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A MODERN RENAISSANCE OR AN ETHICAL CONUNDRUM: REVIEWING THE IMPLICATIONS OF ARTIFICIAL INTELLIGENCE IN THE FIELD OF RADIOLOGY

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ABSTRACT

Recent progress in the field of artificial intelligence has found its way into the diverse realms of medical imaging and radiology, raising questions regarding its potential, efficiency, accuracy, and reliability. This review aims to educate radiologists and medical students regarding the uncharted world of artificial intelligence through the discussion of its achievements in radiology while keeping an ethical and prognostic outlook in mind. Artificial intelligence, through the application of its subsets (i.e. machine learning and deep learning), has caused vast expansions in radiology, such as automating diagnoses. Pneumonia, pneumothorax, pulmonary tuberculosis, pulmonary nodules, etc. can now be detected through the use of various artificial intelligence algorithms. However, the acceptability of these highly accurate systems is still a matter of massive doubt. Educating the healthcare professionals in this regard would alleviate the fear of an unknown computing system while also answering numerous misconceptions. Moreover, with acceptability comes a huge moral and ethical responsibility. Ethical codes need to be devised that provide appropriate solutions to the moral problems connected with artificial intelligence. Thus, with all of these factors under consideration, artificial intelligence has enormous potential in the field of radiology and will broaden the horizon of healthcare professionals by creating a greater number of computing-related opportunities. ***Keywords:*** Artificial intelligence, radiology, ethics, deep learning, machine learning

INTRODUCTION

The past century has inarguably added numerous technological advancements to the list of developments in the field of radiology and medical imaging. The recent progress made in the young yet thriving field of artificial intelligence (AI) has shown that it has not only earned its place on this list but has created opportunities for future developments as well. With the use of machine intelligence, AI technology is capable of receiving, processing, and interpreting external data. However, the ability of AI to learn from said data and use it towards the achievement of certain goals while being able to flexibly remodel, readjust, and transform, is what makes it unique. Hence, AI mainly deals with the advancement of computers that can partake in intellectual processes similar to those of a human being (1).

Radiologists are particularly interested in the aspects of AI concerned with high-level visual processing through the use of computers. The field that can materialize this interest is conveniently termed as 'Computer Vision' (2). The deep model of most interest in this regard is object detection through the use of a 'Convolutional neural network' (CNN); which imitates the ability of a human brain to process information by developing a multilayered organized network of neurons (3). Deep learning is a subclass of machine learning and is persuaded by the process of image recognition and interpretation in the human brain (4, 5). Classical machine learning requires human intervention between its two phases (extraction of features and classification of image), but deep learning uses a multilayered artificial architecture of neurons to realize its set goals and does not require any human intervention (5). Machine learning is essentially the basis for computer-aided diagnosis (CADx); which was developed to assist image reading (3). Both of these novel fields fall under the broad classification of AI technologies and find immense potential in medicine as well as surgery. As seen, changes are inevitable in the ever-growing field of radiology with the advent of higher degrees of machine intelligence. Therefore, a strong sense of innovation and adaptability must be ingrained in the minds of radiologists in order to assist their traditional diagnostic practices with the technological advancements in their field.

WHERE DO WE STAND CURRENTLY?

The importance of diagnosis made on radiological data (X-ray, computerized tomography (CT), ultrasonography, magnetic resonance imaging (MRI), etc.) is undeniable in the management of clinical patients, but according to the World Health Organization, two-thirds of the world population lacks access to radiological diagnostics (6). There is also a shortage of experts who can interpret radiographs even if the availability of imaging equipment is made certain (3). The incorporation of AI has a vast scope in areas suffering the impacts of such shortages.

Among the medical imaging techniques performed annually, the chest radiograph is the most common modality with 2 billion procedures performed each year (7). Hence, there is a large number of datasets of chest radiographs that is available to researchers

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working on the development of AI systems. Using this modality, the currently available models can detect clinical anomalies, such as pneumonia, mass, edema, and fibrosis, with performance potential comparable to a practicing radiologist (8). Scanning of chest radiographs and flagging of suspicious ones containing moderate to large pneumothorax has also been made possible by a deep CNN algorithm. This algorithm was successfully able to detect 80-84% of the images showing moderate to large pneumothorax but failed to detect smaller anomalies since the algorithm had not been trained to do so (9). Artificial intelligence also becomes prominent in the refinement of workplace dynamics by tagging radiographs with potential abnormalities, resulting in prompt identification of anomalies by the radiologist and prioritization of the patients based on the urgency of treatment and severity of their disease. The reporting turnaround time for chest examination was reduced by 44% with the development of a Computer-aided detection (CADe) system that automatically detects abnormal chest radiographs by using density and textural features (10). Following this point, extensive researches conducted in the development of AI technologies to diagnose various radiologically detectable thoracic anomalies have been reviewed to provide a detailed outlook on the potentials of this growing field.

