Original Article
Quality assessment of abdominal CT images: an improved ResNet algorithm with dual-attention mechanism

Boying Zhu[1,2], Yuanyuan Yang[1,2]

[1]Shanghai Institute of Technical Physics, Chinese Academy of Sciences, Shanghai 200083, China; [2]University of Chinese Academy of Sciences, Beijing 100049, China

Abstract: Objectives: To enhance medical image classification using a Dual-attention ResNet model and investigate the impact of attention mechanisms on model performance in a clinical setting. Methods: We utilized a dataset of medical images and implemented a Dual-attention ResNet model, integrating self-attention and spatial attention mechanisms. The model was trained and evaluated using binary and five-level quality classification tasks, leveraging standard evaluation metrics. Results: Our findings demonstrated substantial performance improvements with the Dual-attention ResNet model in both classification tasks. In the binary classification task, the model achieved an accuracy of 0.940, outperforming the conventional ResNet model. Similarly, in the five-level quality classification task, the Dual-attention ResNet model attained an accuracy of 0.757, highlighting its efficacy in capturing nuanced distinctions in image quality. Conclusions: The integration of attention mechanisms within the ResNet model resulted in significant performance enhancements, showcasing its potential for improving medical image classification tasks. These results underscore the promising role of attention mechanisms in facilitating more accurate and discriminative analysis of medical images, thus holding substantial promise for clinical applications in radiology and diagnostics.

Keywords: LDCTIQA, abdominal CT, deep learning, attention mechanisms

Introduction

The quality of medical images is crucial for ensuring accurate results in tasks such as medical imaging genomics, lesion segmentation, and annotation, which rely on standardized images for their effectiveness [1]. To improve the accuracy of disease diagnoses and treatments, it is important to establish specific standards for the quality of medical images used by pathologists. Setting lower and upper limits for image quality is crucial for ensuring the effective use of these images before a diagnosis is made [2].

The evaluation of the quality of medical image datasets involves a tedious and time-intensive process that results in increased expenses, subjective outcomes, and smaller datasets [3-5]. Utilizing costly and risky repeated imaging sessions, coupled with a shortage of skilled specialists, to generate more beneficial medical images is not a viable approach to improving the quality of such images [6]. Therefore, more practical solutions are required to tackle the challenge of limited quantity and diverse types of small samples. Artificial intelligence (AI) has made significant advancements in various fields and has demonstrated great potential in handling tasks that may otherwise be challenging. Furthermore, deep learning algorithms, categorized as data-driven approaches, require extensive collection of high-quality datasets to perform tasks of increased complexity [7].

We selected the TID2013 dataset as the standard to assess the quality of medical images suitable for deep learning algorithms [8]. This dataset contains medical images intentionally distorted based on known quality scores, comprising information loss and quality degrada-

tion during compression, storage, and transmission, which variably reduces the quality of these images [9]. As the quality issue of actual medical images cannot be resolved by repeated scanning of patients, a standard method in assessing image quality is to use high-dose raw images to simulate the generation of low-dose sub-images [10, 11]. Instead of a reference of a high-quality image, a pre-restoration algorithm is employed to generate a post-restoration image when using a distorted image. However, these pre-processed datasets are not publicly shared, making it challenging to replicate study results [12-14]. Thus, this research focuses on the development of algorithms using real medical images with labeled information to evaluate their quality.

We use the publicly available abdominal CT image dataset from Stanford University, which allows for licensing, reliability, and reproducibility for pre-training models. To improve the quality evaluation of medical images, we proposed a ResNet algorithm, Double Attention ResNet Network, which integrates two different attention mechanisms. The Double Attention ResNet Network is an extension of the ResNet architecture that incorporates two distinct attention mechanisms to enhance the network's ability to learn relevant features from medical images, such as abdominal CT scans. This structure effectively integrates channel and spatial attention, allowing it to focus on more valuable channels, enhance discrimination learning ability, and improve algorithm accuracy. The incorporation of attention mechanisms in deep learning models for medical imaging is prominent, as it enables the network to automatically prioritize the most diagnostic regions of the image. This prioritization can vary depending on the specific condition or abnormality being detected, leading to more precise and robust models. These attention mechanisms also make the model less sensitive to variations in image appearance.

