Developing an AI Framework for Multimodal Medical Imaging Diagnostics based on Medical Data

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Abstract: Artificial intelligence (AI) has been applied in medical diagnostics. There are still some challenges for AI clinical processing that need to be addressed. These challenges exist from the beginning when the AI model is designed. The main challenge is that AI can't clearly handle the characteristics of Medical Imaging (MI) data in clinical data processing. This study analyses the data characteristics of MI data. Making clear details of X-ray, computed tomography (CT), and magnetic resonance imaging (MRI) to solve the problem in AI clinical processing. The result of this study highlights the influence of MI data characteristics for medical AI models. Through analysis of the implication of MI data characteristics to medical AI, this research found several challenges in clinical AI applications. These include the mismatch between medical imaging science and computer graphics, the risks of excessive data preprocessing, model interpretability, and symptom overlap. This research proposes a theoretical framework that connects medical imaging science with computer graphics to build medical AI interpretability. This framework is based on multimodal AI medical models that strictly adhere to the characteristics of clinical medical data. The framework that utilizes the characteristics of MI data to support and constraint the rationalization of clinical AI models and provides developers with references in both concept and practice. The framework of this research can help any kind of AI algorithm design with the physical and clinical realities of the data. It is an effective way to improve model accuracy and interpretability.

Keywords: multimodal imaging; diagnostic framework; trustworthy AI; medical imaging

1. Introduction

Artificial intelligence (AI) is one of the most ambitious fields in computer science. Its goal is to simulate cognitive functions and build systems that can learn and reason like humans [1]. In medicine, the convergence of AI, Medical Imaging (MI), image noise reduction, decision-making, and disease classification is now almost expected. Mentioning these topics often evokes familiar measures of medical AI model data processing for researchers.

This stereotypical image may prevent researchers from asking more probing questions. For example, it is uncertain whether medical AI truly comprehends all the essential data and features in medical images. Is it possible the theories used to build these AI models and whether they adhere to key medical imaging processing standards. Many medical AI models use data as a driving force rather than a robust medical theoretical foundation. This design logic of medical AI makes it hard for doctors and patients to trust medical AI's results or understand why it makes certain decisions. Combine the core ideas of medical imaging, computer graphics, and synthesize the characteristics of MI data to create a more solid foundation to build medical AI that doctors can truly reliance.

1.1. Clinical Significance of Medical Imaging and Computer Graphics

MI provides the primary data for most medical AI systems. MI data includes various types of scans (such as magnetic resonance imaging (MRI), computed tomography (CT), and X-rays). MI data offers complex visual information and medical logic regarding human anatomy and pathology. The information in these MI images must adhere to medical principles and diagnostic standards. The information of MI carried by these data is far more extensive and sophisticated than that carried by ordinary natural images. If a medical AI model wants to be accurate, it must understand the specific medical background knowledge carried by the MI. From the perspective of application, it needs to learn how to link the visual features in the images with anatomical structures or signs of diseases. Only after achieving full data and logic interpretability can medical AI models truly and reasonably be applied in a wide range of medical scenarios.

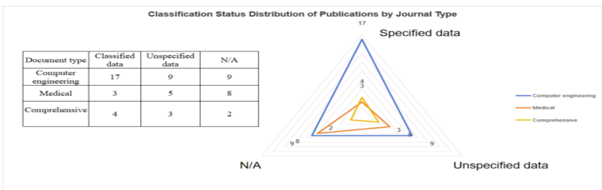
Computer Graphic (CG) provides algorithmic and representational methods for image synthesis, transformation, enhancement, and AI data processing. CG enables medical AI systems to simulate, process, and predict complex anatomy. CG is a key component in AI creating interactive visualization tools and augmented reality systems, laying the foundation for the digital medical process [2].

CG and Medical Imaging Science have conflicts in terms of their goals and operations [3]. Medical Imaging Science prioritizes clinical authenticity and retains all data details. CG places more emphasis on computational efficiency and obtaining the answer quickly using appropriate, clear data and fast algorithms. These preferences of CG may bring some potential problems affecting the integrity and accuracy of clinical data and the results of clinical. Solving the problem between CG and Medical Imaging Science can make AI models more reliable and trustworthy. Computational efficiency should respect the limitations and standards of biomedicine, and the clinical imaging process should also be open to the new opportunities brought by AI algorithms. How they work together determines whether the training and deployment of medical AI models are technically feasible and determines how much trust and recognition the AI system can gain in clinical practice.

In this study, one of the objectives is to use "X-ray" as the core keyword for searching on Google Scholar. At the same time, this study also employed other keywords (such as medical AI algorithm, CT, and MRI) to help find more relevant or broader papers. The reason why this study chose X-ray as the focus is because it is a very fundamental and standard tool in medical diagnosis.

This research's goal is to determine whether all medical AI algorithms, medical applications, research, and experiments that use MI data have paid attention to, identified, and utilized the specific features and characteristics of the MI data itself. This research makes the literature in three classifications to determine this phenomenon. Characteristics of the MI data are widely used in all application fields. Characteristics of the MI data are limited to specific professional fields. Characteristics of the MI data exhibits different manifestations in various application environments.

Taking these classifications can help us identify the application boundaries of MI data. It enables researchers to determine how much the data characteristics are fully utilized or ignored. In this research, 60 research papers were selected in connection with MI data. These research papers include medical AI models, medical processing software, and the application of MI. The selected journals include computer science, medicine, and radiology to ensure that the research papers encompass diverse disciplines and show details of the phenomenon in MI data.



Document type	Classified data	Unspecified data	N/A
Computer engineering	17	9	9
Medical	3	5	8
Comprehensive	4	3	2

Figure 1. Classification status distribution of publications by journal type

Figure 1. shows the selected research papers distribution of this study. The research papers were chosen based on journal's scope and research topic. It will influence whether MI data is effectively differentiated to determine the classification of literature. Classify data clearly utilizes the inherent characteristics of MI data and conforms to professional definitions. "N/A" indicates that the item is not applicable, or the source does not indicate whether the data is classified. "Unspecified data" includes some articles that failed to distinguish between these data types, treating these MI data as ordinary natural image data or confusing different MI modalities.

