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EVALUATION OF LOW-DOSE TO HIGH-DOSE CT IMAGES USING AI AND DEEP LEARNING

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ABSTRACT

In clinical practice, Computed Tomography (CT) is indispensable for medical imaging. CT can deliver patient depicts in various dimensions. Low-dose CT occasionally produces impression with lesser resolution than standard CT, in spite of the reality that it may reduce the radiation hazards associated with CT scanning. In CT scanning, reducing the X-ray exposure the dosage can contribute to a significant deterioration in the clarity of the image, increasing the possibility of misinterpretation and missing diagnosis. The area of CT has repeatedly encountered substantial mathematical challenges, including reducing the radiation dose and developing images of outstanding quality to meet therapeutic diagnostic requirements. This paper discusses major objectives is to validate a reinforcement CT image denoising method for ultra-low-dose CT images. Neural network with convolutional auto-encoder and pairs of standard-dose CT and ultra-low-dose CT image patches were used for image denoising conventional CT image reconstruction approach with a benchmark outline, along with each one's benefits and drawbacks. A comprehensive description using artificial intelligence and machine learning applied to the Low Dose CT imaging process has been put forward. Furthermore, an experimental analysis utilizing the comparative result with an existing protocol has been assessed and evaluated based on the performance metrics using suitable simulators.

Keywords: Radiation Dose, Image Quality, Automatic Exposure Control, Contrast Agents, Dose Modulation, Phantom Studies

1. INTRODUCTION

CT imaging, or computed tomography imaging, is a medical imaging technology that provides extensive cross-sectional visuals of the body's internal organs. It combines X-ray data gathered from many different perspectives and employs computer processing to produce pictures that reveal bones, blood vessels, and soft tissues in amazing detail. This strategy is commonly used to diagnose various kinds of illnesses, arrange medical treatments, and guide specific operations. The major objectives of the Low Dose to High Dose CT Imaging using AI and ML are as follows.

1) Enhanced Image Quality:
2) Improved Diagnostic Accuracy
3) Optimal Radiation Dose Management
4) Customization for Specific Cases
5) Patient Safety and Comfort

Enhanced Image Quality provides low-dose CT images as vibrant and detailed as high-dose images through the application of complex AI and ML strategies to denoising and sharpen low-dose CT images. Improved Diagnostic Accuracy provides that the enhanced images were sufficiently precise for the proper diagnosis, likely incorporating AI-powered medical devices to assist radiologists spot anomalies. Optimal Radiation Dose Management established approaches that use artificial intelligence (AI) to respond for various client requirements and scanning environments while reconciling the lowest radiation dose with the highest possible image quality. Customization of Specific Cases Customize the AI and ML models to cope with certain types of scans or patient circumstances, such as pediatric or cardiac imaging, to provide the best possible results for an assortment of clinical environments. Patient Safety and Comfort limits radiation exposure in order to enhance patient safety while also alleviating scan time periods and enhancing the overall patient experience during imaging procedures.

To reduce the dose of radiation, researchers have examined several kinds of strategies, including optimal scan techniques, auto-milliampere seconds (mAs) control, raw data preliminary treatment, and proficient reconstruction algorithms. Among these strategies, minimizing the mAs in gathering data is an effective and simple strategy for reducing radiation dosage. However, the associated images would be seriously degraded if no adequate noise control is applied during image reconstruction. It is an intriguing and practical task to design a low-dose CT simulation technique from high-dose scans in order to optimize the minimal radiation dose with accurate diagnostic information using complex image reconstruction algorithms. Several techniques for resembling low-dose CT scans have been put out thus far. Notably, subject to the scan protocols and measurement noise characteristics, injecting Poisson or a combination of Poisson and Gaussian noise into high-dosage scan data is capable of producing some simulated low dose projection data when the raw data is readily available Zhang et al. (2024).

Medical imaging is an essential tool for research in medicine and biological studies, and imaging systems commonly provide final image visualizations using an image reconstruction approach. Information from the sensor domain is mapped to the image domain via the inverse mathematical strategy termed as image reconstruction Zhang and Seeram (2020). One essential element for creating high-quality images from sensors is an effective image reconstruction. At the lowest feasible cost and patient risk, medical image reconstruction aims to provide high-quality medical images for clinical application Woeltjen et al. (2022). Artificial intelligence and machine learning (ML) approaches provide a promising approach over reconstruction of images, with aberration reduction and reconstruction speed-up, as part of a rapidly developing discipline. In low-dose and under-sampled circumstances, the Deep Neural Network (DNN)-based image an augmentation in medical imaging results in beneficial results.

