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Review of medical imaging systems, medical imaging data problems, and XAI in the medical imaging field☆

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ABSTRACT

Currently, artificial intelligence (AI) is being applied in the medical field to collect and analyze data such as personal genetic information, medical information, and lifestyle information. In particular, in the medical imaging field, AI is being applied to the medical imaging field to analyze patients' medical image data and diagnose diseases. Deep learning (DL) of deep neural networks such as CNN and GAN have been introduced to medical image analysis and medical data augmentation to facilitate lesion detection, quantification, and classification. In this paper, we examine AI used in the medical imaging field and review related medical image data acquisition devices, medical information systems for transmitting medical image data, problems with medical image data, and the current status of explainable artificial intelligence (XAI) that has been actively applied recently. In the future, the continuous development of AI and information and communication technology (ICT) is expected to make it easier to analyze medical image data in the medical field, enabling disease diagnosis, prognosis prediction, and improvement of patients' quality of life. In the future, AI medicine is expected to evolve from the existing treatment-centered medical system to personalized healthcare through preemptive diagnosis and prevention.

☞ keyword : Artificial intelligence (AI), Deep learning (DL), Medical imaging equipment, medical image data, Picture Archiving and Communication System (PACS), Explainable artificial intelligence (XAI)

1. Introduction

Artificial intelligence (AI) that currently developing rapidly, is a SW technology that implements the entire human thought process, including cognitive learning, reasoning, and judgment, through algorithm design. It is increasing its influence across all industrial fields. In particular, AI processes big data beyond human capabilities and facilitates accurate, efficient, and fast decision-making. Therefore, AI is emerging as a solution to productivity improvement and problems in various fields [1-6]

Recently, as the acquisition of large-scale medical big data has become easier due to the increase in the aging population and the development of IT medical devices, the application of AI-based medical technology utilizing such big data is gradually spreading.[7]

AI is critical for data-driven decision-making in various industries, especially healthcare. Massive amounts of data, rapidly advancing computations, and high-performance models validated against natural images deliver results that exceed doctor'diagnostic and interpretive capabilities. Using AI to increase resource utilization, operational performance, and quality of service in healthcare operations can significantly improve care outcomes and increase patient satisfaction while reducing costs. A study by Bennett et al. reported that using AI algorithms to diagnose diseases improved diagnostic performance by 41.9% and reduced healthcare costs by 58.5% [8].

In the medical imaging field, machine learning (ML) and deep learning (DL) are applied to analyze medical images of organs, and this field constitutes an active area of research. DL algorithms and model structures have been introduced to DL-based medical image analysis, and studies on lesion detection, quantification, and classification are ongoing [9]. Indeed, healthcare is shifting towards personalized approaches, such as proactive diagnosis and prevention of individual diseases. Therefore, the collection and analysis of

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large-scale big data such as genetic, medical, and living information by applying AI are essential [10].

In Korea, research on AI medical software called Doctor Answer has been ongoing since 2018, with the participation of the government, hospitals, and companies, to find a medical approach suitable for Koreans. Doctor Answer 2.0 has been developed [11]. AI medicine is being applied to the imaging diagnosis of various diseases such as the brain, heart, lungs, and breasts, and the big data and AI medical device market is expected to grow significantly to KRW 27.5 trillion by 2030. Representative domestic AI medical companies include Viewno, Lunit, and JLK Inspection.

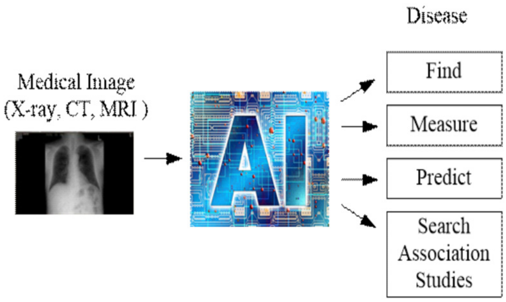
In this paper, we examine medical imaging systems, problems with medical imaging data, and XAI in radiology to understand various phenomena that occur when rapidly developing AI is applied to the medical field. The structure of the paper is as follows. Section 2 discusses related research on AI and the medical field. Section 3 explains medical imaging systems. Section 4 presents problems with medical imaging data. Section 5 presents conclusions.

