age assessment (SAA) serves as an essential instrument for pediatric endocrinologists to evaluate a child's growth status. Due to the visually predictable pattern of skeletal growth, assessing bone age is an endeavor especially well-suited for artificial intelligence. The automated evaluation of bone age using CNNs was a prevalent issue addressed by the deep learning research community [46-52]. This program garnered attention due to the RSNA Pediatric Bone Age Machine

Learning Challenge, which had over 100 applications competing for the title of the most precise automated bone age assessment tool [48]. A dataset including more than 14,000 hand radiographs has been made publicly accessible to developers. The training dataset included 12,611 annotated photos. Ground truth labels were established based on estimations documented in the corresponding radiology reports and assessed by a pediatric radiologist using the Greulich and Pyle approach. Algorithms were graded based on the mean absolute deviation (MAD) between AI estimations and the actual reference values. The premier method created by Cicero and Bilbily at the University of Toronto used Google's Inception V3 network for image processing. Shaheen et al. demonstrated that the diagnostic performance of bone age assessment is superior when a radiologist is boosted by AI software, compared to AI alone, a radiologist alone, and a pooled cohort of experienced radiologists [52]. In a distinct investigation, Kim et al. showed that the reading durations of radiologists decreased by around 30%, from 1.8 to 1.38 minutes in each trial when enhanced with software [55].

9. Conclusions

Advancements in deep learning within musculoskeletal radiology may be categorized as lesion detection, classification, segmentation, and non-interpretive tasks. In recent years, several instances of deep learning attaining expert-level performance in particular tasks across all four categories have been proven, however, a thorough interpretation of imaging studies remains unaccomplished. Interest in deep learning among academics, radiology leadership, and industry is on the rise, and these advancements are expected to influence the routine practice of musculoskeletal radiology in the future.

References

1. Choy G, Khalilzadeh O, Michalski M, Do S, Samir AE, Pianykh OS, et al. Current applications and future impact of machine learning in radiology. Radiology. 2018;288:318–28.
2. Soffer S, Ben-Cohen A, Shimon O, Amitai MM, Greenspan H, Klang E. Convolutional neural networks for radiologic images: a radiologist's guide. Radiology. 2019;290:590–606.
3. Chartrand G, Cheng PM, Vorontsov E, Drozdzal M, Turcotte S, Pal CJ, et al. Deep learning: a primer for radiologists. RadioGraphics. 2017;37:2113–31.
4. Kruskal JB, Berkowitz S, Geis JR, Kim W, Nagy P, Dreyer K. Big data and machine learning—strategies for driving this bus: a summary of the 2016 Intersociety Summer Conference. J Am Coll Radiol. 2017;14:811–7.
5. Rosenkrantz AB, Nicola GN, Allen B, Hughes DR, Hirsch JA. MACRA, MIPS, and the new Medicare quality payment program: an update for radiologists. J Am Coll Radiol. 2017;14:316–23.
6. Mazurowski MA. Artificial intelligence may cause a significant disruption to the radiology workforce. J Am Coll Radiol. 2019;0. Available from: https://www.jacr.org/article/S1546-1440(19)30064-X/abstract
7. Yamashita R, Nishio M, Do RKG, Togashi K. Convolutional neural networks: an overview and application in radiology. Insights Imaging. 2018;9:611–29.
8. Levine AB, Schlosser C, Grewal J, Coope R, Jones SJM, Yip S. Rise of the machines: advances in deep learning for cancer diagnosis. Trends Cancer. 2019;5:157–69.
9. Krittanawong C, Johnson KW, Rosenson RS, Wang Z, Aydar M, Baber U, et al. Deep learning for cardiovascular medicine: a practical primer. Eur Heart J.; Available from: https://academic.oup.com/eurheartj/advance-article/doi/10.1093/eurheartj/ehz056/5366208.
10. Yasaka K, Akai H, Kunimatsu A, Kiryu S, Abe O. Deep learning with convolutional neural network in radiology. Jpn J Radiol. 2018;36:257–72.
11. Russakovsky O, Deng J, Su H, Krause J, Satheesh S, Ma S, et al. ImageNet Large Scale Visual Recognition Challenge. ArXiv14090575 Cs. 2014; Available from: http://arxiv.org/abs/1409.0575.
12. Krizhevsky A, Sutskever I, Hinton GE. ImageNet classification with deep convolutional neural networks. In: Pereira F, Burges CJC, Bottou L, Weinberger KQ, editors. Adv Neural Inf Process Syst 25. Curran Associates, Inc.; 2012. p. 1097–1105. Available from: http://papers.nips.cc/paper/4824-imagenet-classification-with-deep-convolutional-neural-networks.pdf.