Lung Cancer

Lung cancer is the most prevalent form of cancer and is also responsible for 18% of the deaths caused by all cancers; thus, adding to the fact that it is cancer that causes the most deaths globally (11). The development of DeepConvSurv has aided the utilization of Convolutional neural networks (CNNs) in the survival prediction of patients suffering from lung cancer (12). This prediction was made possible based on pathological images. Moreover, extensive experimentation has also established the superiority of using CNNs for survival prediction (12). An accuracy of 82.5% in detecting lung cancer was obtained by Paul et al. (13), using a pre-trained CNN and merging it with a quantitative approach by extracting features from CT images. The deep learning-based algorithm developed by Nam et al. (14), was able to outperform the physicians in the detection of malignant pulmonary nodules and, when used as a second reader resulted in enhanced nodule detection ability in all physicians.

Pulmonary Nodule

For timely detection and management of lung cancer, the identification of pulmonary nodules is a crucial factor. Pulmonary nodules are the early manifestations of lung cancer and are often classified on chest radiographs as small circular low contrast masses of tissue characterized by a wide variety in size and density (15). A major application of the CADx system is the diagnosis of pulmonary nodules on the radiograph. The computer-aided diagnosis systems are classified into two major groups; CADe and CADx (16). Oftentimes a combination of both CAD systems is used. A CADe scheme, with a sensitivity of 76% on a dataset of the Japanese Society of Radiological Technology (JSRT) and 77% on a University of Chicago dataset was developed to detect nodules on chest X-ray (CXR), and it can potentially improve the nodule detecting abilities of the radiologists as well (15). Additionally, the author acknowledged that the higher sensitivity was obtained with the dataset of the University of Chicago since the average nodule size was larger and quality of the digitally obtained images was better when compared with the JSRT dataset (15). To establish that the CAD system (the combination of CADe and CADx) is clinically useful to the radiologists in detecting pulmonary nodules, an observer performance study was conducted by Kobayashi et al. (17), which resulted in the successful trial of 16 radiologists and resultantly, showed statistically significant improvement in the radiologists' performance to detect lung nodules when the CAD scheme was utilized.

Pneumonia and Pulmonary Edema

Lung areas appear white or light gray on CXR when the patient is suffering from pneumonia. The sputum or water-filled lung areas absorb more radiation resulting in the color change. Using this approach, the physicians can ascertain the degree of infection. A deep learning algorithm called 'Chexnet' was trained by Rajpurkar et al. (18) and its comparison was made with the performance of practicing radiologists. The result indicated outperformance of the algorithm in comparison to an average radiologist (18). The use of CNN in the detection and location of pulmonary edema has also been made possible (19).

Tuberculosis

Tuberculosis (TB) is one of the top 10 leading causes of death resulting in 1.4 million deaths worldwide and 10 million patients being infected in 2019 (20). The abnormal manifestation of TB on CXR results from the variations in the lung texture and geometry, such as consolidations, infiltrations, and cavitation. Different types of manifestations make it difficult to detect TB on CXR, thus, algorithms that focus on different manifestations need to be combined. The prevalence of TB in low-to-middle income areas is relatively high, making the automation of its radiological diagnosis necessary in those zones; since expert radiologists are often lacking there as well (21).

A multitude of different appearing TB manifestations has to be detected in order to achieve an accordant result in different populations. Textural, focal, and configurational abnormality analyses have been used in combination to achieve automatic detection of TB on a CXR (22). Furthermore, the development of a deep learning-based automatic detection algorithm has not only aided the diagnoses of active infections of pulmonary TB but has also outperformed physicians, including thoracic radiologists (23).

Retraining of two deep convolutional neural networks (DCNNs), AlexNet and GoogLeNet, have accurately classified TB on chest radiograph. The best performing classifier, obtained by combining both DCNNs, had an area under the curve of 0.99 (24). But as addressed by the author, the model was initially trained to differentiate between normal and abnormal CXR with regards to TB and may give a false-positive result in pathological conditions with presentations similar to TB on imaging (24). This limitation confines the use of these algorithms in areas where TB is endemic, such as underdeveloped areas.