The Characteristics of the MI data. will affect the rigor of AI models and the reliability of the data. Some of the research papers haven't fully used the features of MI data which pose challenges for medical AI models in terms of interpretability and reliability. To reduce the AI model's lack of understanding of MI data and the problem of mixed images, this research assist model developers in understanding the characteristics of MI data in detail.

1.2. X-ray Imaging: Principles and Data

The intensity of X-ray photons decreases differently when passing through tissues of different densities and types. When X-rays interact with matter will lead to photoelectric absorption and Compton scattering. These two effects result in changes in image contrast on the detector [4]. For example, structures with high density, such as bones, absorb more X-rays and thus appear brighter, while areas with low density, such as the lungs, absorb less and appear darker.

1.2.1. Data characteristics of X-ray images

Based on the above imaging principle, medical X-ray images have the following characteristics compared to ordinary images:

- Dynamic range: Images typically have a depth of 12-16 bits, which can provide fine contrast performance [5].
- Brightness non-uniformity: Factors such as beam hardening, scattering, and variations in detector response can cause intensity gradients in the image.
- Low contrast: In soft tissues with similar densities, the problem of low contrast is particularly prominent.
- Noise sensitivity: The image noise is mainly composed of quantum noise and system white noise, and it is particularly prominent in low-dose imaging [6].
- Clinical annotation characteristics: The annotation information typically targets specific areas with lesions, rather than pixel-level texture or covering all tissues.

1.2.2. Overview of major human tissue densities

The density of human tissues is of vital importance for helping medical AI systems operate and interpret images. The different unit masses of tissues affect how the structure is displayed in different imaging examinations. These results in imaging examinations influence precision in medical X-ray imaging systems, and medical AI should utilize them to identify symptoms. Medical AI systems are designed based on medical theory and logic, respect and adopt the factual evidence provided by MI. If medical AI ignores these density differences, it may misidentify subtle lesions, miss signals in different density tissues, or wrongly focus on non-disease areas.

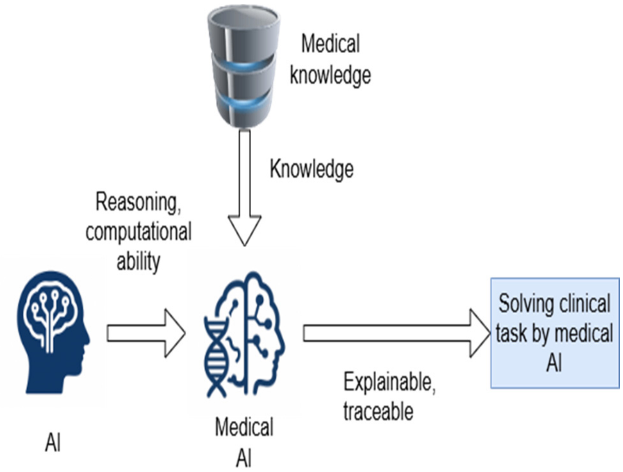


Figure 2. Interpretable medical AI components

As shown in Figure 2, tissue density is a medical concept that links physics, physiology, and clinical diagnostic thinking. Apart from considerations regarding computational load, incorporating prior knowledge based on density into the medical AI architecture enables the model to reason from pixels and from the underlying physical principles of medical imaging. This integration transforms medical AI from a purely data-driven system into a system that conforms to the principles of radiology science. Thus, medical AI can obtain more accurate, easily interpretable, and clinically significant results.

In radiology and imaging physics, the mass density ($\rho, g/cm^3$) and linear attenuation coefficient (μ, cm^{-1}) of various human tissues directly influence the gray values observed in images after X-rays pass through them. The data supporting this relationship can be found in reference [7] and are presented in Table 1.

Table 1. Common tissue density distribution in the human body

Tissue	Mass Density $\rho, g/cm^3$	Typical Attenuation Coefficient μ (70 keV)	X-ray Appearance
Air (alveoli)	≈ 0.0012	≈0	Very dark
Fat	≈0.92	0.15-0.18	Dark gray
Soft tissue	≈1.05	0.18-0.22	Medium gray
Blood	≈1.06	≈0.20	Medium gray
Cartilage	≈1.10	≈0.23	Light gray
Cortical bone	1.85-2.00	0.35-0.45	Bright white
Dentin	2.7-3.0	0.50+	High-intensity white

Core Principle of X-ray Imaging: X-ray Passing and Image Shades. When X-rays go through the body, they get weaker following a basic scientific rule, shown in (1):

$$\mathrm{I} = \mathrm{I}_0 e^{-\mu \cdot d} \quad (1)$$

I_0: Incident X-ray intensity.

I: Transmitted X-ray intensity.

μ: Linear attenuation coefficient (dependent on photon energy and tissue density), representing the ability of tissue to absorb or scatter X-rays.

d: Tissue thickness (cm).

The shade seen on the detector matches how much X-ray gets through, shown in (2):

$$G \propto -\log\left(\frac{I}{I_0}\right) \approx \mu \cdot d \quad (2)$$

So, the image shade for each tissue depends on its thickness and density, as well as the amount of X-ray it blocks. The rough shade for different body parts is shown in (3). If using 0-255 for image scale:

$$G_{organ} = k(\mu_{organ} \cdot d_{organ}) \quad (3)$$

k: k is normalization coefficient, used to scale calculated grayscale values. Denotes the normalization coefficient.

μ : μ is linear attenuation coefficient (cm^{-1}). It determines the exponential rate of absorption.

d: d is tissue thickness. Measured in centimeters, it represents the distance that X-rays travel through tissue.

G: G is approximate grayscale value. On an 8-bit scale (0-255), represents the detected X-ray intensity.

To clarify these relationships, the attenuation characteristics of typical tissues and organs are presented in Table 2, along with their corresponding grayscale values.

Table 2. Typical organs and the corresponding gray values

Tissue/Organ	$\mu(cm^{-1})$	Thickness d (cm)	Approximate Grayscale G (0-255)
Lung	0.02	15	≈30
Heart (muscle + blood)	0.20	12	≈150
Liver	0.19	15	≈170
Pelvic bone	0.35	2	≈210

Table 2 shows that tissues with higher density and atomic number have larger μ values. This means that more photons are absorbed, the transmission intensity becomes weaker, and ultimately, it is displayed as a higher gray value (white area) on the X-ray image. While tissues with low density have lower μ values, allowing more photon to pass through, they appear darker in the image.

