

REVIEW ARTICLE

Future of Artificial Intelligence and Nuclear Cardiology

Akihiro Kikuchi, PhD¹⁾ and Takashi Kawakami, PhD²⁾

Received: February 22, 2018/Revised manuscript received: May 16, 2018/Accepted: May 16, 2018

J-STAGE Advance published: August 3, 2018

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Abstract

In recent years, the application of artificial intelligence (AI) to medical images has advanced rapidly. Especially since the learning method called deep learning has spread, we have made remarkable progress including precision. Its application ranges from detection of abnormal lesion on the image to screening assistants or selection of drugs necessary for treatment.

Study of nuclear medicine is progressing with AI, and reports are also made on bone scintigraphy and PET images. In nuclear cardiology, software for detecting abnormal lesion of myocardium using artificial neural network (ANN) by machine learning and making it useful for image interpretation aid has been developed. In the future, it is expected that study and development will also advance interpretation assistance by deep learning and abnormal lesion detection. However, for deep learning, the number of images required for study becomes enormous and it is a point of discussion.

Keywords: Artificial intelligence, Convolution neural network, Deep learning, Machine learning, Training data
Ann Nucl Cardiol 2018; 4 (1): 79–82

In recent years, the term “artificial intelligence (AI)” has been used increasingly frequently. Many people conceptualize AI as the kind of thinking humanoid robot often seen in anime. However, in reality, AI often refers to a computer program and computer algorithm and overall architecture that operates according to a specific purpose. In natural language processing such a system reads documents (1) and performs syntax analysis. In the field of digital image, it recognizes and identifies specific objects in an image. In the field of control systems, it automatically controls automobiles and machines. In addition, an AI system that utilizes logical thinking to play (and win) shogi and go was recently developed. In this way, AI has penetrated into daily life. Turning to the medical field, AI that has learned enormous amounts of data as training data has made it possible to diagnose diseases more accurately and find the optimal treatment. For example, a system for detecting a suspected illness from an endoscopic image has been developed. Depending on the size of the lesion, the detection rate of polyps and early cancers in 2,000 clinical endoscopic

images has increased to over 90% (2). It can therefore be said that this system is very useful as an image interpretation aid. The Ministry of Health, Labour and Welfare is currently promoting the utilization of AI, and its active use in medical treatment is expected in the near future. However, for its development, a huge amount of training data is needed, and this is a matter of concern. In the current research environment, it is difficult to learn with medical images from only one facility. Therefore, a multicenter study involving data collection from more facilities is necessary, and recent developments in Internet technology are thus very useful. In addition, unlike previous machine learning approaches, deep learning doesn't need identify detailed image features; it can perform rough sorting, albeit extremely accurately, into categories such as “abnormal” or “normal”. Feeding these data to the system as training data could be expected to save substantial amounts of labor and time compared with previous systems.

doi: 10.17996/anc.18-00055

1) Akihiro Kikuchi

Department of Radiological Technology Faculty of Health Sciences,
Hokkaido University of Science, Sapporo, Hokkaido, Japan
E-mail: kikuchi-a@hus.ac.jp

2) Takashi Kawakami

Department of Information and Computer Science, Hokkaido
University of Science, Sapporo, Hokkaido, Japan

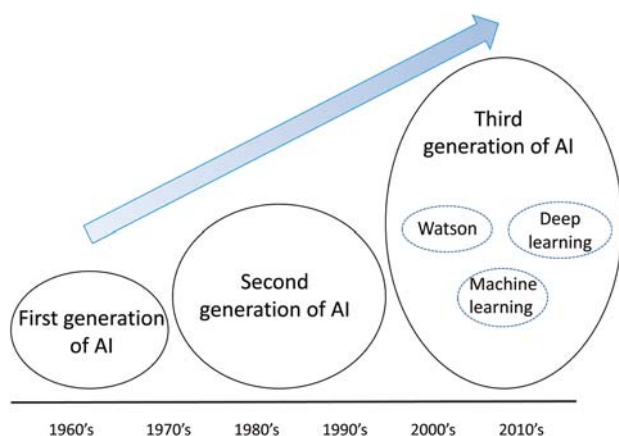


Fig. 1 The history of artificial intelligence.

About the history of AI generation from the 1960s to the present.