Chronic Obstructive Pulmonary Disease

Computerized tomography (CT) is the medical imaging technique that is ideal for the characterization and diagnosis of emphysema and airway diseases (25). One of the earlier techniques involved in the detection of emphysema called density mask analysis was unable to differentiate between the subtypes of emphysema (26). Visual inspection can overcome this limitation but in doing so implicates its shortcoming: interobserver variability can not be ruled out during visual inspection (27).

To overcome these challenges, the trend has shifted towards textural analysis using machine learning. Various features are extracted from the region of interest on the lung field and then subjected to categorization. This technique was used successfully in the classification of various obstructive patterns of the lung parenchyma, but recently, deep learning has taken over and proven to be more advantageous; since using the deep learning algorithms has allowed for the task to be completed without any human interposition (28). CNNs have been used in the classification of emphysema using textural analysis with higher classification rates (29).

The use of CNNs in the diagnosis of chronic obstructive pulmonary disease has proved to be of value but building a CNN from scratch requires large computing resources and extensive availability of datasets, which is difficult to obtain in medical science (28). However, it has been shown that the use of a pre-trained CNN with fine-tuning detected pulmonary embolism more accurately than a CNN developed from scratch (30). Thus, the use of transfer learning, as well as fine-tuning pre-trained CNNs could prove to be more efficient and effective in detecting various other conditions.

A LOOK INTO THE ETHICAL OBSTACLES

The ultimate goal of a healthcare practitioner is to ensure an efficient delivery of the best possible outcome for the patient, and so both the radiologist and the autonomous AI system need to follow a set of rules that directs positive results in favor of the patients. Additionally, three prime ethical points of concern have been identified while recognizing the moral implications of AI technology; safety, judicial transparency, and privacy (31). While dealing with technology, these are crucial points of a potential contravention when neglected.

The essence of medical ethics is formed around the fulfillment of patient safety through the accurate provision of four basic values; justice, autonomy, non-maleficence, and beneficence (32). These principles derive the fact that any AI system should be riskless, reliable, accurate, and unfailing. Furthermore, legislative reforms to interject supportive amendments in the existing laws must perpetuate the assurance of data protection and data usage within the boundaries of the patient's consent.

Data ethics is the novel field that is essentially concerned with the evaluation of moral problems associated with data, algorithms, and related practices (33). Privacy, informed consent, ownership, objectivity, and 'big data divide' are five major areas of concern in terms of data ethics and when they are not properly protected, they become five central areas of infringement (34). Multiple violations may strike the privacy of patient data if the balance between personal information and advancing artificial intelligence is not maintained (35). To avoid such breaches, radiology should focus on an important aspect of data ethics which is the 'Ethics of practices'. Ethical AI practices should be defined and documented to ensure the promotion of technical growth while still maintaining patient consent, user privacy, and use of secondary data (35).

A sense of responsibility is always associated with the act of making a decision. Hence, in the case of any harm, the human being responsible for the action holds accountability but an ethical question arises when decisions or actions that resulted in harm are ascribed to the use of AI technologies. To delve deeper into the attribution of accountability, in the case of harm caused by an AI system, it is important to look into Aristotle's ethics. Two traditional conditions attributed to attainment of responsibility have been described since Aristotle; the control condition (also called the freedom condition), inferring if one could be exempt for an act owing to the lack of freedom, and the epistemic condition (also referred to as the knowledge condition) (36). Full responsibility is only attributed when the epistemic condition is fulfilled along with the control condition. The control condition holds you responsible for an act only if it is committed by you, but the epistemic condition makes it necessary for someone to know the nature of the act to be held fully accountable for it (36). The AI does not meet the traditional Aristotelian conditions for full moral responsibility (37). Therefore, it only makes sense if the AI is not expected to act voluntarily since it is not conscious of what it is doing. This assumption also leaves behind only the radiologist to be attributed to the responsibility of harm.

Furthermore, the unanswered ambiguity of including CAD results in the patient's radiological report and complete disclosure of the information that the diagnosis is supported by an AI system is still under debate. Additionally, bound by the limitations of the human body, there are certain features on images that the radiologist cannot quantify. For instance, textural analysis can generate numerous features that are undetectable and unquantifiable by a human being. Therefore, if the radiologist is required to validate the output of an AI system, they will potentially be exposed to the risk of validating the unknown (36). Another major aspect that could potentially lead to gaps in the provision of excellent patient care is the risk of automation bias. Automation bias is the proclivity of the human mind to accept suggestions generated by an automated program and ignore non-automated contradictory information, even if it is correct. Unfortunately, the risk of automation bias also exists in the field of radiology (38). The AI designers should be mindful of the fact that a high degree of automation without maintaining the reliability of the systems could drastically result in numerous negative impacts and impeding completely the operators' decision-making process could even prove to be deadly (39).