2. AI and Medical field

2.1 AI

AI technology is classified into ML and DL, as shown in Figure 1. The analysis and diagnosis of diseases using AI are presented in Figure 2. According to a STAT News report in 2019, Google AI has outperformed six radiologists in detecting lung cancer, identifying 5% more cancers and reducing false positive rates by 11% [12]. According to a paper published in Nature Medicine in 2019, 6716 cases of lung cancer detected using AI-based computed tomography (CT) imaging exhibited an accuracy of 94%. The accuracy of magnetic resonance imaging (MRI) for brain tumors, which are difficult to judge, was >85%. The accuracy of Google AI-based diagnosis of breast and lung cancers was 99% and 95%, respectively; and the accuracy for the diagnosis of metastatic cancer was significantly higher. Moreover, a paper published in Nature in 2020 reported that Google's DeepMind algorithm may be more accurate than real-life doctors for identifying breast cancers [13].

In particular, in the field of radiology, AI technology applies deep learning-based image restoration functions to image data acquired from medical imaging devices such as tables to extract information of interest and provides high spatial resolution and contrast image modes that help medical staff interpret images. Among AI image processing methods, CNN (Convolutional Neural Network) is a representative image processing method that can efficiently extract image features and has been successfully applied to support disease diagnosis.



(Figure 1) AI-based medical field

2.1.1 DL Structure and Analysis Process

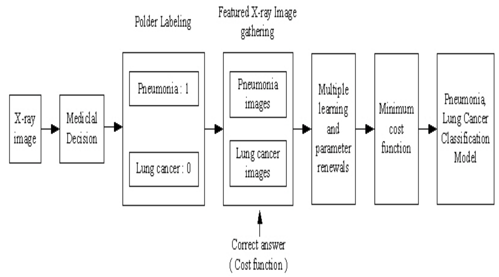
The analysis of medical images using DL includes learning and reading processes. First, the diagnosis results should be learned by DL. Labeling is the correct answer for a medical image, and most software tools support folder labeling, which brings the name of a folder to the judgment value due to convenience. For example, if pneumonia and lung cancer are diagnosed using chest X-ray imaging with DL, the learning and reading processes are as follows [14]:

(1) Learning process: The process of learning algorithms to diagnose pneumonia and lung cancer using chest X-ray imaging is presented in Figure 2(a). Here, 1 and 0 are the matching rates of the disease judgment for the characteristics of each image. Essentially, labeling images with a 100% matching rate for each disease judgment can be viewed as the correct answer to the image feature for the corresponding judgment from the algorithm position. The correct answers are used to calculate the cost function.

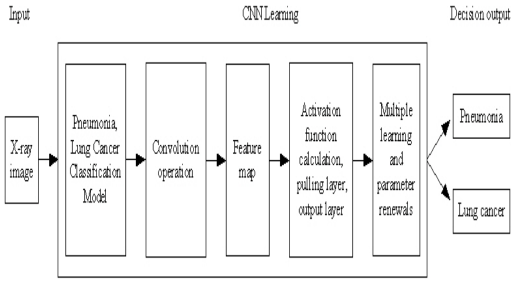
(2) Reading process: The process of detecting pneumonia and lung cancer through chest X-ray imaging using DL

(CNN) is presented in Figure 2(b). This process involves the following steps:

- Chest X-ray images are entered in the "Pneumonia Lung Cancer Classification Model", where the knowledge of the doctor is fully learned.
- Feature map calculation, which is the response that performs the compound product operation for the feature kernels that classify optimized lung cancer and pneumonia, respectively, through learning.
- Compression of information through the activation function calculation, pooling layer, and output layer.
- Output of judgment values for each classification.



(a) Learning process.