13. Hinton GE, Srivastava N, Krizhevsky A, Sutskever I, Salakhutdinov RR. Improving neural networks by preventing co-adaptation of feature detectors. ArXiv12070580 Cs. 2012; Available from: http://arxiv.org/abs/1207.0580
14. Abadi M, Agarwal A, Barham P, Brevdo E, Chen Z, Citro C, et al. TensorFlow: Large-scale machine learning on heterogeneous distributed systems. ArXiv160304467 Cs [Internet]. 2016 [cited 2019 May 4]; Available from: http://arxiv.org/abs/1603.04467.
15. Tomita N, Cheung YY, Hassanpour S. Deep neural networks for automatic detection of osteoporotic vertebral fractures on CT scans. Comput Biol Med. 2018;98:8–15.
16. Roth HR, Wang Y, Yao J, Lu L, Burns JE, Summers RM. Deep convolutional networks for automated detection of posterior-element fractures on spine CT. ArXiv160200020 Cs. 2016;97850P.
17. Olczak J, Fahlberg N, Maki A, Razavian AS, Jilert A, Stark A, et al. Artificial intelligence for analyzing orthopedic trauma radiographs: deep learning algorithms—are they on par with humans for diagnosing fractures? Acta Orthop. 2017;88:581–6.
18. Urakawa T, Tanaka Y, Goto S, Matsuzawa H, Watanabe K, Endo N. Detecting intertrochanteric hip fractures with orthopedist-level accuracy using a deep convolutional neural network. Skelet Radiol. 2019;48:239–44.
19. Rajpurkar P, Irvin J, Bagul A, Ding D, Duan T, Mehta H, et al. MURA: a large dataset for abnormality detection in musculoskeletal radiographs. 2017; Available from: https://arxiv.org/abs/1712.06957v4.
20. Chung SW, Han SS, Lee JW, Oh K-S, Kim NR, Yoon JP, et al. Automated detection and classification of the proximal humerus fracture by using a deep learning algorithm. Acta Orthop. 2018;89:468–73.
21. Kim DH, MacKinnon T. Artificial intelligence in fracture detection: transfer learning from deep convolutional neural networks. Clin Radiol. 2018;73:439–45.
22. Lindsey R, Daluiski A, Chopra S, Lachapelle A, Mozer M, Sicular S, et al. Deep neural network improves fracture detection by clinicians. Proc Natl Acad Sci. 2018;115:11591–6.
23. Pranata YD. Deep learning and SURF for automated classification and detection of calcaneus fractures in CT images. Comput Methods Prog Biomed. 2019;11.
24. Couteaux V, Si-Mohamed S, Nempont O, Lefevre T, Popoff A, Pizaine G, et al. Automatic knee meniscus tear detection and orientation classification with Mask-RCNN. Diagn Interv Imaging. 2019.
25. Roblot V, Giret Y, Bou Antoun M, Morillot C, Chassin X, Cotten A, et al. Artificial intelligence to diagnose meniscus tears on MRI. Diagn Interv Imaging. 2019.
26. Lassau N, Estienne T, de Vomecourt P, Azoulay M, Cagnol J, Garcia G, et al. Five simultaneous artificial intelligence data challenges on ultrasound, CT, and MRI. Diagn Interv Imaging 2019.
27. Bien N, Rajpurkar P, Ball RL, Irvin J, Park A, Jones E, et al. Deep-learning-assisted diagnosis for knee magnetic resonance imaging: development and retrospective validation of MRNet. PLoS Med. 2018;15:e1002699.
28. Pedoia V, Norman B, Mehany SN, Bucknor MD, Link TM, Majumdar S. 3D convolutional neural networks for detection and severity staging of meniscus and PFJ cartilage morphological degenerative changes in osteoarthritis and anterior cruciate ligament subjects. J Magn Reson Imaging;0. Available from: http://onlinelibrary.wiley.com/doi/abs/10.1002/jmri.26246.
29. Liu F, Zhou Z, Samsonov A, Blankenbaker D, Larison W, Kanarek A, et al. Deep Learning approach for evaluating knee MR images: achieving high diagnostic performance for cartilage lesion detection. Radiology. 2018;289:160–9.
30. Abidin AZ, Deng B, DSouza AM, Nagarajan MB, Coan P, Wismüller A. Deep transfer learning for characterizing chondrocyte patterns in phase contrast X-ray computed tomography images of the human patellar cartilage. Computers in Biology and Medicine. 2018;95:24–33.
31. Pedoia V, Lee J, Norman B, Link TM, Majumdar S. Diagnosing osteoarthritis from T2 maps using deep learning: an analysis of the entire osteoarthritis initiative baseline cohort. Osteoarthr Cartil 2019.
32. Chang PD, Wong TT, Rasiej MJ. Deep learning for detection of complete anterior cruciate ligament tear. J Digit Imaging. 2019; Available from: http://link.springer.com/10.1007/s10278-019-00193-4.