The extensive use of AI in the field of radiology may potentially result in the reduced motivation of younger doctors to incorporate themselves in this field. It may also result in fewer training opportunities since the same workload could be successfully met in a shorter amount of time by an AI system which reduces the need for radiologists. This message resonates with everyone associated with the healthcare profession. A survey conducted in 17 Canadian medical schools concluded that 67.7% of medical students agreed that AI would reduce the demand for radiologists, a minority (29.3%) believed that AI would replace radiology, and considering radiology as a career choice, in these times of automation, caused anxiety among 48.6% of the students (40). This raises many more ethical questions related to the potential unemployment of many aspiring radiologists and professionals associated with the field of medical imaging.

WHERE ARE WE HEADED?

The utilization of computing technologies to the benefit of a profession is indispensable for the attainment of modernity, and the field of diagnostic imaging has always had a close traditional association with the newer, finer, and superior computing machinery. The role of the computer was drastically dilated in the field of radiology in the 1970s after being initially introduced in the 1960s. Although it was an expansive step towards the future, the use of computers was still limited to administrative tasks only. The earliest use of computers for imaging was reported first in the nuclear medicine digital subtraction angiography (41). CT in the 1970s and MRI in the 1980s were the next major adaptations of computing technology in radiology (41). This historical analysis indicates that the field of radiology will continue to incorporate newer technology in the future as well but questions like 'Will AI entirely replace the field of radiology?' raise various suspicions in the minds of resident physicians as well as medical students (42). However, it is clear that AI technologies only serve a supplemental purpose therefore, are often more appropriately and conveniently approved as augmentation equipment rather than replacement tools (42, 43). Nevertheless, some people associated with the healthcare profession predict a complete replacement would take part and this prediction instills a sense of anxiety (40). Such a poor prognosis of this field results from the gross lack of education regarding AI. A survey conducted to understand the impact of the rise of AI in radiology concluded that 73.3% of the radiologists estimated that they had received insufficient knowledge regarding AI but an estimated 94.4% were willing to attend continuous medical education in this field (44). This proves that radiologists are open to accepting such changes when educated in the relative field.

Moreover, a recent survey has indicated that AI will outperform humans in many activities including the performance of surgeries (45). The experts also believed in the high likelihood of AI surpassing humans in the next 45 years (45). Therefore, a sense of employment insecurity due to a fear of complete replacement has taken over the radiologists. Yet, the trend recently has shifted from a sense of complete replacement to the notion that AI will not replace the radiologists, but rather that the radiologists who use AI will replace those that do not. Hence, indicating that radiologists will have to keep up with the advancements in order to have a sense of security in their field.

Moreover, the potential uses of deep learning models in the training of residents and general radiologists cannot be overlooked. The images labeled by specialists can be of immense utility to instill confidence in the young radiologists by training them for the recognition of difficult diagnoses. Furthermore, AI technology can be used as a tool to alert radiologists towards patients that require urgent care. It also finds potential in decreasing a radiologist's daily workload, which would increase the optimization of the workforce (46).

Considering all of these aspects, it can be safely stated that the eagerness associated with the future of AI should be met with appropriate planning. However, the potential of AI, although vast, should not be over-glorified. Since an AI system is trained in only one aspect, it cannot make associations about context, and hence, it is unlikely that AI will completely replace radiologists (47). Even further, it has the potential to broaden the scope of the radiologists' work by connecting them with technology and becoming a source of superior tools.

CONCLUSION

The development of potent algorithms has indicated promising outcomes in the future. It appears that AI not only finds applications in radiology, but has the potential to revolutionize other fields of medicine and surgery as well. However, the fast-growing world of AI also demands the upgradation of the code of ethics. Under no circumstances should the ethical obstacles be overshadowed by the complications faced during the development of AI systems. The ethical code should also be reformed with each development in automation technology, and the opinions of radiologists and AI engineers should be incorporated to ensure the formation of an all-inclusive code of ethics; the goal of which is to direct physicians towards the best possible outcome for the patients. Recognizing these weaknesses and challenges as potential threats for disseminating AI systems and devising policies for the regulation of technological expansion, maintenance of quality, and protection of patient data will surely help highlight the promising future of interdisciplinary uses of AI.