Materials and methods

Datasets

In this study, a publicly accessible dataset containing recently released abdominal CT images along with their associated quality scores was selected. This dataset is sourced from the Low-Dose Computed Tomography

Perceptual Image Quality Assessment Contest 2023 (LDCTIQAC2023), a competition jointly organized by universities and institutions such as Medical-AI and Stanford University in April 2023, ensuring the data used is authoritative and up-to-date. We chose Residual Network (ResNet) (13) as the basic network structure and trained ResNet-18 and three other variants with more complex network layers, ResNet-34, ResNet-50, and ResNet-101, with different network structures to suit different task requirements.

Technical solutions

The various depths of ResNet architectures are categorized into shallow and deep layers, each designed with different configurations of residual blocks, ultimately forming the structure of the entire network. The shallow networks, namely ResNet-18 and ResNet-34, incorporate two 3×3 convolution kernels per residual block. Conversely, the deeper networks, ResNet-50 and ResNet-101, utilize a sequence of 1×1, 3×3, and again 1×1 convolution kernels in each residual block. These networks leverage shortcut connections to facilitate additional residual and identity mappings. Activation within the network is achieved through the ReLU function, ensuring the integrity and performance of each residual block. ResNet-18, along with ResNet-34, ResNet-50, and ResNet-101, were rigorously trained. The most promising model was selected for further enhancements, which involved adjustments and retraining using two distinct attention mechanisms: spatial and channel. Performance comparisons were subsequently conducted to gauge the improvements.

Datasets processing and classification

Original dataset: Medical images are often subjectively evaluated using a five-point scoring system. For instance, in a study on the subjective quality assessment of MRI images, Chabert et al. [7] employ a panel of three neurosurgeons to score 75 selected images using this five-level scoring scale, and calculated the average score. In the analysis of the LDCTIQAC2023 dataset involving a total of 1000 abdominal CT images of soft tissues, with a window width of 350 and a window level of 40, the images were scored by five radiologists

Table 1. Original grade criteria of LDCTIQAC2023

Scores	Grades	Diagnostic Quality Standards
0	Very bad	Features required for diagnosis are missing
1	Bad	Not applicable for diagnosis
2	Qualified	Applicable to some clinical diagnoses
3	Good	Excellent quality for clinical interpretation
4	Excellent	Highly visible anatomical structures

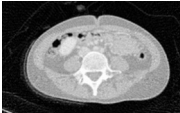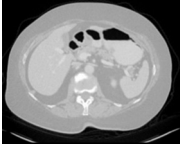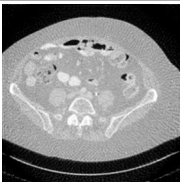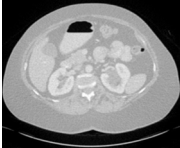**Table 2.** Binary dataset based on LDC-TIQAC2023
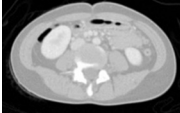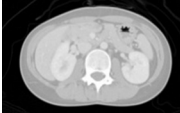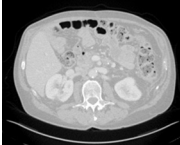
Quality Grades	Quantity	Examples
[0, 2] Unqualified	467	
[2, 4] Qualified	533	

Table 3. Quinary dataset based on LDC-TIQAC2023

Quality Grades	Quantity	Examples
Very bad [0, 1]	156	
Bad [1, 2]	311	
Qualified [2, 3]	273	
Good [3, 4]	224	
Excellent [4]	36	

within a quinary scoring framework with clinical relevance. Finally, the scores of five radiologists were averaged to obtain the final quality score. See **Table 1**.

A binary dataset: The quality grade was assigned by using the interval [0, 4], which is split into 2 non-overlapping subintervals to classify the quality of medical images. The images in [0, 2] were classified as low-quality groups that do not meet the needs of diagnosis and treatment, while the images in [2, 4] are considered to be high-quality groups that meet the needs of diagnosis and treatment (**Table 2**). In this study, multiple statistical methods were combined to comprehensively analyze the training losses and select appropriate models accordingly. We first used descriptive statistics to understand the data, then used hypothesis testing to determine significant differences between models, and finally used cross-validation to assess the generalization ability of the models.