33. Jamaludin A, Kadir T, Zisserman A. SpineNet: Automatically Pinpointing Classification Evidence in Spinal MRIs. In: Ourselin S, Joskowicz L, Sabuncu MR, Unal G, Wells W, editors. Med Image Comput Comput-Assist Interv – MICCAI 2016. Cham: Springer International Publishing; 2016. 166–75.
34. Lang N, Zhang Y, Zhang E, Zhang J, Chow D, Chang P, et al. Differentiation of spinal metastases originated from lung and other cancers using radiomics and deep learning based on DCE-MRI. Magn Reson Imaging. 2019.
35.
36. Cheng C-T, Ho T-Y, Lee T-Y, Chang C-C, Chou C-C, Chen C-C, et al. Application of a deep learning algorithm for detection and visualization of hip fractures on plain pelvic radiographs. Eur Radiol. 2019; Available from: https://doi.org/10.1007/s00330-019-06167-y.
37. Chung SW, Han SS, Lee JW, Oh K-S, Kim NR, Yoon JP, et al. Automated detection and classification of the proximal humerus fracture by using a deep learning algorithm. Acta Orthop. 2018;89:468–73.
38. Belharbi S, Chatelain C, Hérault R, Adam S, Thureau S, Chastan M, et al. Spotting L3 slice in CT scans using deep convolutional network and transfer learning. Comput Biol Med. 2017;87:95–103.
39. MURA Dataset: Towards Radiologist-Level Abnormality Detection in Musculoskeletal Radiographs [Internet]. [cited 2019 May 4]. Available from: https://stanfordmlgroup.github.io/competitions/mura/.
40. Antony J, McGuinness K, Connor NEO, Moran K. Quantifying Radiographic Knee Osteoarthritis Severity using Deep Convolutional Neural Networks. ArXiv160902469 Cs. 2016; Available from: http://arxiv.org/abs/1609.02469.
41. Tiulpin A, Thevenot J, Rahtu E, Lehenkari P, Saarakkala S. Automatic knee osteoarthritis diagnosis from plain radiographs: a deep learning-based approach. Sci Rep. 2018;8.
42. Lu J-T, Pedemonte S, Bizzo B, Doyle S, Andriole KP, Michalski MH, et al. DeepSPINE: Automated Lumbar Vertebral Segmentation, Disc-level Designation, and Spinal Stenosis Grading Using Deep Learning. ArXiv180710215 Cs. 2018; Available from: http://arxiv.org/abs/1807.10215.
43. Lootus M. Automated radiological analysis of spinal MRI. Ph.D. Thesis. University of Oxford; 2015. Available from: http://www.robots.ox.ac.uk/~vgg/publications/2015/Lootus15/lootus15.pdf.
44. Koitka S, Demircioglu A, Kim MS, Friedrich CM, Nensa F. Ossification area localization in pediatric hand radiographs using deep neural networks for object detection. Najarian K, editor. PLOS ONE. 2018;13:e0207496.
45. Larson DB, Chen MC, Lungren MP, Halabi SS, Stence NV, Langlotz CP. Performance of a deep-learning neural network model in assessing skeletal maturity on pediatric hand radiographs. Radiology. 2018;287:313–22.
46. Halabi SS, Prevedello LM, Kalpathy-Cramer J, Mamonov AB, Bilbily A, Cicero M, et al. The RSNA pediatric bone age machine learning challenge. Radiology. 2018;290:498–503.
47. Iglovikov V, Rakhlin A, Kalinin AA, Shvets A. Pediatric bone age assessment using deep convolutional neural networks. 2018; Available from: http://biorxiv.org/lookup/doi/10.1101/234120.
48. Spampinato C, Palazzo S, Giordano D, Aldinucci M, Leonardi R. Deep learning for automated skeletal bone age assessment in X-ray images. Med Image Anal. 2017;36:41–51.
49. Lee H, Tajmir S, Lee J, Zissen M, Yeshiwas BA, Alkasab TK, et al. Fully automated deep learning system for bone age assessment. J Digit Imaging. 2017;30:427–41.
50. Tajmir SH, Lee H, Shailam R, Gale HI, Nguyen JC, Westra SJ, et al. Artificial intelligence-assisted interpretation of bone age radiographs improves accuracy and decreases variability. Skelet Radiol. 2019;48:275–83.
51. Kapinski N, Zielinski J, Borucki BA, Trzcinski T, Ciszkowska-Lyson B, Nowinski KS. Estimating Achilles tendon healing progress with convolutional neural networks. ArXiv180605091 Cs 2018; Available from: http://arxiv.org/abs/1806.05091.
52. Yune S, Lee H, Kim M, Tajmir SH, Gee MS, Do S. Beyond Human Perception: Sexual Dimorphism in Hand and Wrist Radiographs Is Discernible by a Deep Learning Model. J Digit Imaging. 2018; Available from: http://link.springer.com/10.1007/s10278-018-0148-x.