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REFERENCES

1. Kok JN, Boers EJW, Kosters WA et al. Artificial intelligence: Definition, trends, techniques and cases. Encyclopedia of Life Support Systems 2010;1096–7.
2. Huang TS. Computer vision: Evolution and promise. Urbana (IL): University of Illinois at Urbana-Champaign. 1997.
3. Chassagnon G, Vakalopoulou M, Paragios N et al. Artificial intelligence applications for thoracic imaging. Eur J Radiol 2020;123:108774.
4. Paeglis A, Strumfs B, Mezale D et al. A review on machine learning and deep learning techniques applied to liquid biopsy. Liquid Biopsy (serial online) 2018 November (cited 2021 January 12). Available from: URL: https://www.intechopen.com/books/liquid-biopsy/a-review-on-machine-learning-and-deep-learning-techniques-applied-to-liquid-biopsy.
5. Khanna SK. Machine learning vs deep learning. 2019;455–8.
6. Mollura DJ, Azene EM, Starikovsky A et al. White paper report of the rad-aid conference on international radiology for developing countries: Identifying challenges, opportunities, and strategies for imaging services in the developing world. J Am Coll Radiol 2010;7(7):495–500.
7. Raoof S, Feigin D, Sung A et al. Interpretation of plain chest roentgenogram. Chest 2012;141(2):545–58.
8. Rajpurkar P, Irvin J, Ball RL et al. Deep learning for chest radiograph diagnosis: A retrospective comparison of the CheXNeXt algorithm to practicing radiologists. PLoS Med 2018;15(11):1–17.
9. Taylor AG, Mielke C, Mongan J. Automated detection of moderate and large pneumothorax on frontal chest X-rays using deep convolutional neural networks: A retrospective study. PLoS Med 2018;15(11):1–15.
10. Kao EF, Liu GC, Lee LY et al. Computer-aided detection system for chest radiography: Reducing report turnaround times of examinations with abnormalities. Acta Radiol 2015;56(6):696–701.
11. Boyle P, Levin B. World Cancer report 2020. Vol. 199, Cancer Control 2008.p.512.
12. Zhu X, Yao J, Huang J. Deep convolutional neural network for survival analysis with pathological images. 2016 IEEE International Conference on Bioinformatics and Biomedicine (BIBM), Shenzhen, 2016.p.544-7.
13. Paul R, Hawkins SH, Hall LO et al. Combining deep neural network and traditional image features to improve survival prediction accuracy for lung cancer patients from diagnostic CT. IEEE International Conference on Systems, Man, and Cybernetics; 2016 Oct; 2017.p.2570–5.
14. Nam JG, Park S, Hwang EJ et al. Development and validation of deep learning-based automatic detection algorithm for malignant pulmonary nodules on chest radiographs. Radiology 2019;290(1):218–28.
15. Chen S, Suzuki K, MacMahon H. Development and evaluation of a computer-aided diagnostic scheme for lung nodule detection in chest radiographs by means of two-stage nodule enhancement with support vector classification. Med Phys 2011;38(4):1844–58.
16. Firmino M, Angelo G, Morais H et al. Computer-aided detection (CADe) and diagnosis (CADx) system for lung cancer with likelihood of malignancy. Biomed Eng Online 2016;15(1):1–17.
17. Kobayashi T, Xu XW, MacMahon H et al. Effect of a computer-aided diagnosis scheme on radiologists' performance in detection of lung nodules on radiographs. Radiology 1996;199(3):843–8.
18. Rajpurkar P, Irvin J, Zhu K et al. CheXNet: Radiologist-level pneumonia detection on chest X-rays with deep learning. arXiv 2017;3–9.
19. Islam MT, Aowal MA, Minhaz AT et al. Abnormality detection and localization in chest x-rays using deep convolutional neural networks. arXiv 2017, arXiv:1705.09850. [Online]. Available from: URL: http://arxiv.org/abs/1705.09850.
20. Tuberculosis. World Health Organization Website. Available from: URL: https://www.who.int/news-room/fact-sheets/detail/tuberculosis.
21. Centers for Disease Control and Prevention (CDC). Tuberculosis: data and statistics. Available from: URL: https://www.cdc.gov/tb/statistics/default.htm.
22. Hogeweg L, Sánchez CI, Maduskar P et al. Automatic detection of tuberculosis in chest radiographs using a combination of textural , focal , and shape abnormality analysis. IEEE Trans Med Imaging 2015;34(12):2429-42.
23. Hwang EJ, Park S, Jin K et al. Development and validation of a deep learning-based automatic detection algorithm for active pulmonary tuberculosis on chest radiographs. Clin Infect Dis 2019;69:739–47.
24. Paras Lakhani M, Baskaran Sundaram M. Deep learning at chest radiography: automated classification of pulmonary tuberculosis by using convolutional neural networks. Radiology 2017;284(2):574–82.
25. George R. Washko MDM. The role and potential of imaging in COPD. Med Clin North Am 2012;96(4):729–43.