A quinary dataset: The quinary scoring system further subdivides the [0, 4] interval into four distinct non-overlapping intervals: [0, 1], [1, 2], [2, 3], and [3, 4]. Out of the entire dataset, 36 images were rated at the highest possible score of 4 by five physicians, qualifying them as the top-performing segment (**Table 3**). Cluster analysis was used to divide the dataset with a five-point scoring system into different groups or categories based on their scoring characteristics. Next, the Classification and Regression Trees (CART) algorithm was applied to classify or predict the scoring data. Finally, cross-validation and hyperparameter adjustment were conducted to assess model performance and stability, and to select the optimal network model.

Experimental design

The experiment was conducted on Ubuntu Linux 18.04.5 and compiled by Python 3.6.12, Pytorch 1.10.1, and CUDA 10.1.243. The ratios of the training set and the test set were in a 7:3 ratio.

First, ResNet networks with different layers, like ResNet-18, ResNet-34, ResNet-50, and ResNet-101, were trained by adjusting parameters on binary tasks and quinary tasks, respectively by using quality scores of abdominal low-

Table 4. Training loss and Val. accuracy for the binary dataset

Binary Classification	Training Loss	Val. Acc.
ResNet18	0.052	0.940
ResNet34	0.069	0.903
ResNet50	0.063	0.906
ResNet101	0.071	0.909

dose CT medical images. Then, considering the parameter scale, complexity, and validation accuracy (Val. Acc.) of the models, the basic network was selected.

This study improves the algorithm on the selected model architecture, tries to introduce the attention mechanism block, and adds the channel attention block and the spatial attention block to the Residual Block concurrently. The improved network was retrained and compared with the original model.

Results

Network selection based on binary dataset

The batch size was set to 8 medical images, and the learning rate was set to 0.001. Upon reaching 200 epochs, the Training Loss and Validation Accuracy (Val. Acc.) of four networks are listed in **Table 4**.

Figure 1A depicts that beyond 150 epochs, the Training Loss gradually converges, and the model effect tends to be stable.

It is important to note that the final Val. Acc. does not show the obvious difference among the ResNet networks. So, ResNet-18, with its simpler architecture, was selected for further development to ensure a lightweight network structure for practical applications, minimizing equipment burden.

Network selection based on a quinary dataset

Upon segmenting the dataset for quinary analysis, five models were trained with a batch size of 4 medical images, and the learning rate was still maintained at 0.001. For the quinary dataset, the performance of each model is demonstrated in **Table 5**.

Table 5 illustrates the training progress of the Dual-attention ResNet model across consecu-

tive epochs. It can be discerned that as the epoch exceeds 700, the training loss gradually stabilizes and converges, indicating the model's improved learning capability and resilience to overfitting. Specifically, from this point, the loss reduction slows, suggesting the model's capacity to discern finer details within the dataset and optimize predictive accuracy. This sustained training process allows for refined model representations, enhancing the accuracy of predictions. The robustness and effectiveness of the Dual-attention ResNet model in capturing complex patterns without overfitting are evident from these observations. For the quinary dataset, ResNet-34 was observed with a higher accuracy, while more complex models, such as ResNet-101, perform less effectively without additional training data. Refer to **Figure 1B** for visual data.

Finally, ResNet-18 was selected as the basic model for the qualified binary dataset. For the quinary dataset, ResNet-34 was chosen as the basis for further improvements in the subsequent efforts.

Integration of the ResNet network with spatial and channel attention mechanisms

In this study, we introduced an attention-enhanced short-cut operation for basic residual blocks. Before the short-cut operation, the feature maps were processed by a channel attention block and a spatial attention block sequentially. The channel attention block extracted important information from each channel by using global maximum pooling and global average pooling, and then passed them through a shared multi-layer perceptron. The adaptive convolution kernel was used to compress each channel, and ReLU activation function was applied for nonlinear transformation, expanding the number of channels to augment feature extraction. The output feature maps were normalized using Sigmoid activation function, and the enhanced channel attention features were obtained.