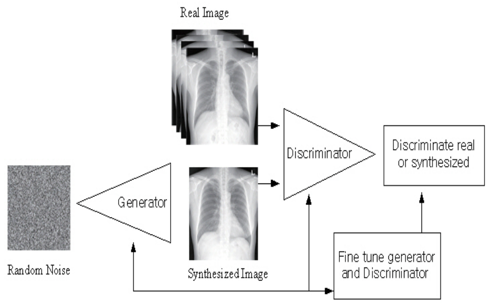


(b) Reading process

(Figure 2) DL (CNN)-based pneumonia and lung cancer classification model

2.1.2 GAN Structure and Analysis Process

GANs and generational and hostile neural networks have recently been widely introduced for the creation of artificial images in natural images, conversion between images, and improvement of resolution. Studies on GANs among the generative models of AI-based DL are an active field of research. GAN is an AI algorithm of the non-leadership learning method (Figure 3) [15~19] that self-learns the characteristics of input data and generates new data. The learning process of GAN is used to determine the generated image with the generator generating the image. At the start of learning, the generator is input with random noise to the entry value. The generator network is fine-tuned and the image is created. After the system learns the features of the input images and the discriminator distinguishes images and composite images, the generator network is updated. When learning is completed by repeating the process of generating, discriminating, feedback, and model modification, learning data augmentation is achieved through the synthesized image by removing only the learned generation and generating a new synthetic image for any latent vector [20].



(Figure 3) Basic architecture of generative adversarial networks (GANs)

GANs have been used to generate synthetic medical data and analyze medical images. GAN-based methods such as DCGAN, PGGAN, and 3D-cGAN have been published in clinical trials.

2.2 Medical data type

Medical data can be divided into three types: complex medical data such as patient medical records and genetic data stored in electronic medicalrecords or charts, medical imaging data such as X-rays, CTs, and MRIs, and continuous medical data such as patient clinical data. AI is used to analyze, interpret, and predict diseases based on the three types of data.

2.3 AI medical devices

AI medical devices are standalone SW-type medical devices that analyze medical big data to diagnose and predict diseases [21]. In other words, SW such as Clinical Decision Support Systems (CDSS) and Medical Image Diagnostic Assistance (CAD), they analyze medical big data based on machine learning and deep learning methods to recognize specific patterns and diagnose and predict diseases, thereby providing customized treatments.

3. Medical imaging equipment and Data

3.1 Medical imaging equipment

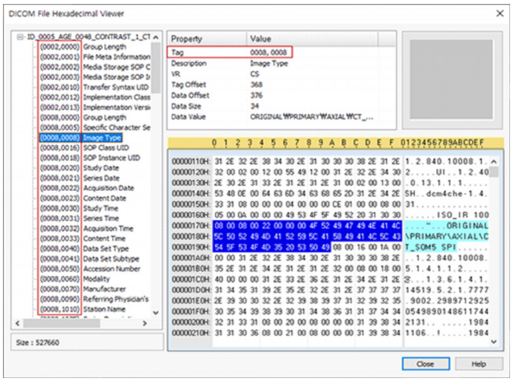
Medical imaging methods for image acquisition are listed in Table 1.

(Table 1) Medical imaging equipment

Source	Method	Use and characteristics
Visibleray	Endoscopy	Used for intestinal endoscopy, with a light source and CCD sensor in front of the endoscope
	Microscopy	While examining tissue, microscope eyepieces and objective lenses are used to magnify small objects
Radiation	X-ray	Light source is emitted from an X-tube and passes through the body; image is created by the transmitted x-ray intensity difference of tissue at each site
	CT	Captures x-ray images from various angles around cross-section of the human body, integrates two or more 2D x-ray images into one 3D image, and generates 3D images within a few seconds
	Positron emission tomography (PET)	A radioactive drug (radioactive glucose) emitting positrons is injected into the body and is transformed into 3D images after 360 analysis of the human body
Magnetic field	MRI	Based on a magnetic field, hydrogen atoms in the body generate 3D images based on the difference in the speed of transmission through muscles and fat
	Ultrasonic wave	Used for heart, stomach, lung, and fetal tests
Digital pathology	Virtual microscopy WSI (whole-slide imaging)	Sub-field of pathology that focuses on data management based on information generated from digitized specimen slides. Using computer-based technology, digital pathology utilizes virtual microscopy or WSI.Can be used for feature detection of mitotic figures, epithelial cells, or tissue-specific structures such as lung cancer nodules, glomeruli, or vessels; or estimation of molecular biomarkers such as mutated genes, tumor mutational burden, or transcriptional changes.