Outline of AI

AI has been able to extract information that was previously inaccessible and arrive at new conclusions by learning a huge amount of information (big data). In this process, the system is often constructed by combining “inference” and “learning.” AI has been under development for over 50 years and has witnessed several generations (Fig. 1). The first was called “perceptron” (3), the second, “backpropagation technology (BP: A method of efficiently calculating the error of “weight” and “bias” using differentiation) (4), and the third, “deep learning” (5). A perceptron is a conceptual model of visual and brain functioning that makes pattern recognition possible. The BP technique, which uses the output error of one layer to calculate the weights of the previous layer in an n-layer neural network (NN), uses an error-minimizing method to find results. In this case, weights are set for a layer the optimal solution is obtained while updating over numerous update iterations. In deep learning, enormous amounts of data (big data) are often used as training data using a convolution NN (5, 6), which is based on the idea of an NN of more layers. At present, in some cases, image recognition accuracy can be obtained in image recognition technology owing not only to theoretical improvements, but also to dramatic improvements in the processing speed of general purpose computation on graphics processing units, which makes it possible to learn and use a huge amount of data in a short time (7-14). In addition, digital images, the spread of smartphones, and online cloud storage have dramatically increased the amount of image data (teacher data) available for research, thereby creating a generation. Deep learning is particularly compatible with images, enabling advanced recognition technology for tasks such as identifying handwritten characters (15-17). This method, called the error BP method, is used for learning a hierarchical network, and is also applied to the recognition of numbers and three-dimensional objects. And now there are various methods for image recognition. For example, in a

concrete system configuration, there is what is called “Region-convolutional NN (R-CNN) features”, as shown in Fig. 2 (12). At present, this technology is used as a tool for detecting abnormal features in medical images and interpretation. Research on computed tomography (CT) in the lung region is actively being conducted, and image processing technology using deep learning is expected to be utilized in many areas in the future.

Nuclear medicine and AI

In the field of nuclear medicine, compared with CT and magnetic resonance images, the number of images per patient is small, only specific organs are provided, and the amount of information is limited. However, images reflecting the functions of tissues and organs are provided, and variations are seen in the accumulation mechanism. How to make AI software learn this imaging information is important for the application to nuclear medicine.

In bone scintigraphy, Horikoshi and Nakajima et al. have developed software called “BONENAVI” (FUJIFILM RI Pharma Co., Ltd., Tokyo, Japan) that detects abnormal hot spots using machine learning (18-20). The artificial neural network (ANN) technique learned hot spot features, including size, number of counts, shape, and bilateral symmetry, using more than 1,500 cases. Therefore, it is necessary to learn all the detailed features for each hot spot. In addition, when learning is performed on the system, the output value also changes depending on how much the feature quantity is the weights for the individual features; therefore, it is necessary to construct a system in accordance with clinical results (ex fracture lesion, osteoblastic lesion). In nuclear cardiology, “cardioREPO” software (FUJIFILM RI Pharma Co., Ltd., Tokyo, Japan), which uses an ANN, is currently provided. It was originally developed by Nakajima et al. (21) based on over 1,000 cases in a multi-center trial. The features are learned by the training data, and then compared with the features of the patient data to be analyzed. Next, part of the abnormal accumulation is estimated and then displayed as the risk value and shown as an image. Fig. 3 shows an example of this type of analysis. Based on the stress, rest image, and differential image thereof, comparison and inference with the teacher data are performed, and the abnormal part is displayed as the risk score. BONENAVI and cardioREPO introduced in the previous section, were programs originally developed by the European venture company EXINI to gather teaching data for multicenter research and the development of a new system in Japan. When the teaching data is different from the other data analyzed (e.g., racial differences), it affects the accuracy of the results (18) and the teacher data, as the textbook is very important in ANNs.

In the case of nuclear cardiac images, even in the same

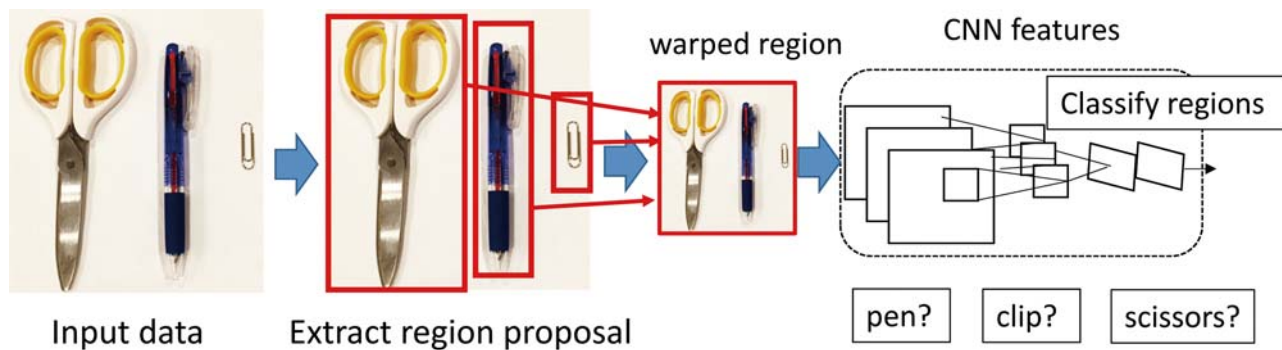


Fig. 2 Image recognition and classification.

Classification is performed for each part from image recognition by Region-convolutional NN (R-CNN).