2. A STATE OF ART RELATED WORK

Sources for this state-of-the-art-related work have been collected from various databases. The initial search was carried out through Google Scholar, z-Library, MDPI and Springer Data-base to explore available across multiple databases. Broad search terms of ''Artificial Intelligence'', ''Deep Learning" and ''CT image reconstruction'' were employed. Selected scopus indexed journal papers were considered as their references for the enhancement of the research

The analysis of Machine learning and Deep learning approaches for low-dose CT image restoration complied with the following methodologies.

1) Review plans
2) Selection and extraction of data or information
3) Outcome of the experiments
4) feedback or strategic plan based on their benefits and limitations.

The prime contributions towards a benchmark approaches are as follows:

The authors in paper Moen et al. (2021), Chen et al. (2017) propose a noise extraction module that encompasses several attention strategies, including spatial, channel, and scale attention. These various attention processes improve the network's ability to extract and suppress noise by focusing on the image's ranged dimensions and shapes. Based on prior noise distribution information, we developed a denoising system comprising a generator network, a discriminator network, and a feature extraction autoencoder network Chen et al. (2023). This paper employs an Autoencoder model for reinforcement learning on a specific project dataset. The encoder aspect of the Autoencoder is then used to calculate perceptual loss. This strategy enables the model to measure the differences between manufactured and real images in a high-dimensional feature space with greater precision. The generator network is responsible for eliminating noise and delivering high-quality CT pictures, whereas the discriminator network helps discriminate between actual and denoised images, hence improving the generation effect.

The author Jeong et al. (2024), Son et al. (2024) presents a novel generator network design with BlurPool layers to minimize aliasing and enhance image quality in low-dose scenarios. The hierarchical feature synthesis module enhances feature extraction and depiction in medical imaging by exploiting spatial information without loss. A multi-scale discriminator to facilitate the bias of small characteristics like edges and patterns, which results in higher-quality image reconstructive surgeries.

The author in paper Kang et al. (2019), Yin et al. (2023) developed a CycleGAN for inconsistency multiphase CT angiography denoising. The GAN-CIRCLE proposed the Wasserstein distance into the framework based on CycleGAN and demonstrated that by employing mismatched datasets, the model can effectively learn additional structure-related characteristics of Cycle-free CycleGAN. Chen et al. (2023) The author modified CycleGAN using an attention gate to extract useful salient features and intended at enhancing denoising performance.

The author Chen et al. (2023), Zhang et al. (2024) contributes a novel ASCON strategy for investigating fundamental anatomical information in LDCT denoising, which is essential for its interpretability. creating an ESAU-Net with a channel-wise self-attention mechanism that captures both local and global contexts. A MAC-Net with a disentangled U-shaped design that includes both global non-contrastive and local contrastive modules. This allows for the extraction of inherent anatomical semantics at the patch level while also increasing anatomical consistency at the pixel level. Extensive experimental findings show that ASCON outperforms existing approaches and provides anatomical interpretability for LDCT denoising.

Sohl-Dickstein et al. (2015) Diffusion models have recently emerged as a strong alternative to GANs for a variety of image synthesis tasks, including medical imaging.

Unlike GANs, which generate images through adversarial training methods, diffusion models optimize a noisy image iteratively towards the ideal image distribution. This method has been verified to be extremely successful for generating high-quality photos that have fewer artifacts.

The author Arslan et al. (2024) developed a self-consistent recursive diffusion bridge for medical image translation, which excelled prior approaches in cross-modality synthesis tasks such as CT to MRI conversion. Combining mathematical models of diffusion into CT denoising frameworks has the potential to improve image quality by reducing noise and artifacts.

The author Xiang and Pang (2018) proposed in this paper Compare it to standard denoising techniques such as original Denoising Auto-encoders, BM3D, total variation minimization, and non-local mean algorithms. Experiments demonstrate that Improved Denoising Auto-encoders establish less non-existent artifacts and are more resilient than other innovative denoising algorithms in both PSNR and SSIM indexes, especially under low SNR.