The spatial attention block, which receives input from the channel attention block, focuses on the spatial attributes of the feature maps. It performs maximum and average pooling across each channel at every spatial position and combines these outputs through splicing. Convolution and Sigmoid activation functions
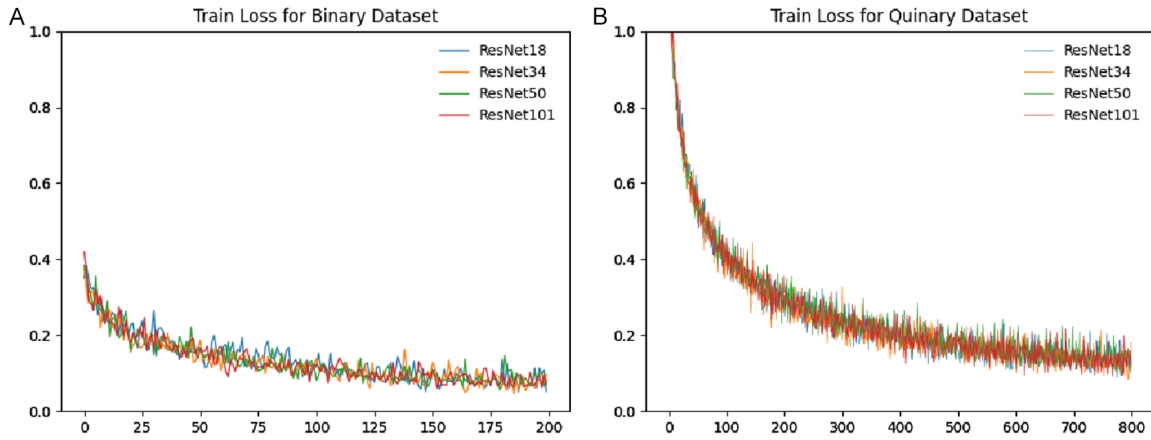
Figure 1. The image shows the training loss of the dataset. A: Binary dataset. B: Quinary dataset.

Table 5. Training Loss and Val. Acc. for quinary dataset

Quinary Datasets	Training Loss	Val. Acc.
ResNet18	0.094	0.663
ResNet34	0.147	0.757
ResNet50	0.132	0.626
ResNet101	0.143	0.657

are applied to the combined output, enhancing features based on spatial positions. This mechanism prioritizes the characteristics at each position, ensuring a more refined and focused attention to detail. The enhanced features from both attention blocks are then multiplied together, contributing to the subsequent computations within the residual block. Refer to **Figure 2A** for a visual representation of the channel attention process and **Figure 2B** for the spatial attention operations.

Improved performance of dual-attention ResNet model in quality classification

This research incorporates spatial and channel attention mechanism blocks into the algorithm and adjusts the ResNet network structure, resulting in optimized model performance. The combined utilization of both channel and spatial attention mechanisms allows for the focused examination of important features in two dimensions. The spatial attention block targets task-related areas in quality classification tasks, adaptively capturing subjective position areas and emphasizing them within the features. Complementing this, the channel attention block addresses the limitations of the spa-

tial attention mechanism by adjusting feature emphasis across different channels, considering the specific characteristics of individual tasks.

Retraining the ResNet-18 network with two attention mechanisms, employing a binary dataset and the same batch size, achieved a validation accuracy (Val. Acc.) of 0.940 for the novel model, marking a 0.04 improvement over the performance of the ResNet-18 model (Val. Acc. of 0.900). Similarly, when utilizing the quinary datasets, the addition of two different attention mechanisms to the ResNet-34 network increased the Val. Acc. from 0.686 to 0.757, confirming the effectiveness of integrating targeted attention mechanisms into the network architecture. To assess the impact of attention mechanisms, a comparison was made between the proposed Dual-attention ResNet model and conventional ResNet networks lacking attention mechanisms. Results exhibited a significantly higher accuracy in the Dual-attention ResNet model across both classification configurations. These findings illustrate the notable enhancement in accuracy attributed to the integration of attention mechanisms into the ResNet model, underscoring the efficacy of the proposed approach.