The gray-scale range roughly corresponds to the tissue type: areas of the lungs filled with air have the lowest gray-scale values, soft tissues fall within the middle gray range, and dense bone has the highest gray-scale values [5,6]. These gray-scale distributions are influenced by physical density and depend on the parameters of the imaging system, which include the tube voltage of the X-ray tube, the detector sensitivity, and the image processing algorithm.

1.3. CT Imaging: Principles and Data

CT is an advanced MI technique that reconstructs cross-sectional images of the human body. It does so by processing multiple X-ray projections acquired from different angles. In CT, each image element is a voxel (volumetric pixel). A voxel corresponds to a three-dimensional cuboid in physical space. The pixel spacing determines the in-plane dimensions (x, y) of a voxel, while the slice thickness defines the z-axis dimension. In the idealized isotropic case, pixel spacing equals slice thickness, and the voxel is a perfect cube. Based on this characteristic, when converting CT images into three-dimensional models, the reconstruction methods can simply stack all the voxels in their original positions to achieve the three-dimensional reconstruction process. In most clinical CT acquisitions, the voxel is an anisotropic cuboid because in-plane resolution and slice thickness differ [8]. CT is unlike traditional protective radiological imaging (such as X-ray films), where such imaging generates two-dimensional images with overlapping areas. CT can eliminate tissue overlaps, thereby providing a more accurate display of anatomical structures. CT achieves this by using mathematical algorithms (such as filtered back-projection or iterative reconstruction) to reconstruct three-dimensional data [4]. Therefore, it can do this. CT can clearly display anatomical structures and provide high spatial resolution as well as good contrast for soft tissues.

When developing a CT-based medical AI, it is crucial to standardize and understand the Hounsfield unit (HU). The HU contains important information about tissue composition and density. The HU ensures the MI data is consistent. HU provides a usable idea for medical AI which can easily understand different data sources and data sets. If medical AI models trained with non-standardized HU data are prone to confusing body tissue features, it will affect the model's data processing traceability and diagnostic reliability. The developer of medical AI utilizes HU can help medical AI models understand physics-based human tissue structures and make the results of medical AI reasonable. After fully understanding the characteristics of HU, medical AI can distinguish between pathological changes in the patient's body and machine-generated artifacts.

As shown in (4), the HU units are a standard that linearly maps tissue density to grayscale intensity. HU is calculated using the linear attenuation coefficients for the material (μ), water ($\mu_{(water)}$), and air ($\mu_{(air)}$). μ_t represents the coefficient for the specific tissue of interest.

$$HU = 1000 \times \frac{\mu_t - \mu_{water}}{\mu_{water} - \mu_{air}} \tag{4}$$

Using the HU unit as a reference can eliminate the influence of the equipment and data sources. This is helpful for accurate image classification and segmentation, and the development of AI models. By understanding HU unit distributions, the developer of medical AI can make the AI more stable. Using the HU unit provides medical AI with a consistent method for analyzing CT data from various locations. Figure 3 shows the typical HU distributions for organs (on the right) and examples in human CT images (on the left) [5,6].

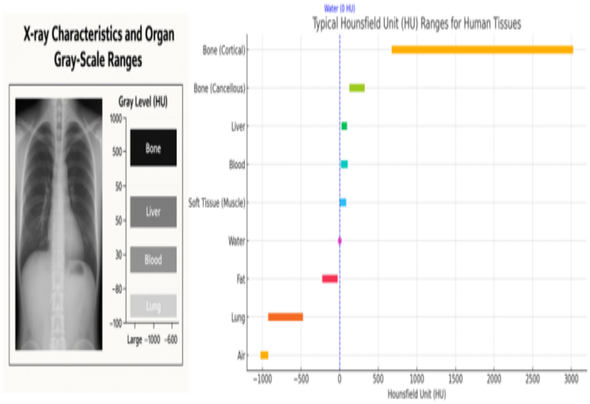


Figure 3. Common organ-HU correspondence relationship

Table 3 [9] lists representative HU values. AI models can use these values to establish a reference frame. These HU units improve the accuracy and range, which can show clinical diagnoses and clinicians' trust in the AI.

Table 3. Representative HU values

Tissue	HU Range (Approx)
Air	-1000
Fat	-100 to -50
Water	0
Muscle	35 to +55
Liver	+45 to +50
Blood	+40 to +80
Cancellous bone	+150 to +300
Cortical bone	+700 to +3000

Besides tissue density, imaging display settings such as window width and window level also affect AI model performance. These settings adjust the clarity of anatomical structures and lesions. This influences the results of segmentation and classification models. Therefore, every medical AI developer needs the knowledge to interpret the characteristics of data, such as CT scans.

1.4. MRI Data and Features

MRI is a non-invasive imaging method based on the principles of nuclear magnetic resonance. It enables high-contrast anatomical and functional images. The method mainly uses the behavior of hydrogen nuclei. These nuclei are exposed to a strong static magnetic field (B_0) and Radio Frequency (RF) excitation. An RF pulse at the Larmor frequency disturbs the net magnetization vector from its resting state. Next, relaxation processes-longitudinal (T_1) and transverse (T_2)-cause time-dependent signals. Gradient magnetic fields spatially encode these signals. The signals are then reconstructed into cross-sectional images using the Fourier Transformation. MRI data is inherently three-dimensional data.

When using MRI as a medical AI data source, it is worth noting that the Fourier Transformation has been applied to the MRI data. The Fourier Transformation used does not introduce new noise to the data. It only acts as a linear process on the signal, which already contains noise components [10]. In actual practice, medical AI models often employ additional methods (such as frequency-domain filtering, k-space weighting, and compressed sensing) before or after the Fourier Transformation to modify noise levels or properties [11]. In developing medical AI and using MRI data, it's essential to distinguish the role of the In developing medical AI and using MRI data, it's essential to distinguish the role of the Fourier Transformation from noise reduction steps to prevent overprocessing when evaluating image quality (such as a Low-pass filter can reduce high-frequency noise in the final image and decrease the image's spatial detail [12]).