26. Müller NL, Staples CA, Miller RR et al. "Density Mask" an objective method to quantitate emphysema using computed tomography. Chest 1988;94(4):782-7.
27. Hersh CP, Washko GR, Jacobson FL et al. Interobserver variability in the determination of upper lobe-predominant emphysema. Chest 2007;131(2):424-31.
28. Das N, Topalovic M, Janssens W. Artificial intelligence in diagnosis of obstructive lung disease: current status and future potential. Curr Opin Pulm Med 2018;24(2):117–23.
29. Pei X. Emphysema classification using convolutional neural networks. In: Liu H., Kubota N., Zhu X., Dillmann R., Zhou D, editors. Intelligent Robotics and Applications. ICIRA 2015. Lecture Notes in Computer Science, vol 9244 Springer: Cham; 2015.p.455-61.
30. Tajbakhsh N, Shin JY, Gurudu SR et al. Convolutional neural networks for medical image analysis: full training or fine tuning? IEEE Trans Med Imaging 2016;35(5):1299–312.
31. Liew C. The future of radiology augmented with artificial ıntelligence: a strategy for success. Eur J Radiol 2018;102:152-6.
32. Beauchamp TL, Childress JF. Principles of biomedical ethics. New York; Oxford: Oxford University Press; 2013.
33. Floridi L, Taddeo M. What is data ethics? Philos Trans A Math Phys Eng Sci 2016;374(2083):20160360.
34. Mittelstadt BD, Floridi L. The ethics of big data: current and foreseeable issues in biomedical contexts. Sci Eng Ethics 2016;22(2):303–41.
35. Kohli M, Geis R. Ethics, artificial intelligence, and radiology. J Am Coll Radiol 2018;15(9):1317–9.
36. Neri E, Coppola F, Miele V et al. Artificial intelligence: who is responsible for the diagnosis? Radiol Medica 2020;125(6):517–21.
37. Giubilini A, Savulescu J. The artificial moral advisor. the "ideal observer" meets artificial intelligence. Philos Technol 2018;31(2):169-88.
38. Geis JR, Brady AP, Wu CC et al. Ethics of artificial intelligence in radiology: summary of the Joint European and North American Multisociety Statement. Radiology 2019;293(2):436-40.
39. Cummings ML. Automation bias in intelligent time critical decision support systems. Collect Tech Pap - AIAA 1st Intell Syst Tech Conf. 2004;2:557–62.
40. Gong B, Nugent JP, Guest W et al. Influence of artificial intelligence on Canadian medical students' preference for radiology specialty: a national survey study. Acad Radiol 26(4):566–77.
41. Mayo RC, Leung J. Artificial intelligence and deep learning – radiology's next frontier? Clin Imaging 2018;49:87–8.
42. Yasaka K, Abe O. Deep learning and artificial intelligence in radiology: Current applications and future directions. PLoS Med 2018;15(11):e1002707.
43. Forney MC, McBride AF. Artificial intelligence in radiology residency training. Semin Musculoskelet Radiol 2020;24(1):74-80.
44. Waymel Q, Badr S, Demondion X et al. Impact of the rise of artificial intelligence in radiology: what do radiologists think? Diagn Interv Imaging 2019;100(6):327-36.
45. Grace K, Salvatier J, Dafoe A et al. When will AI exceed human performance? Evidence from AI experts. J Artif Intell Res 2018;62:729–54.
46. Syed AB, Zoga AC. Artificial intelligence in radiology: current technology and future directions. Semin Musculoskelet Radiol 2018;22(5):540–5.
47. Hosny A, Parmar C, Quackenbush J et al. Artificial intelligence in radiology. Nat Rev Cancer 2018;18(8):500–10.