R-CNN : Regions with CNN features

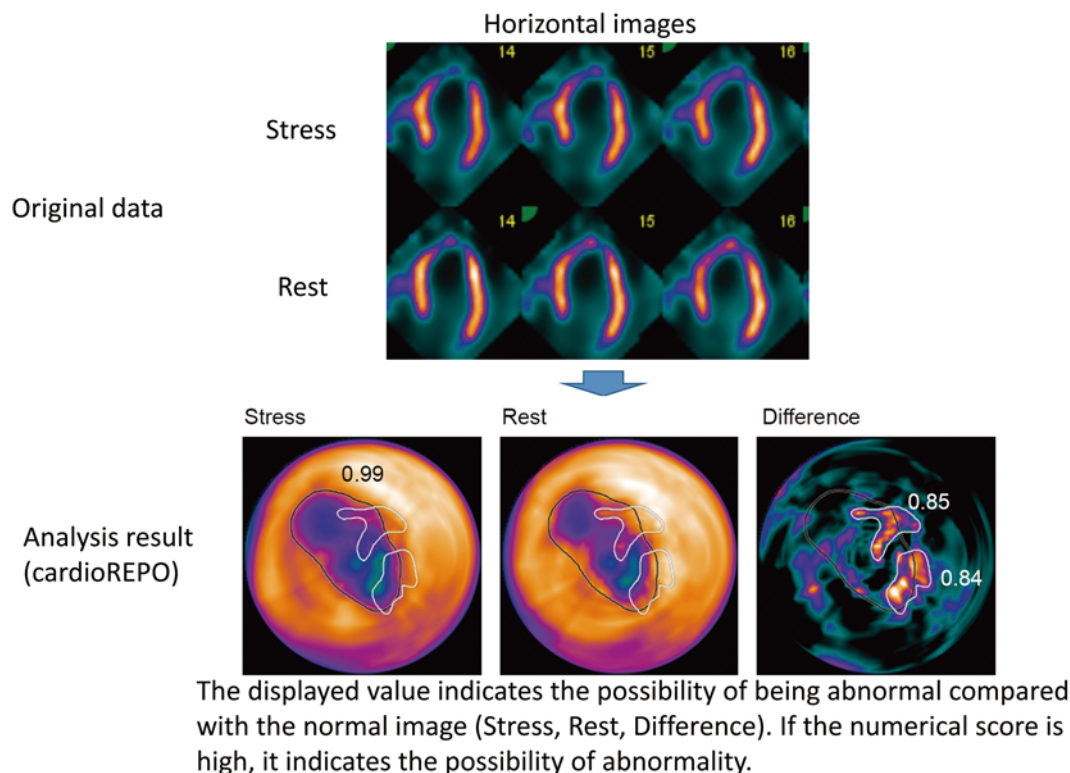


Fig. 3 Image analysis of abnormal lesion.

An example of risk classification by ANN using cardiac nuclear medicine images.

An 82-year-old patient with double-vessel disease involving left anterior descending coronary artery (LAD) and right coronary artery (RCA). This patient had antero-apical old myocardial infarction and stenting was performed to both LAD and RCA. Since the patient had angina symptom, stress myocardial perfusion study was performed to examine the possibility of inducible ischemia. Both visual assessment and artificial neural network showed mild ischemia (area 15%) in the apex along the border of infarction.

patient, many factors can influence the image, such as differences in the acquisition equipment and methods (e.g., 180-degree vs. 360-degree acquisition), in the radiopharmaceuticals used, and in image processing. To construct an effective support system, it is therefore necessary to prepare at least 1,000 training instances from multiple facilities. For single-photon emission CT images, software that automatically calculates scores and left ventricular ejection fractions is mainly used in image processing technology, but AI is expected to be applied to image correction in the near future.

The authors' assumption is that AI will be applied to the correction of attenuation and scatter, as well as the elimination of extra-cardiac activity. For image interpretation support, it is also assumed that such a system will also incorporate information such as the relationship with vascular lesions and blood data. Deep learning is an excellent image recognition technology, and by using data obtained by segmenting an image into regions utilizing R-CNN (22), which is another AI technology, beforehand, it would be possible to improve the accuracy. The application of AI technology in various ways is

indispensable for technological development in the future, and the development of image recognition technology using existing AI that can be applied to images in cardiac nuclear medicine is possible.

Conclusion

The application of AI to medical images is expected to develop further in the future. This should also be promoted in cardiac nuclear medicine, because it can be expected to be an effective tool for improving diagnostic accuracy through applying training data and image processing technology for data processing.

Acknowledgments

The authors would like to thank Dr. Kenichi Nakajima and Prof. Masahisa Onoguchi for providing the data as well as valuable advice. The authors have no conflicts of interest to declare in regard to this study.

Sources of funding

None.

Conflicts of interest

None.

Reprint requests and correspondence:

Akihiro Kikuchi, PhD

Department of Radiological Technology Faculty of Health Sciences, Hokkaido University of Science, 7-Jo 15-4-1 Maeda, Teine, Sapporo, Hokkaido, 006-8585, Japan.

E-mail: kikuchi-a@hus.ac.jp

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