3.2 Digital Imaging and Communications in Medicine (DICOM)

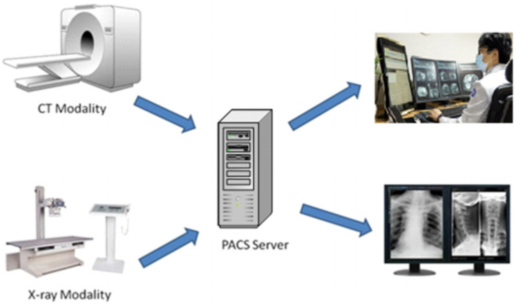
DICOM is an international standard used in digital image representation and communication in medical devices. DICOM was developed in the 1990s by the North American Radiological Society (RSNA) [22-24]. A single DICOM file format (.dcm) includes a header and image information and is provided in the same format (Figure 4). The header contains additional metadata, such as patient information and image acquisition data by tag. Header information is crucial for conversion calculation, such as the reference direction and real size of pixels and voxels when extracting the necessary part from the image. This is relevant when the voxel spacing of images is adjusted based on this information.



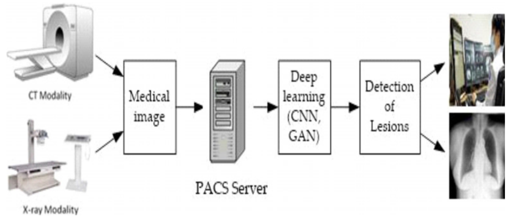
(Figure 4) Header information of a DICOM file

3.3 Picture Archiving and Communication System (PACS)

The Picture Archiving and Communication System (PACS) is a large-scale system in radiology that coordinates image information throughout the hospital and is used in connection with most departments [25]. To build a PACS environment (Figure 5), technologies such as Image Display and Processing, Data Communication and Networking, Database system, Information Management, User Interface, and Data Storage/Archive must be integrated. PACS stores images obtained by advanced imaging devices such as general X-ray, CT, MRI, DSA, ultrasound, and nuclear medicine in a computer as digital images and transmits them to each terminal for simultaneous image search anywhere in the hospital.



(a) Genenal PACS



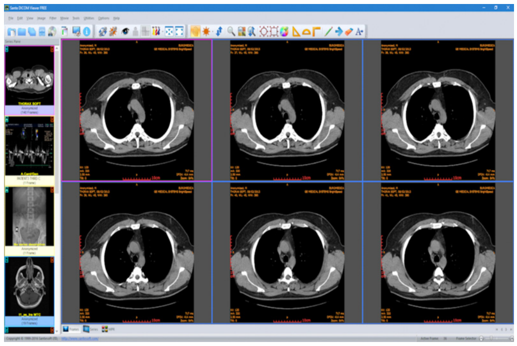
(b) PACS using DL

(Figure 5) PACS

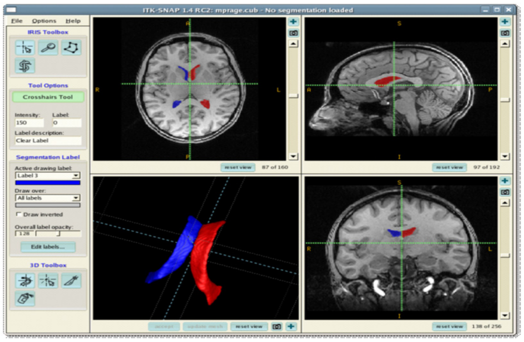
3.4 Visualization tools for medical imaging data

Tools for visualizing medical imaging data include simple usage methods, the Santa DICOM Viewer with an intuitive user interface, ITK-snap (a good draw ofsegmentation), Qupath optimized for pathological image analysis, MITK, MRICron, 3D Slicer, and ImageJ. Imaging data contains image information in compressed bitmap or uncompressed form (such as jpeg and gif) (Figure 6). Other formats exist, such as Nifti (nii), which comprises two files: video information and header information.