MRI offers several methods for administering contrast by adjusting the Repetition Time and Echo Time. This allows MRI to create weighted images for visualizing anatomical detail and weighted images for highlighting changes. More advanced methods, such as functional MRI, provide doctors with even more diagnostic tools [13]. But these doctor-friendly methods pose a problem for medical AI models and AI developers. When processing specific MI data generated by different MRI optimization methods, medical AI needs to assess the accuracy of the results and the rationality of the strategies based on the specific strategies employed. From the perspective of medical AI developers, the development process of medical AI models requires adding support and recognition capabilities for MRI data strategies. This requirement places higher demands on the development of medical AI models.

1.5. Comparative Characteristics of MRI, CT, and X-ray Modalities

AI has been proven to be able to improve the accuracy of processing tasks using images from a variety of sources [14]. The MRI, CT, and X-ray lead to very different image properties. These data discrepancies and the lack of transparency in medical AI training data impact the effectiveness of AI models. Doctors and patients are skeptical of the ability and logic of medical AI models to provide accurate clinical judgments. Developers should find a balance between making medical AI models efficient and keeping medical AI's ability and logic easy to understand. Improve the ability of medical AI models to understand various types of MI data. is key to making medical AI reliable and trustworthy in hospitals.

Comparing different kinds of MI data comprehensively helps medical AI developers know where their technologies differ and how they can complement each other. These features of MI data impact on how well medical AI models can identify data features, process data, and utilize the data.

Different MI data modalities provide unique characteristics. MRI is very good at seeing soft tissue structures. CT collects volumetric data. X-ray imaging is fast and cost-effective.

From the perspective of AI, MRI can create a rich feature space. The grayscale range of CT images is stable and reliable, making it easy for AI to analyze intensity values. X-rays mainly display shapes and edges, which help to quickly identify structural problems.

Each MI data has its drawbacks. MRI scans are long and sensitive to motion. CT uses ionizing radiation and is not suitable for frequent monitoring. X-rays are 2D images and make tissues overlap and lack depth information.

AI can bridge the gap between different types of medical data by inferring one kind of imaging data from another, such as estimating CT-like features from MRI scans. Or use CT or MRI data to verify the results of CT data reconstruction. When faced with segmentation tasks, medical AI can integrate multiple MI data to analyze pathological structure and distribution from multiple perspectives.

Researchers must have a deep understanding of the characteristics, acquisition methods, and diversity of medical imaging data. Grasp the application status of the latest medical equipment and the characteristics of equipment processing data in real time. Combining specific medical domain knowledge with AI is beneficial and a prerequisite for the widespread application of medical AI in hospitals in the future.

1.6. Implications for AI Models

Differences in MI data in spatial resolution, contrast, noise, artifacts, and intensity calibration affect how developers choose preprocessing steps and shape feature extraction. These factors ensure the ability of MI-based medical AI models. To evaluate whether the MI-based medical AI model is suitable, this section connects the characteristics of MI data to the medical AI model's needs. This approach ensures balanced optimization between diagnostic sensitivity and specificity in medical AI models.

1.6.1. Bridging MRI imaging and AI models

In clinical applications, MRI requires a long time to acquire data and is sensitive to motion and metal artifacts. The signal quality of MRI varies greatly depending on scan settings. Medical AI models need to solve these problems to use MRI as the primary data source. MRI data itself carries voxel information of corresponding body tissues, and medical AI models should support the ability to analyze two-dimensional images obtained from MRI scans at specific angles. Medical AI can process these individual slides and use their slide information and tissue characteristics to infer pathological information of the body tissues.

Medical AI models need to support methods that incorporate either missing or fused features from different sequences to fully refine clinical inference information. Medical AI needs to be able to handle MRI intensity. MRI voxel intensity lacks an absolute physical scale, and medical AI needs to minimize the influence of acquisition equipment on AI model results when dealing with MRI data from different sources within the same hospital. This capability is crucial for mitigating the impact of changes in MRI data sources, making medical AI models more robust when processing clinical MRI data. Uniform noise and intensity asymmetry exist at various points in MRI data. These can severely interfere with AI models' feature extraction, leading to decreased model performance. Systematically integrating data processing steps into the AI workflow can effectively improve performance during feature extraction. Deep learning-based methods have shown advantages in this area [15]-, learning to correct for uneven intensity distributions in the data. This process can more effectively improve the accuracy of subsequent medical AI analysis. MRI has high-dimensional spatiotemporal characteristics. Medical AI models should be designed to jointly encode the spatial structure and temporal variation.

1.6.2. Bridging CT imaging and AI model

For medical AI models, a major benefit of CT is that the physical scale of HU values is consistent. Preprocessing CT data is very important for medical AI. Medical AI should use HU units and normalization of CT that more accurately match specific body parts and tasks. Preprocessing in CT enables medical AI models to accurately highlight the density of target tissues. Medical AI models need to be robust to CT noise when using lower radiation doses, where poor image quality can make diagnosis more difficult. For feature extraction tasks, medical AI models should focus on local density changes of CT images and texture descriptions, as these details are crucial for detecting lesions and clinical tasks.

1.6.3. Bridging X-ray imaging and AI model

X-ray imaging has a lack of depth information, structural overlaps, and difficulty seeing low-contrast objects. Medical AI models should use projection to solve the lack of depth information. Medical AI models can utilize textures, edges, and a wide range of other contextual clues to infer missing depth. The brightness of the X-ray will image the results of the medical AI vision processing algorithm. The brightness of X-rays is affected by a variety of physical and technical factors. This will cause device dependence and unstable intensity changes in the medical AI image data process. To overcome this issue, this study proposes that medical AI should apply prior knowledge of human anatomy as a guide in the data preprocessing stage, employing computer vision (CV) and deep learning denoising algorithms. The method [16] used for low-radiation CT images has the potential to be extended to X-ray imaging applications. DU-GAN learned how to remove noise while strictly preserving the fine anatomical structures crucial for diagnosis, replacing simple filtering. This targeted preprocessing strategy effectively improves the stability of subsequent AI model feature extraction, ensuring both high diagnostic accuracy and good clinical interpretability in its output.