Discussion

In China, the oversight of radiological image quality predominantly relies on periodic spot-checks by local quality supervision authorities [15]. These checks are intended to ensure that the radiological images across various hospitals and departments meet established quality
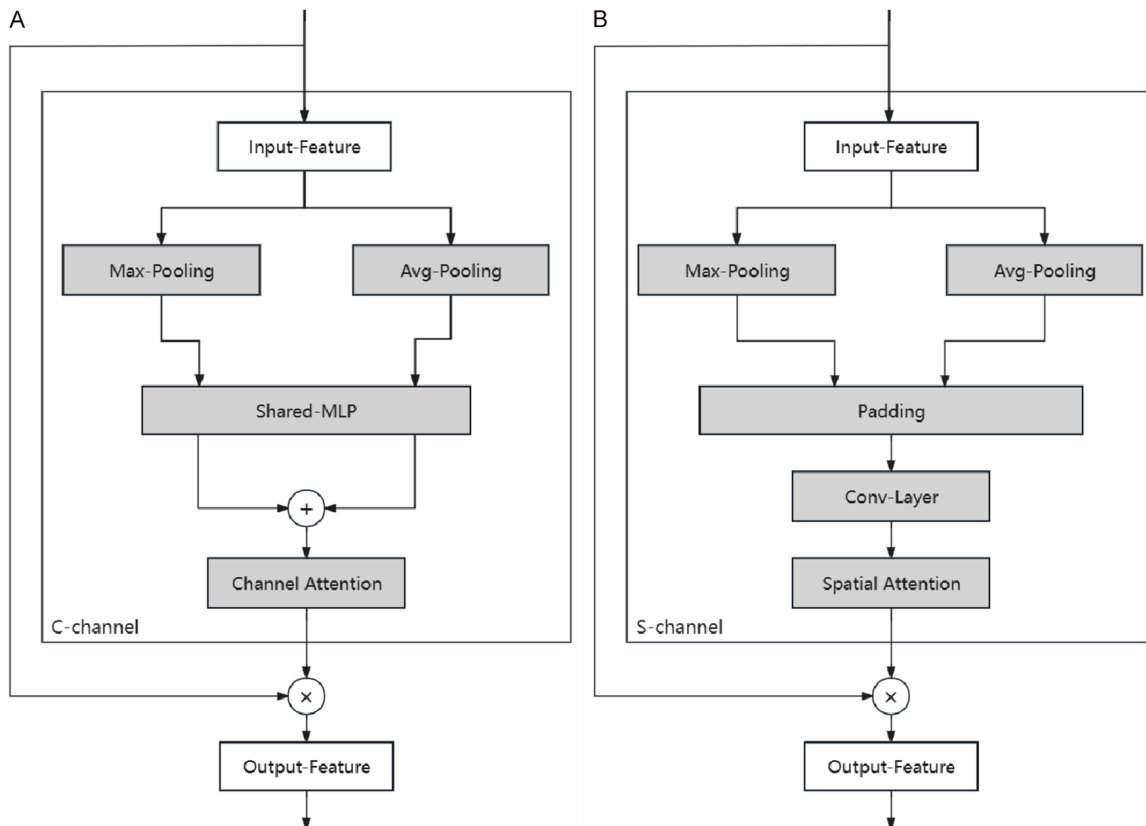
Figure 2. The output of channel and spatial attention blocks is connected with multiplication to obtain attention enhancement features. A: The block of channel Attention Mechanism. B: Spatial Attention Block Mechanism.

standards. However, the subjective assessment of CT medical image quality often lacks precision due to the unique and sensitive nature of medical images [16]. This deficiency in subjective evaluation poses a significant challenge to the advancement of artificial intelligence (AI) in the realm of medical image quality assessment and enhancement. The reliance on human judgment introduces variability and subjectivity into the evaluation process, leading to inconsistent outcomes and inaccuracies. As a result, AI systems, which are increasingly being leveraged to automate and standardize tasks in healthcare, face a considerable hurdle in effectively contributing to medical image quality control [17, 18]. This situation underscores the need for more objective and reliable methods to evaluate image quality, which is essential for the successful application of AI in medical imaging and, subsequently, for improving patient care and outcomes.