53. Kim JR, Shim WH, Yoon HM, Hong SH, Lee JS, Cho YA, et al. Computerized bone age estimation using deep learning-based program: evaluation of the accuracy and efficiency. Am J Roentgenol. 2017;209:1374–80.
54. Jamaludin A, Lootus M, Kadir T, Zisserman A, Urban J, Battié MC, et al. ISSLS Prize In Bioengineering Science 2017: Automation of reading of radiological features from magnetic resonance images (MRIs) of the lumbar spine without human intervention is comparable with an expert radiologist. Eur Spine J. 2017;26:1374–83.
55. Wndchrm – an open-source utility for biological-image analysis Available from: https://scfbm.biomedcentral.com/articles/10.1186/1751-0473-3-13.
56. Winklhofer S, Held U, Burgstaller JM, Finkenstaedt T, Bolog N, Ulrich N, et al. Degenerative lumbar spinal canal stenosis: intra- and inter-reader agreement for magnetic resonance imaging parameters. Eur Spine J. 2017;26:353–61.
57. Miskin N, Gaviola GC, Huang RY, Kim CJ, Lee TC, Small KM, et al. Intra- and Intersubspecialty variability in lumbar spine MRI interpretation: a multi-reader study comparing musculoskeletal radiologists and Neuroradiologists. Curr Probl Diagn Radiol. 2019.
58. Deniz CM, Xiang S, Hallyburton RS, Welbeck A, Babb JS, Honig S, et al. Segmentation of the proximal femur from MR images using deep convolutional neural networks. Sci Rep. 2018;8:16485.
59. Huo T, Xie Y, Fang Y, Wang Z, Liu P, Duan Y, Zhang J, Wang H, Xue M, Liu S, Ye Z. Deep learning-based algorithm improves radiologists' performance in lung cancer bone metastases detection on computed tomography. Frontiers in Oncology. 2023 Feb 8;13:1125637.

دمج التعلم العميق في الأشعة العضلية الهيكلية: التطبيقات الحالية والتوجهات المستقبلية

الملخص

الخلفية :يُحدث الذكاء الاصطناعي(AI) ، خاصة من خلال تقنيات التعلم العميق، تحولاً كبيراً في مجال الأشعة العضلية الهيكلية. يعزز دمج الشبكات العصبية الالتفافية (CNNs) من الكشف وتصنيف الحالات العضلية الهيكلية، مما يساعد في تلبية الطلب المتزايد على أطباء الأشعة.

الطرق :تُجمع هذه المراجعة الأدبيات الحالية حول تطبيقات التعلم العميق في التصوير العضلي الهيكلي. تم اتباع نهج سردي لتحليل البيانات المستخلصة من قاعدة بيانات PubMed باستخدام مصطلحات بحث عامة ومحددة تتعلق بالتعلم العميق في الأشعة. وتم اختيار الدراسات السريرية الرئيسية بناءً على أهميتها للتطبيقات العملية اليومية.

النتائج :تُظهر التطورات الحديثة أن خوارزميات التعلم العميق قادرة على تحديد الكسور، وإصابات الغضاريف، وتمزقات الأربطة بدقة، حيث تصل أحياناً إلى مستويات أداء مماثلة لأطباء الأشعة الخبراء. على وجه الخصوص، أظهرت الشبكات العصبية الالتفافية دقة تشخيصية عالية في الكشف عن كسور الأطراف العلوية والسفلية، مع تفوق بعض النماذج على المتخصصين البشر. تسلط المراجعة الضوء على التقييمات الآلية لمرض هشاشة العظام، وتضيق العمود الفقري، ونضج الهيكل العظمي، مما يُظهر إمكانات الذكاء الاصطناعي في تحسين سير العمل ودقة التشخيص.

الاستنتاج :يوفر صعود التعلم العميق في الأشعة العضلية الهيكلية فرصاً كبيرة لتعزيز عمليات التشخيص. وعلى الرغم من أن العديد من الخوارزميات تُظهر أداءً على مستوى الخبراء، إلا أن الحاجة إلى تفسير دقيق للدراسات التصويرية لا تزال ضرورية. ومع تطور تقنيات الذكاء الاصطناعي، فإنها مهيأة للعب دور حاسم في مستقبل الأشعة العضلية الهيكلية، مما قد يعيد تشكيل الممارسات السريرية.

الكلمات المفتاحية :الذكاء الاصطناعي، التعلم العميق، الأشعة العضلية الهيكلية، الشبكات العصبية الالتفافية، التصوير التشخيصي.