2. Challenges in Clinical Translation of AI Medical Models

The important value of medical AI lies in solving practical problems. Four challenges in the medical field have slowed down the pace of the full-scale clinical application of medical AI. Theoretical foundation problem. Excessive data processing problem. model interpretability problem. Symptom overlaps problem. This section will address these four issues.

2.1. Fundamental Differences between Medical Imaging and Computer Graphics

MI is gradually becoming the foundation of modern diagnosis and treatment. The global shortage of radiologists, the demand for medical AI models increases [17]. Medical AI models need to process multidimensional and information-rich data and require in-depth clinical knowledge. These models are adjusted based on the specific clinical problem and MI data. This situation leads to a dual knowledge deficit: AI researchers lack expertise in the medical field, while clinicians may be unfamiliar with AI concepts.

The core issue of medical AI is whether CG or MI should serve as the theoretical foundation of medical AI. This issue determines whether the design of medical AI models should prioritize task efficiency or pursue the traceability of clinical logic. The similar foundation in image processing between MI and CG hides a difference in application-driven objectives. MI requires that the data cannot be compressed, details cannot be lost, the data is accurate, and the results can be traced. [18]. CG focuses on the realism of physical simulations and computational efficiency.

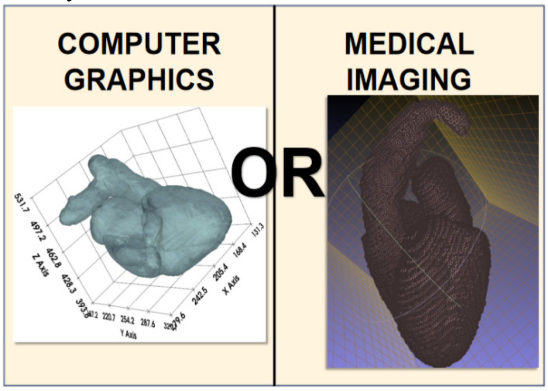


Figure 4. Divergence between CG and MI

Figure 4 shows an example comparison of the CT 3D reconstruction results under different processing methods. The left image is the reconstruction result implemented in Python in this study. To balance computational efficiency, the voxel sampling process was simplified, resulting in some blurred details. In contrast, the right image was directly generated by open-source CT software, preserving richer original details.

This comparison shows that simply treating medical image data as ordinary images can easily lead to the loss of key information. In Figure 4, the lost details primarily involved texture features that hold clear clinical diagnostic value. The loss of such information is a direct cause of the decline in the interpretability and reliability of AI models in clinical applications [10,19] and confirms the view that simply replacing training data to transfer CV models carries potential risks [4,6]. In conclusion, to improve the clinical reliability of medical AI, it is necessary to deeply integrate medical prior knowledge and clinical evaluation standards throughout the entire process of medical AI model construction , rather than merely pursuing numerical accuracy improvements, so as to ensure that its computational methods meet the rigorous requirements of medical practice [20].

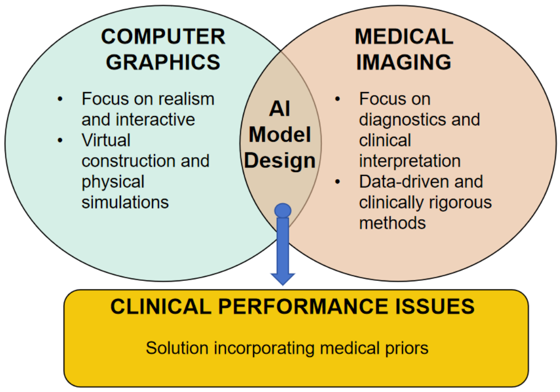


Figure 5. The relationship between CG and MI

MI records real body information, whereas CG only generates artificial calculation results that are compromised due to computational efficiency (as shown in Figure 5 [21,22].) Due to the differences between the two fields, AI models trained in natural images will encounter challenges when applied to MI. These challenges include grayscale variation patterns, resolution limitations, and quantum noise (small, random changes in pixel values) inherent in radiographic imaging systems. Even the definition of advanced high-resolution imaging technology is restricted by factors such as the modulation transfer function, and is essentially different from the statistical characteristics of natural images [23]. Simply put, if AI does not understand the particularities of MI, even if it works quickly and yields accurate results, it may not be clinically applicable.

2.2. Pitfalls of Data Overprocessing in Medical AI

Ignoring the critical feature of MI data carries some risks. Denoising or adjusting contrast can improve model running efficiency and they can easily distort features that are important for diagnosis [5]. Overprocessing operations create gaps between the raw data, and the data processed by the model. In X-ray imaging, this problem is particularly serious because the pixel values directly represent the density of tissue and lesions. Any changes to the data will affect the final image the medical AI sees. Subtle pixel changes in medical images can alter structural details, ultimately compromising the reliability and accuracy of clinical decision-making. Similarly, although medical AI models process data that has been denoised and adjusted to contrast, it can improve the model's understanding of the data or sharpen the edges of MI data. However, these treatments have the potential to change the process and results of clinical judgment.

Overprocessing is a big problem in medical imaging AI. There is a contradiction: researchers invest approximately 70% of the development effort in data preparation (such as noise reduction and contrast adjustment [24]), but these processes may compromise the clinical value of the image. For example, when both high-contrast and low-contrast lesions are present in MI data, excessive smoothing can obscure low-contrast features [25]. Significantly reducing the resolution of high-resolution MI data on CT, MRI, and pathology images also risks losing important details [26]. After all, all clinical MI data need to be processed based on uncompressed original data and resolution. AI models may be able to tolerate some data degradation to extract patterns, but clinical diagnosis cannot afford to lose any valuable, fine-grained features. For example, AI commonly uses lossy compression, but clinical imaging requires high-resolution, uncompressed data to ensure diagnostic accuracy. Simply put, overly aggressive preprocessing measures will significantly reduce the usability of the AI model in actual patient care and the rationality of clinical treatment plans, thereby significantly reducing its effectiveness.

Common image enhancement techniques (such as histogram equalization or contrast stretching [27-30]) are likely to amplify noise or cover up small lesions [31]. Taking histogram equalization as an example, it may extend the grayscale range but at the same time reduce the signal-to-noise ratio in critical areas [32]. Similarly, without considering clinical diagnosis needs, arbitrarily adjusting the size of pathological images to the most suitable size for the medical AI model will cause key information to be discarded [26].