To establish unified standards, minimize labour expenses, and achieve standardized quality monitoring on a larger scale, this study investigated the potential to establish unified standards by employing multiple deep-learning networks to classify the quality grading of abdominal CT medical images. In pursuit of practical performance and manageable model complexity, the foundational ResNet-18 network was chosen as the baseline for improvement. The selected ResNet-18 network was then enhanced by integrating its structural and spatial characteristics with a dual attention mechanism, focusing on the channel and spatial dimensions. This integration aims to refine the model's application performance in navigating the complexities of abdominal CT image quality assessment. The enhanced ResNet-18 model benefits from the dual attention mechanism's ability to prioritize and analyze the most relevant features of the images, thereby improving its discriminative power and overall accuracy [19]. This is particularly crucial in the context of abdominal CT images, where variations in anatomy, contrast, and other factors can significantly affect image quality. By leveraging the power

of deep learning and the specific advantages of the ResNet-18 network equipped with the dual attention mechanism, this research seeks to develop a model that can provide a standardized and automated approach to classifying the quality grading of abdominal CT images [20]. Such a model has the potential to streamline quality control processes, reduce reliance on manual labour, and ultimately enhance the efficiency and consistency of medical imaging services [21]. Furthermore, the model's versatility makes it suitable for various clinical settings and populations, providing a scalable solution for enhancing CT image quality across different organs and imaging techniques. The integration of the dual attention mechanism into the ResNet-18 network represents a significant step towards achieving a more standardized and automated approach to medical image quality assessment, ultimately contributing to better patient care and outcomes.

In the meantime, the dataset utilized in this study is the newly released abdominal CT medical image dataset in 2023 [22] with ensured timeliness and authority. This study categorized specific scores into different grade levels to comply with the scoring standards during actual quality control. The research demonstrated the practicality of deep learning networks on classifying the quality of abdominal CT medical image. In terms of further development, it necessitates more support from multiple medical institutions to propose a more detailed assessment system and diversified data to achieve data and technology sharing, thereby improving the quality and quantity of the datasets. Today, the rise of technologies like medical cloud platforms has also enhances the feasibility of these advancements.

The substantial performance enhancement achieved by the Dual-attention ResNet model serves as a gateway to understand the significance of attention mechanisms in image classification tasks. Previous studies by Samo M [23] and Sanjaya P et al. [24] have demonstrated the pivotal role of attention mechanisms in enhancing the discriminative capability of deep learning models. Building upon this theoretical foundation, our findings echo the observed performance improvements, elucidating how attention mechanisms effectively enable the model to focus on salient image regions while minimizing distractions, yielding more refined and accurate predictions. Furthermore, our results align with the work of Wollek A [25], who emphasized the interpretability of attention-based models, allowing for greater transparency in decision-making processes. This aligns with our observed model's capacity to provide interpretable attention maps, thereby fostering trust and understanding in the decision-making process. Consequently, these findings not only confirm the theoretical underpinnings but also extend the practical viability of attention mechanisms, underscoring their transformative impact on the field of medical image classification.

In considering the implications of our findings, it is indispensable to acknowledge several limitations inherent to this study. Firstly, our research focused solely on a specific medical imaging dataset, which may limit the generalizability of our model to other diverse datasets and clinical scenarios. Additionally, the performance of the Dual-attention ResNet model was evaluated using standard evaluation metrics; however, further validation through external datasets and independent testing would strengthen the robustness and generalizability of our results. Moreover, as with many deep learning models, the interpretability of the attention mechanisms remains an ongoing challenge; while our model provides attention maps for interpretability, the complexity of the learned representations may warrant further investigation. Finally, the computational resources required for training and fine-tuning the model should be considered in the context of real-world deployment. These limitations collectively emphasize the need for cautious interpretation of the findings and warrant continued research to address these constraints for broader applicability and translational impact.

In summary, the integration of attention mechanisms within the ResNet model has achieved significant performance enhancements, showcasing its potential for improving medical image classification tasks. The results of this study underscore the promising role of attention mechanisms in facilitating more accurate and discriminative analysis of medical images, thus holding substantial promise for clinical applications in radiology and diagnostics.

Acknowledgements

Disclosure of conflict of interest

None.