ITK-SNAP visualizes 3D volume images by stacking them with supporting basic image processing, such as observing images in 3D, controlling contrast, only viewing specific areas, segmenting the desired area, and drawing several chapters (Figure 6(b)).



(a) DICOM Image



(b) ITK-SNAP MRI Image

(Figure 6) Medical image visualization

4. Problems of Medical Imaging Data

4.1 Problems and Analytical Methods of Medical Imaging Data

Medical imaging datasets include vast of data used to train DL to classify specific diseases. It is common to use data for pre-learning and analyzing for performance verification of AI Model Medical imaging datasets exhibit the characteristics of volume, diversity, velocity, reliability, and value, which are the five major factors in big data. Obtaining big data from medical images with annotations is challenging because it requires professional manpower and is time-consuming to read and comment on medical images. In addition, patient consent is required for the use of big data towith patient medical images. The limitations of medical imaging data are listed in Tables 2 and 3, respectively.

(Table 2) Limitations of medical imaging data

Clause	Content
Quality	Difficulty in obtaining large amounts of labeled data
Pixel size	There are many 3D images, and image size is quite large
Small object size	Object size is relatively small
Compensating	The same tissue image of the same disease requires correction for age
Additional information	Use other information such as sex, smoking, and drinking for classification analysis

(Table 3) Four analysis methods of medical image data〔23〕

Clause	Content
Classification	Computer vision problems, images, and normal or patient classification
Segmentation	Extracting specific areas of interest, such as organs or nodules from images
Enhancement	Extracting specific areas of interest, such as organs or nodules from images
Registration	Extracting specific areas of interest, such asorgans or nodules from images

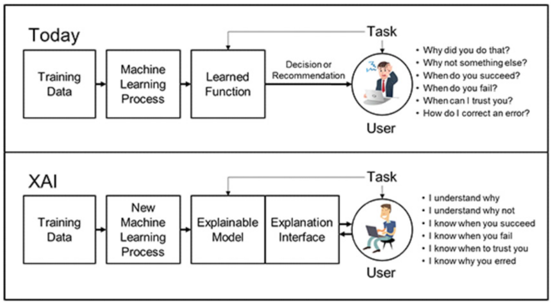
4.2 Problems of Datasets of Medical Imaging Data

Sharing datasets is crucial in DL-based medical image analysis. A dataset constitutes a large set of medical imaging data labeled by a trusted expert group. Datasets are acquired in various ways, such as datasets on chest, Alzheimer's disease, and COVID-19. However, obtaining labeled medical imaging data for all diseases is difficult [26-29]. In addition, label processing by reading medical images requires professional manpower, is time-consuming, and may result in differing opinions among medical staff. Additionally, ethical concerns arise since datasets contain patients'personal information. In this regard, anonymization and limited access to datasets must be considered. To solve the Problems of Datasets of Medical Imaging Data, GAN is used to augment medical data and use it as a dataset [30].

5. XAI technology of Medical Imaging Data

5.1 XAI(explainable artificial intelligence)

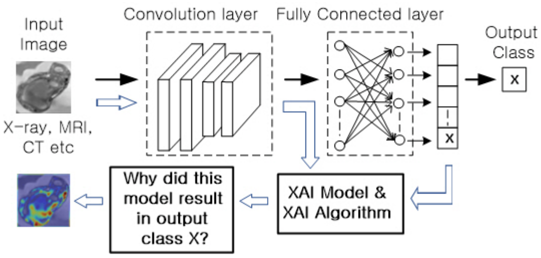
Explainable Artificial Intelligence (XAI) was proposed by Michel van Lent, William Fisher, and Michael Mancuso in 2004. As computing power such as hardware has developed, AI has improved in performance and has been applied to various industries, but there has been a problem in that it is not known exactly what basis the results of AI's decision-making process are formed on. This is called a black box. [31] The method to solve this black box problem is XAI, a technology that explains the decision-making process and results of AI so that people can understand it. However, various XAI techniques are not absolute, and there are limitations in interpreting different answers to the same answer to the same problem, but they are continuously being researched and developed in the medical imaging field. This figure illustrates the concept of XAI.