3. METHODOLOGY AND IMPLEMENTATION

3.1. METHODOLOGY

Numerous CT dosage approaches have been established to preserve doses. However, this might result in poorer CT image quality. The resolution of the images in CT may be assessed by evaluating the signal to noise ratio, image resolution,

CT image reconstruction is an innovative technique that involves developing tomographic depicts from X-ray projection data gathered from various angles around the area of interest. The self-supervised LDCT model aim to improve the quality of LDCT images while minimizing radiation exposure to patients.It exploits the correlation between nearby projection images and doesn't require paired CT images is as shown in Figure 1.

Figure 1

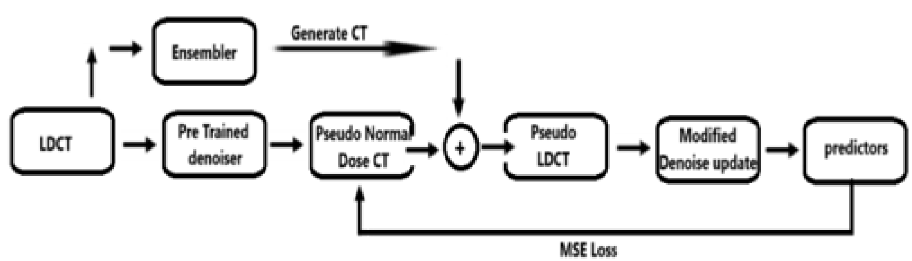

Figure 1 Proposed Self Supervised LDCT Model

There are two main types of reconstruction techniques: analytical reconstruction and iterative reconstruction.

1) Analytical Reconstruction

Filtered Back Projection is the most widely used analytical reconstruction strategy. This method gives a one-dimensional filter to the projection data before backprojecting it into the image space. FBP is popular for its computational performance and numerical stability. Progressively, numerous FBP-type tackles have been developed to fit different kinds of CT data collecting geometries, namely parallel-beam, fan-beam, helical, and multi-slice CT.

2) Iterative Reconstruction (IR)

Iterative reconstruction techniques are more complex, involving multiple attempts to enhance the image. These techniques replicate the data gathering process and repeatedly enhance images by comparing measured projection data to projections determined by present scenario. Iterative reconstruction can considerably reduce noise and enhance image quality, particularly at low radiation doses.

The most recent developments in CT image reconstruction have centered on model-based iterative reconstruction (MBIR) and application-specific reconstruction methods Seeram and Kanade (2024). These strategies use sophisticated optimized algorithms, especially artificial intelligence, to enhance image quality and limit radiation exposure.

In paper Won et al. (2021) CT image reconstruction includes a) Reduced Radiation Dose: AI algorithms can produce clear images with less radiation, making CT scans safer for patients. b) Faster Processing: DL techniques are much quicker than traditional methods, speeding up diagnosis and treatment. c) Improved Image Quality: AI can enhance image clarity and reduce artifacts, leading to more accurate diagnoses.

3.2. IMPLEMENTATIONS

Assume pre-trained LDCT denoiser $f_x(x,y)$ trained with previous Low Dose CT $f(X)$ and Normal Dose CT $f(Y)$ images. f_x trained can be trained using any optimized AI ML algorithms supervised for fine tuning. To achieve this, N generated pre-trained LDCT noise model with pseudo noisy LDCT are compared, the difference between the two become the pseudo–Normal Dose CT image $f(Y')$. The modified proposed LDCT denoiser initialize the weight of $f_x(x,y)$ and update the same at different steps using self- supervised loss between the pseudo CT image with the predictions is as shown in Figure 2 and Figure 3.

Figure 2

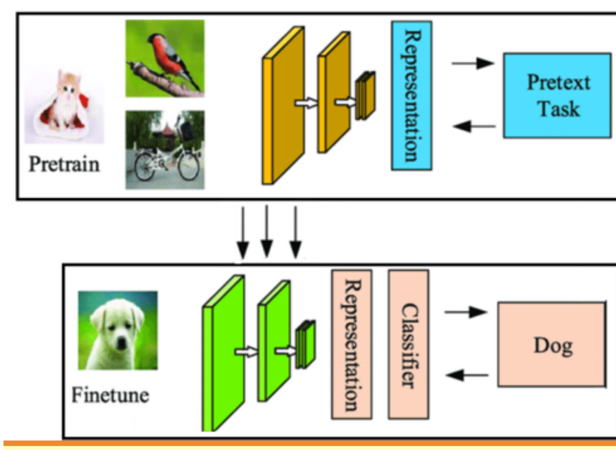

Figure 2 Self Supervisory Learning

The main contributions of this proposed Low dose CT are as follows:

1) Propose a novel self-supervised learning scheme for CT denoising,
2) Create realistic Pseudo LDCT by leveraging diverse noise generated from ensemble noise models.