Address correspondence to: Yuanyuan Yang and Boying Zhu, Shanghai Institute of Technical Physics, Chinese Academy of Sciences, No. 500 Yutian Street, Hongkou District, Shanghai 200083, China. E-mail: yangyuanyuan@mail.sitp.ac.cn (YYY); ORCID: 0009-0006-3736-0052; E-mail: zhuboying1998@163.com (BYZ)

References

[1] Greffier J, Durand Q, Frandon J, Si-Mohamed S, Loisy M, de Oliveira F, Beregi JP and Dabli D. Improved image quality and dose reduction in abdominal CT with deep-learning reconstruction algorithm: a phantom study. Eur Radiol 2023; 33: 699-710.

[2] Li LL, Wang H, Song J, Shang J, Zhao XY and Liu B. A feasibility study of realizing low-dose abdominal CT using deep learning image reconstruction algorithm. J Xray Sci Technol 2021; 29: 361-372.

[3] Park HJ, Choi SY, Lee JE, Lim S, Lee MH, Yi BH, Cha JG, Min JH, Lee B and Jung Y. Deep learning image reconstruction algorithm for abdominal multidetector CT at different tube voltages: assessment of image quality and radiation dose in a phantom study. Eur Radiol 2022; 32: 3974-3984.

[4] Inoue A, Voss BA, Lee NJ, Takahashi H, Kozaka K, Heiken JP, Ehman EC, Vasconcelos R, Fidler JL, Lee YS, Mileto A, Johnson MP, Baer-Beck M, Weber NM, Michalak GJ, Halaweish A, Carter RE, McCollough CH and Fletcher JG. Diagnostic performance in low- and high-contrast tasks of an image-based denoising algorithm applied to radiation dose-reduced multiphase abdominal CT examinations. AJR Am J Roentgenol 2023; 220: 73-85.

[5] Jeukens CRLPN, Brauer MTH, Mihl C, Laupman E, Nijssen EC, Wildberger JE, Martens B and van Pul C. A new algorithm for automatically calculating noise, spatial resolution, and contrast image quality metrics: proof-of-concept and agreement with subjective scores in phantom and clinical abdominal CT. Invest Radiol 2023; 58: 649-655.

[6] Schwartz FR, Clark DP, Rigiroli F, Kalisz K, Wildman-Tobriner B, Thomas S, Wilson J, Badea CT and Marin D. Evaluation of the impact of a novel denoising algorithm on image quality in dual-energy abdominal CT of obese patients. Eur Radiol 2023; 33: 7056-7065.

[7] Lansier A, Bourillon C, Cuénod CA, Ragot E, Follin A, Hamada S, Clément O, Soyer P and Jannot AS. CT-based diagnostic algorithm to identify bowel and/or mesenteric injury in patients with blunt abdominal trauma. Eur Radiol 2023; 33: 1918-1927.

[8] Tamura A, Nakayama M, Ota Y, Kamata M, Hirota Y, Sone M, Hamano M, Tanaka R and Yoshioka K. Feasibility of thin-slice abdominal CT in overweight patients using a vendor neutral image-based denoising algorithm: assessment of image noise, contrast, and quality. PLoS One 2019; 14: e0226521.

[9] van Stiphout JA, Driessen J, Koetzier LR, Ruules LB, Willemink MJ, Heemskerk JWT and van der Molen AJ. The effect of deep learning reconstruction on abdominal CT densitometry and image quality: a systematic review and meta-analysis. Eur Radiol 2022; 32: 2921-2929.

[10] Zeng D, Huang J, Bian Z, Niu S, Zhang H, Feng Q, Liang Z and Ma J. A simple low-dose X-ray CT simulation from high-dose scan. IEEE Trans Nucl Sci 2015; 62: 2226-2233.

[11] Gao Q, Zhu M, Li D, Bian Z and Ma J. CT image quality assessment based on prior information of pre-restored images. Nan Fang Yi Ke Da Xue Xue Bao 2021; 41: 230-237.

[12] Leuliet T, Maxim V, Peyrin F and Sixou B. Impact of the training loss in deep learning-based CT reconstruction of bone microarchitecture. Med Phys 2022; 49: 2952-2964.

[13] Zhang H, Lv W, Diao H and Shang L. Reconstruction algorithm-based CT imaging for the diagnosis of hepatic ascites. Comput Math Methods Med 2022; 2022: 1809186.