(Figure 7) XAI Concept 〔32〕

5.2 XAI Methods

As a result of a review of papers applying explainable artificial intelligence (XAI) to the medical field, XAI was added to CNN-based artificial intelligence to explain AI decisions on classification or segmentation of image data, as shown in the figure [33].



(Figure 8) CNN & XAI

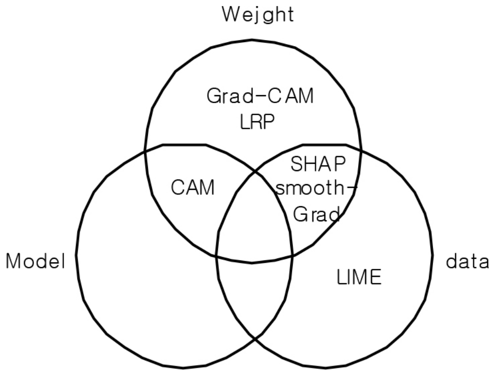
XAI application models are largely divided into three categories: a method of modifying existing learning models such as incorporating a weight inversion process, a method of developing a new learning model that adds an algorithm for explanation, and a method of presenting a basis for prediction results by comparing it to other learning models. The figure shows three classification and XAI models. The six major XAI models with the highest usage were presented.

(1) LIME (Local Interpretable Model-agnostic Explanations)

LIME can be applied regardless of the AI model, and analyzes the influence of the local region of the input data on the model's prediction results [34-36]. Instead of controlling each individual pixel of the input image data, it divides it into 'super-pixels' [34] that group similar pixels. It permutates the combinations that include or exclude the super-pixels, inputs them to the model, and compares the results with the original. It finds the part among the transformed parts that is most likely to estimate the original image.

(2) SHAP (SHapley Additive exPlanations)

SHAP is applicable regardless of the artificial intelligence model, and uses the Shapley value created by adding independence between each feature based on the cooperative (association) theory of game theory [37]. After dividing the image into 'superpixels,' it measures the contribution of each feature to the model's prediction result using a combination of each superpixel as a feature. The Shapley value is obtained using the difference between the contribution of



(Figure 9) Classification of XAI methods

each feature and the average contribution, and the contribution by feature is used to numerically measure how much the model's result value is affected by excluding the relevant element, and the value is inferred as the influence of the element.

(3) LRP (Layer-wise Relevance Propagation)

LRP shows which part of the input data led to the classification result in the form of a heatmap [38]. It is a method to interpret the results classified by a deep neural network model by calculating the contribution of the input data features to the result using relevance propagation and decomposition in reverse order. It starts the calculation from the output value and calculates the contribution (Relevance Score) in reverse direction and distributes the weight. Relevance propagation distributes the weight of the cause of a specific result, and decomposition is the process of reducing the cause obtained by relevance propagation to weights and dissecting it. Decomposition is a method to decompose how much an input value (feature) affects the result, and can determine whether a pixel of a specific image is helpful in deriving the result or not.

(4) CAM (Class Activation Map)

CAM shows the image region associated with a specific class selection in the form of a heatmap in a deep learning classification model using CNN [39]. By applying Global Average Pooling (GAP) instead of the last flatten layer of the CNN structure, it is easy to find the local region that