3) Empirical results confirm that proposed method improves the performance of several existing methods

Figure 3

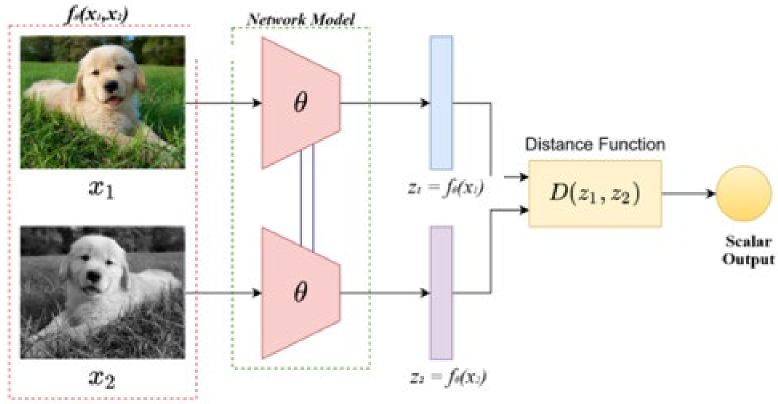

Figure 3 Energy Based Model Using Embedded System Architecture

3.3. PRE-TRAINED PROPOSED NOISE MODEL

A pre trained low dose CT noise model predicts CT noise $f_\theta(x,y)$ from $f(X)$. The difference between LDCT $f(X)$ and NDCT $f(Y)$ generates N hoped-for values for map Z noise through Embedded network model. Several N equal networks subjected to CT images trained are used as a set of database LDCT noise models. For all subsequent data, these models are fixed without any parametric updates.

3.4. CT IMAGE GENERATION

Pseudo-CT image generation is a fascinating application of AI in medical imaging It involves creating CT-like images from other imaging modalities, such as MRI, without exposing patients to additional radiation.

To generate pseudo images for supervision, both $f_\theta(x,y)$ and N are employed. Pseudo CT images consists of pair of $f_\theta(x)$ and $f_\theta(y)$ which are reformed as follows,

$$f_\theta(y) = f_\theta(X) \quad \text{--(1)}$$

$$Zm = Nm(X) \quad \text{--(2)}$$

$$f_\theta(x) = f_\theta(y) + Emsemble(Z) \quad \text{--(3)}$$

Where , m is the index of N

Once $f_\theta(x)$ fed to $f_\theta(x,y)$ a clean version of $f_\theta(X)$ and is denoted by pseudo normal dose CT of $f_\theta(y)$. The ensemble of N predicts the generated $f_\theta(x)$ by feeding $f(X)$ into Nm to predict noise Zm for all image pixels. By adding $Ensemble(Z)$ to $f_\theta(y)$ can obtain pseudo low dose CT image $f_\theta(x)$.

Formally,The mean squared error (MSE) is utilized as the loss function $f'_\theta(x,y)$ is given by

$$L(\tilde{Y}, \hat{Y}) = \frac{1}{K}\sum_{k=1}^{K} \quad ||f_\theta(\widetilde{X}) - \tilde{Y}||_2^2 \quad \text{--(4)}$$

where $\hat{Y}$ is prediction from $f'\theta(x,y)$ and K is the mini-batch size per step.

4. CONCLUSIONS AND DISCUSSIONS

AI and ML significantly enhanced CT imaging, in particular transforming from low-dose to high-dose investigations. These technologies enabled the creation of excellent images while limiting radiation exposure, solving a significant issue in medical imaging. The inclusion of AI and ML in CT imaging has increased the image quality and cut back processing times, making it a viable tool in medical scenarios.

The development of deep learning algorithms, such as convolution neural networks, has been vital in improving image reconstruction. These algorithms adequately reduce noise and artifacts, leading to more efficient, more accurate images.To despite the progress, challenges remain, such as the need for extensive training data, ensuring model interpretability, and integrating these advanced techniques into clinical workflows.

Future Directions of research will likely focus on refining AI algorithms, improving data acquisition methods, and expanding the application of these technologies in various medical imaging modalities.

CONFLICT OF INTERESTS

None.

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