[14] Burns JE, Yao J, Chalhoub D, Chen JJ and Summers RM. A machine learning algorithm to estimate sarcopenia on abdominal CT. Acad Radiol 2020; 27: 311-320.

[15] Zeng Q, Li N, Wang Q, Feng J, Sun D, Zhang Q, Huang J, Wen Q, Hu R, Wang L, Ma Y, Fu X, Dong S and Cheng X. The prevalence of osteoporosis in China, a nationwide, multicenter DXA survey. J Bone Miner Res 2019; 34: 1789-1797.

[16] Schaffter T, Buist DSM, Lee CI, Nikulin Y, Ribli D, Guan Y, Lotter W, Jie Z, Du H, Wang S, Feng J, Feng M, Kim HE, Albiol F, Albiol A, Morrell S, Wojna Z, Ahsen ME, Asif U, Jimeno Yepes A, Yohanandan S, Rabinovici-Cohen S, Yi D, Hoff B, Yu T, Chaibub Neto E, Rubin DL, Lindholm P, Margolies LR, McBride RB, Rothstein JH, Sieh

W, Ben-Ari R, Harrer S, Trister A, Friend S, Norman T, Sahiner B, Strand F, Guinney J, Stolovitzky G; and the DM DREAM Consortium, Mackey L, Cahoon J, Shen L, Sohn JH, Trivedi H, Shen Y, Buturovic L, Pereira JC, Cardoso JS, Castro E, Kalleberg KT, Pelka O, Nedjar I, Geras KJ, Nensa F, Goan E, Koitka S, Caballero L, Cox DD, Krishnaswamy P, Pandey G, Friedrich CM, Perrin D, Fookes C, Shi B, Cardoso Negrie G, Kawczynski M, Cho K, Khoo CS, Lo JY, Sorensen AG and Jung H. Evaluation of combined artificial intelligence and radiologist assessment to interpret screening mammograms. JAMA Netw Open 2020; 3: e200265.

[17] Li G, Wu X and Ma X. Artificial intelligence in radiotherapy. Semin Cancer Biol 2022; 86: 160-171.

[18] Gore JC. Artificial intelligence in medical imaging. Magn Reson Imaging 2020; 68: A1-A4.

[19] Jin X, Tang L, Li R, Ji J and Liu J. Selective transplantation method of leafy vegetable seedlings based on ResNet 18 network. Front Plant Sci 2022; 13: 893357.

[20] Jing E, Zhang H, Li Z, Liu Y, Ji Z and Ganchev I. ECG heartbeat classification based on an improved ResNet-18 model. Comput Math Methods Med 2021; 2021: 6649970.

[21] Odusami M, Maskeliūnas R, Damaševičius R and Krilavičius T. Reply to Nicholas et al. using a ResNet-18 network to detect features of Alzheimer's disease on functional magnetic resonance imaging: a failed replication. Comment on "Odusami et al. analysis of features of Alzheimer's disease: detection of early stage from functional brain changes in magnetic resonance images using a finetuned ResNet18 network. Diagnostics 2021, 11, 1071". Diagnostics (Basel) 2022; 12: 1097.

[22] Ahmad M, Liu X, Morani AC, Ganeshan D, Anderson MR, Samei E and Jensen CT. Oncology-specific radiation dose and image noise reference levels in adult abdominal-pelvic CT. Clin Imaging 2023; 93: 52-59.

[23] Samo M, Mafeni Mase JM and Figueredo G. Deep learning with attention mechanisms for road weather detection. Sensors (Basel) 2023; 23: 798.

[24] Sanjaya P, Maljanen K, Katainen R and Waszak SM; Genomics England Research Consortium; Aaltonen LA, Stegle O, Korbel JO and Pitkänen E. Mutation-attention (MuAt): deep representation learning of somatic mutations for tumour typing and subtyping. Genome Med 2023; 15: 47.

[25] Wollek A, Graf R, Čečatka S, Fink N, Willem T, Sabel BO and Lasser T. Attention-based saliency maps improve interpretability of pneumothorax classification. Radiol Artif Intell 2022; 5: e220187.