Preprocessing is a complex process and whether it is appropriate is not easily demarcation. Overprocessing can lead to a mismatch between model results and clinical outcomes. Insufficient processing can lead to the omission of key features. Modeling clinical medical knowledge as a constraint can address this issue. This constraint essentially provides a domain-specific regularization term for the model's optimization objective and helping it to find the optimal balance. This approach can improve efficiency and enhance clinical rationality and reliability of medical AI. The diagnosis of medical AI accuracy is related to subtle features. Applying general computer vision technology without guidance from medical professionals is likely to bias the model and reduce its accuracy in various scenarios. Future research must consider both computational and clinical needs so that medical AI remains explainable, stable, and trustworthy.

2.3. Interpretability in Medical AI

Medical AI models have reached the level of radiologists in interpreting single MI data [33-35]. Medical AI still faces several fundamental obstacles before it can be fully integrated into clinical practice. The most important aspect of medical AI is interpretability. Some models reveal nothing about how they make their decisions. The opacity carried by AI models reduces doctors' trust in them [36]. All decisions made during the clinical process require the traceability of cause and effect. Medical AI systems rely on probabilistic inference and lack a clear modeling of pathological knowledge [37]. The obscurity of medical AI models raises potential leading doctors to over-reliance on the wrong automatic output of AI in image enhancement and auxiliary diagnosis.

Data overprocessing is an important issue from the perspective of model interpretability. Medical AI data processing steps typically aim to improve the efficiency and accuracy of medical models. Multiple rounds of data processing may implicitly alter or suppress important clinical signals in MI data, potentially reducing the transparency of medical AI models. Unnoticed excessive filtration may mask subtle lesions or blood vessel tears that physicians rely on for diagnosis [25]. The process of medical AI data processing is opaque, and it is difficult to cross-verify its output and processing with doctors' judgments. Data processing in these cases is that it may eliminate key features for diagnosis, unless guided by prior knowledge in the medical field [26]. Enhancing the interpretability of medical AI data processing, the medical AI should maintain structural features relevant to clinical diagnosis. Retaining this information allows tracing the basis of medical AI model processes and provides clinical practice-level validation support for traceable results.

From the interpretation of medical AI, modulation the theoretical foundation of medical AI requires a higher priority. CG focuses on optimizing computational efficiency and MI is fundamentally driven by diagnostic accuracy. This difference is particularly evident in medical AI. If medical AI models that excessively pursue computational efficiency may quickly obtain near-correct conclusions by simplifying case details. When medical AI output fails to fully reflects the true pathological features, it struggles to provide clinicians with diagnostically valuable evidence.

When medical AI models compress features to improve computational efficiency, it will cause certain crucial pathological features to be overlooked. Sacrificing image resolution to accelerate processing may lead to the loss of minute nodular features. A small lack of such data does not necessarily affect the results. It cumulatively erodes the medical AI model's interpretability. It will influence the clinician's confidence in medical AI.

The development of medical AI models often draws on techniques from natural image processing [38]. Medical images differ significantly from natural images in terms of outcome evaluation criteria and image processing requirements. This disparity necessitates that medical AI models be specifically adapted to the unique patterns of medical data. The degree to which medical AI adapts to medical data will affect the interpretability of medical AI. The computational logic of medical AI models cannot replicate the integrative process of a physician's diagnostic thinking, resulting in a "black box." This will affect doctors' understanding of the outcomes and processes of medical AI. This misunderstanding, once accumulated, can lead to distrust of clinical AI.

For medical AI to gain credibility in clinical practice, it is necessary to keep high accuracy and able to "explain" its decisions. Researchers are using various interpretability tools to open the "black box" of these models. These tools can visualize the AI's reasoning process. Highlighting what it perceives as key lesions in images, allowing doctors to intuitively understand its diagnostic logic.

Methods have emerged that incorporate interpretable modules or model interpreters into AI to enhance the interpretability of medical AI. Integrating interpretability into medical AI models cannot be handled by simply adding an interpretation module. Its core implementation makes the medical AI model "think" like a doctor. The interpretability of medical AI models can be improved by enabling doctors to understand the AI's thinking process with minimal difficulty. This requires medical AI embedding prior knowledge which is from medical imaging expertise. A principal reason stems from the fact that medical imaging representatives that is one manifestation of the disease. It may cover up the diverse and complex underlying pathologies in medical AI processing. Doctors' diagnoses do not rely on a single feature but rather on a weighted and comprehensive analysis of multiple clues. Only by enabling medical AI to possess this comprehensive analytical capability can doctors understand medical AI and improve the interpretability of the model.

A key for interpretable medical AI is to ground data-driven algorithms in structured medical knowledge. By embedding this knowledge as constraints or features, developers of medical AI can steer the model's decision-making beyond mere data correlation towards pathways that are medically meaningful and verifiable.

2.4. Symptom Overlap

The phenomenon of "same symptoms but different diseases" is common in clinical practice, which importance of integrating multi-source knowledge for differential diagnosis [38]. Medical AI models that rely on single-modality images or clinical indicators have limitations in their diagnostic capabilities and are difficult to cope with complex diagnostic scenarios in the real world. The training paradigm of most medical AI models still focuses on the accurate identification of single diseases rather than solving the problem of differential diagnosis of diseases with overlapping symptoms. When faced with multiple diseases with similar clinical manifestations, the medical AI model is very prone to misjudgment due to the confusion of training data categories and the highly similar imaging features between diseases. The confusion matrix in the literature [39] clearly reveals this limitation.

Medical AI models perform poorly when confronted with overlapping symptoms, a fundamental bottleneck stemming from the "one-to-many" mapping relationship between symptoms and diseases. This complexity makes it difficult for medical AI models to derive an integrated understanding of the underlying disease mechanisms from superficially similar MI data phenomena [40]. The medical AI models would be best to have comprehensive analysis of massive datasets of symptoms and cases. Medical AI also needs to transcend the constraints of single-modality MI data by effectively integrating diverse imaging sources with non-imaging data (such as laboratory reports and electronic medical records [41]). The models can achieve a more accurate reconstruction of the complex features present in real clinical cases through such multimodal data integration. When imaging findings are similar, medical AI can effectively discriminate the true etiology from incidental associations, establishing a diagnostic logic rooted in the core pathology of the disease rather than its superficial symptoms [42]. With the continuous accumulation and cross-validation of multi-source MI data and clinical cases, it can assist in verifying the correctness of the conclusions drawn by medical AI.