〈Table 4〉 Utilize XAI

AI model	Acquiring medical imaging data	Contents	Reference
LIME	MRI	Alzheimer's disease (AD) was classified using ML methods, and LIME was used to interpret how genes were predicted and which genes are particularly responsible for AD patients.	42
LIME	Dataset	To improve the classification accuracy of eight skin lesions, an explainable artificial intelligence (XAI)-LIME-based skin lesion classification system is proposed.	43
LIME	histopathologic scans of lymph node sections	Adequacy of explanation of super-pixel algorithm and visualization method in LIME.	44
LIME, SHAP	endoscopy	Relevance of explanation with regard to XAI methods and characteristics of doctors	46
LIME, SHAP	Dataset	A disease prediction system was created for three chronic diseases: diabetes, heart disease, and breast cancer. LIME and SHAP were analyzed for their applicability to autonomous disease prediction.	43
SHAP	MRI	Applying SHAP to a regression model for density analysis	46
SHAP	Color Fundus Photographs	Using 7-field Color Fundus Photographs to verify field-by-field importance	47
SHAP	Dataset	For diabetes prediction, the Diabetes Prediction Dataset (DPD) was used and implemented by applying SHAP technology.	48
SHAP, Grad-CAM	Dermatoscope Image	Applying XAI to CNN verification	49
CAM	PET/CT	Visualization of individual disease regions through CAM and classification of disease through t-sne clustering using CAM results	50
CAM	Ultrasound	Detecting fetal head structure	51
CAM	thermography	Finding areas that affect the health of newborns by applying CAM to thermal imaging	52
Grad-CAM Smooth-Grad	CT	Lesion location detection	53
Grad-CAMLRP	X-ray	LRP and Grad-CAM investigated the applicability of these two algorithms in the sensitive application of interpreting chest radiographs.	54
Grad-CAM LRP	X-ray	Grad-CAM and LRP were used to highlight regions that differentiate classes to automatically detect COVID-19 symptoms in chest radiography (CXR) images.	55
LRP	MRI	Verification of whether the AI model takes notice of the areas that affect Alzheimer	56
LRP	MRI	Classifying premature infants and newborns using 3D CNN and using LRP to confirm that cerebrospinal fluid is highly correlated with the classification	57
LRP	MRI	Proposing a novel score that can evaluate connectivity with fMRI data using LRP	58

had a significant influence on the decision. Since GAP must be used, the performance of the classification model is somewhat reduced, and the main region appears with the surrounding region in the heatmap and is expressed blurry.

(5) Grad-CAM (Gradient-Weighted CAM)

Grad-CAM is a method that obtains the same result as CAM by using the gradient of the weights of a general CNN model, andcan be used in various CNN models, and visualization is possible at each layer [40].

To complement the weakness of providing a heat map with low spatial resolution, the Guided Grad-CAM method, a visualization method combined with high-resolution features, was also proposed.

(6) SmoothGrad

SmoothGrad is obtained by averaging multiple saliency maps obtained by adding noise to the input image [41]. When the pixel value of the input image changes slightly, there is no difference in the diagnosis result of the human eye or the model, but the gradient changes significantly. By averaging multiple saliency maps, the pixels of the parts that should be viewed are highlighted, and there is an advantage of removing a lot of noise areas for the detection of the region of interest.

6. Use of XAI in medical imaging

The Table 4 shows papers that utilize XAI in medical imaging.

7. Conclusion

Artificial intelligence (AI), which is currently being applied in the medical field both domestically and internationally, is being used in the medical imaging field to analyze patient medical image data on various organs such as the brain, heart, lungs, and breasts, diagnose diseases, and assist CDSS and medical image diagnosis assistance (CAD). DL of deep neural networks such as CNN and GAN is being introduced and utilized in medical image analysis to facilitate lesion detection, quantification, and classification.

In this paper, we examine AI used in the field of medical imaging, and examine the acquisition devices related to related medical imaging data, medical information systems for transmitting medical imaging data, problems with medical imaging data, and the current status of explainable AI that is being actively applied recently. Problems with medical imaging data include dataset labels and personal information, and data augmentation is also being studied to solve these problems. In addition, there is a black box problem in which it is difficult to clearly prove the accuracy of the derivation process for AI disease prediction results, so the utilization rate by medical staff in actual clinical practice has been low. Recently, XAI has been utilized to solve these problems, and we investigated the current status and reviewed and presented related research papers. In the medical field, XAI is expected to further develop the performance of AI through the interconnection between the designer (developer) who designs AI, the practitioner (medical staff) who uses AI, and the end user (patient) regarding the decision of AI.

In the future, AI medicine will utilize medical image data to make analysis easier, enabling disease diagnosis, prognosis prediction, and improvement of patients' quality of life. It is expected that the existing treatment-centered medical systemwill evolve into personalized healthcare through preemptive diagnosis and prevention, as well as personalized treatment.

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