3. Theoretical Foundations and Significance of Multimodal Medical AI

The development of medical AI hinges on its ability to effectively address the core challenges outlined in section 2 (the theoretical foundation of model development, the risk of data overprocessing, model interpretability issues, and the difficulties in AI diagnosis due to overlapping symptoms). The root of these challenges lies in inherent contradictions within the theoretical foundation of medical AI.

Medical AI developers and doctors address this problem by employing a multimodal approach to reconcile these theoretical contradictions. While this approach is conceptually sound, it carries potential risks in practical application. Multimodal fusion of data from multiple sources results in extremely high data dimensionality and increased computational complexity. This increased complexity transforms the problem that medical AI can solve into a highly underdetermined problem (where multiple solutions exist for the same problem). AI might arrive at multiple solutions for the same symptom, potentially interfering with the model's accuracy. The benefit of a single multimodal framework is an uncertain improvement in accuracy; it comes with a significant amount of complex computation.

This research proposes a novel multimodal theoretical framework to address this issue. Multimodal AI makes judgments by fusing and associating information from different sources. The proposed framework uses medical theoretical knowledge as a constraint in the information fusion process. The advantage of this approach is that it can match real-world attributes with multimodal data while filtering redundant information and mapping the filtered data to their respective pathological attributes. It optimizes the interpretability of data processing. The data processing has attributes that make it easier for doctors to trace the entire data processing process and determine the causes. This mechanism of medical AI simulates the actual diagnostic process of doctors. When a diagnosis from a single source of information is in doubt, doctors will comprehensively consider the patient's medical history and test results. By integrating the decision-making process of these multiple sources of data, multimodal models will improve the accuracy of diagnosis. Multiple sources of data make the medical AI model's "thought process" transparent and traceable to doctors. In the diagnosis of medical images, the multimodal model can clearly demonstrate how its judgment is based on which MI data and the patient's described symptoms. A multimodal-based medical AI model effectively solves the trust problem caused by the model's "black box."

Theoretical knowledge from radiation physics, clinical diagnostic ideas, and pathophysiological models provides important priori information. This information helps guide medical AI in encoding, fusion, and final decision-making based on MI data. Integrating clinical knowledge and evidence-based guidelines into medical AI models can enhance the consistency between different modalities, making the model's results more consistent with actual clinical results [40]. Medical AI frameworks are emerging that utilize new algorithms for optimization to help AI models address real-world data biases, and they will enhance the medical AI clinical model's safety and facilitate regulatory approval [43].

Multimodal AI has the potential to help clinical AI solve the problem of overlapping symptoms. Multimodal AI has potential in addressing issues in the lack of a theoretical foundation, data overprocessing, and model interpretability.

As shown in Figure 6, this study proposes that this multimodal theoretical AI framework based on multiple data sources can help solve the shortcomings mentioned in Section 2. This framework is based on the characteristics and principles of MI data, leveraging the computational advantages of AI. Each AI clinical data set should maintain the unique value of each modality. The diagnostic integrity of each MI modality must be maintained to avoid diluting its unique contribution to accurate diagnosis. For each kind of medical AI, one should pay more attention to clinical interpretability. Ensure that AI output results can be clearly explained in clinical diagnostic reasoning and verified by the doctor. The medical AI should have the ability to reliably fuse a variety of different types of MI data while adapting to the uncertainties posed by individual patients and circumstances.

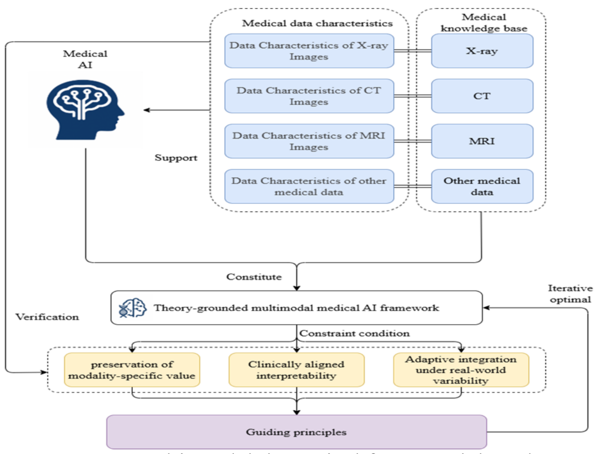


Figure 6. Multi-modal theoretical framework based on integrating MI data

As shown in Figure 6, this research proposed a theory-based multimodal medical AI framework to assist the developer in solving the problems in clinical AI. This framework is designed to integrate MI data from disparate sources while ensuring that the framework is clinically reliable, logically rational, and intelligently adaptable. Each type of MI data has its own unique physical and information characteristics. These characteristics include tissue density, attenuation behavior, contrast generation methods, and differences in spatial or temporal resolution, which together determine the diagnostic value of each type of MI data. The proposed framework focuses on describing the characteristics of these modalities and turning to a unified theoretical structure to guide how to coordinately utilize these modalities in the development of a medical AI model.

The proposed framework lies in its theory-based design principles. These design principles connect the computational approach of AI models to the real-world medical interpretation and medical facts. The proposed framework uses theory-driven approaches and incorporates medical knowledge to constrain the entire process. It will make the model effectively preserve the independent characteristics of different medical AI data. Complete and diverse data sources provide complementary information, offering multiple theory-based support for medical AI entire process. The proposed framework effectively alleviates the overfitting problem in purely data-driven models. It reduces the model's sensitivity to specific noise by introducing prior medical knowledge. It enhances the clinical credibility and interpretability of the model's output.

The proposed framework is different from data-driven frameworks, which focus on the model's result performance, with their internal derivation processes often being highly complex "black boxes." The proposed framework emphasizes the transparency of the model's operational mechanism to clinicians by adding corresponding pathological attributes during data processing. This ensures the reasonableness of each step in the medical AI process within the medical field. Adding pathological attribute constraints during data processing helps developers prune redundant computations. Because data processing is transparent and visible, developers can reduce unreasonable logic, substantially reducing computational power.

The proposed framework uses medical knowledge to build prior knowledge and define processing boundaries for medical imaging data. It performs selective integration when dealing with multi-source imaging data. It analyzes data from the same disease to reduce the dilution of critical diagnostic information. Its core objective is to fully use the unique diagnostic clues from various medical modalities and ensure their preservation during data fusion.

Medical knowledge serves a dual purpose in the proposed framework, which is to support the reasoning and constrain the model. The supporting reasoning mechanism bridges AI inferences with real-world clinical decision-making logic and ensures data processing adherence to medical standards. The feature from medical knowledge constructed through this process helps the medical AI model keep high diagnostic value and enhances its interpretability. It will improve the adaptability to real-world clinical scenarios. The constraining mechanism provides systematic support to clinically challenging problems like the differential diagnosis of diseases with overlapping symptoms after integrating all data constraints and characteristics. It reduces the correlation between irrelevant features during data processing; it can reduce the computing interference caused by data feature redundancy.

4. Discussion

The fields of computer science and medicine are constantly pushing the boundaries and capabilities of AI applications. However, excessive demand has led to several AI models that excessively pursue computational precision. This behavior poses a significant risk to the clinical application of AI in the medical field. Statistical analysis of collected literature reveals that only 40% of studies mention data characteristics. It reflects that developers are unfamiliar with the data in the domains where AI is currently applied, yet they can still find results using AI. Furthermore, the computational process of AI is often a complex and difficult-to-understand black box. This behavior makes doctors and users of medical AI unable to trust AI's decision-making.

This study first introduces the data characteristics of common medical data sources (X-ray, CT, MRI). These three types of data are currently the most frequently combined data sources between computer science and medicine. X-ray images are two-dimensional, while CT images and MRI images are three-dimensional. This study used Python and MashLab to open CT and MRI data, and the results were three-dimensional volumes. However, current research using CT and MRI for three-dimensional reconstruction has limitations. Using a specific CT or MRI image for reconstruction tasks would waste computational resources. This study summarizes the strengths of X-ray, CT, and MRI and outlines their potential connections with AI. For example, X-ray imaging addresses contrast and structural overlap issues; MRI suffers from motion artifacts and metallicity. CT exhibits noise problems under low-radiation conditions. These are all important issues that hinder the application of AI in clinical processing.

This study traces the root causes of developers' insufficient understanding of medical knowledge and finds that the foundation of medical AI is contradictory. Medical AI is a product spanning the fields of computer science and medicine. This process reveals a contradiction on its theoretical basis. The computer science field uses data to drive AI, constantly pursuing high precision and computational efficiency. The medical field uses domain knowledge to limit the practical application of AI.

In analyzing the literature, this study found that the processing of raw data has become standardized. Data processing is performed regardless of the data source or its actual state. While this is feasible in laboratory applications, it carries risks in practical applications. The data acquisition process by instruments already involves noise reduction, and the data input into the AI model undergoes further processing. This process may result in the loss of image details. This study hopes that developers will understand noise reduction and other data processing steps in the data acquisition process when designing AI. Integrating these steps into the data preprocessing process can minimize the risk of data over-processing.

The interpretability of medical AI has been a persistent issue since the inception of AI models. The addition of domain knowledge further exacerbates this problem. The medical field requires relatively reasonable processes, bringing the interpretability of medical AI to the forefront of researchers' attention. There are methods such as adding interpretable modules or using more interpretable models. Medical knowledge further increases the difficulty of interpretation. This study traces this problem back to the contradictions in the theoretical foundation of medical AI. This problem is a manifestation of the contradictions in the fundamental theory of AI. The primary condition for solving this problem is to reconstruct domain knowledge using medical theory, transforming domain knowledge into an encodable and mappable unit. Using this unit to constrain the AI model and incorporating knowledge mapping during data processing can improve the model's interpretability.

Symptom overlaps is a common problem in clinical medicine. The essence of symptom overlapping is a problem with multiple solutions. AI has certain advantages in solving this problem. By increasing data sources, it can provide constraints from more perspectives. All constraints can ultimately reduce the possibility of solutions. AI still faces challenges in processing data, such as a lack of datasets. Single datasets often point to specific diseases, lacking the auxiliary constraints of diverse datasets.

This study proposes a novel multimodal theoretical framework to address these issues. The framework is chosen for its multimodal nature because it allows for the integration and weighing of data from multiple sources. This weighing provides support for data sources with overlapping symptoms. Furthermore, future medical decision-making processes also require data from multiple sources for decision support. Using multimodal data as the foundation of the model framework is appropriate. The proposed framework constructs a constraint using medical knowledge. This constraint internally includes a knowledge base built from various medical theories and data features. The constraint constrains the knowledge and data processing boundaries of the AI. By connecting data with knowledge, the constraint provides theoretical support for AI computation. This alleviates the interpretability problem of medical AI.

5. Conclusion

This study proposes a medical AI theoretical framework based on medical imaging and computer graphics. The study collects 60 relevant studies, which revealed that 40% explicitly mentioned the inherent characteristics of medical imaging data. This shows that current medical AI research may still overly rely on computer graphics, failing to truly establish the fundamental role of medical imaging. This inversion of priorities is hard to integrate with clinical medical judgment logics. This study proposes that medical AI as a tool should be rooted in medical imaging. This study systematically elucidates the roles of both in constructing medical AI models and focuses on the significant value of traditional imaging techniques in assisting clinical AI processing. It emphasizes that ignoring the inherent properties of medical imaging data will inevitably impair the interpretability of AI models, the precision of image processing. It will shake the theoretical foundation of artificial intelligence applications in the medical field.

In the future, it is hoped that more researchers will build theory-driven medical AI models based on this framework. Currently, multimodal healthcare is a mainstream trend in medical AI. However, how to integrate medical knowledge to make it an aid to medical AI is what this research is currently working on. It is hoped that more researchers will refine the theoretical framework of this study. This research will continue to update and refine the theoretical framework for any specific requirements.

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