Neural Rendering Techniques for Medical Imaging: A Comprehensive Survey

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ABSTRACT
Neural rendering is arising as a leading tool at the intersection of computer vision, computer graphics, and artificial intelligence, and allows for generating high-quality, photorealistic images from 2D models, low-resolution images, or sparse data. The review offers a comprehensive outline of the state-of-the-art techniques in neural rendering, including neural radiance fields (NeRF), view synthesis and implicit surface representation models. However, the success of these models is strongly tied to the availability and quality of medical datasets, which often face challenges related to data scarcity, patient privacy, and modality diversity. The article also explores key application in areas such as virtual reality, autonomous systems, and medical imaging, where neural rendering has shown significant promise. This survey reviews state-of-the-art neural rendering methods in healthcare, discusses benchmark datasets, identifies open challenges, and outlines future research directions.

Keywords
NeRF, computer vision, photorealistic, 2D models, artificial intelligence

1. INTRODUCTION
The rapid growth of deep learning in medical imaging has enabled novel possibilities for rendering and interpreting complex anatomical structures. Neural rendering, which uses neural networks to synthesize novel views and modalities, has emerged as a promising technique for improving visualization, diagnosis, and simulation in clinical practice. This survey explores the current landscape of neural rendering in healthcare, offering a structured outline of state-of-the-art methods, their limitations, applications and potential future impact

Neural radiation fields, or NeRFs, greatly improved on conventional 3D reconstruction techniques in a number of crucial areas. NeRFs leverages deep learning techniques to generate photorealistic images from abstract or incomplete input data. Medical imaging plays an essential task in modern healthcare industry, providing non-invasive insights into the anatomy and physiology of the human body. Common imaging modalities include X-ray imaging, Ultrasound, Computed Tomography (CT), Magnetic Resonance Imaging (MRI) and Positron Emission Tomography (PET).

Despite their clinical importance, medical images often present significant visualization and come across challenges such as medical scans typically consist of 3D or even 4D data making visualization and manipulation computationally intensive. Conventional imaging offers only standard anatomical planes which may not capture the full spatial context required for accurate interpretation or surgical planning. As no single modality captures all relevant biological information, thereby MRI offers excellent soft-tissue contrast, while CT excels in imaging bone structures. Integrating and visualizing this multi-source data remains a key challenge.

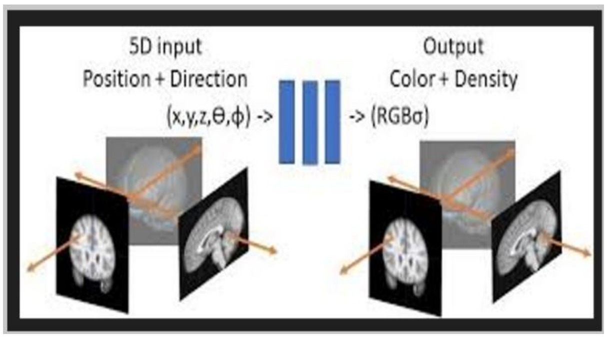

Fig 2: Overview of working Nerf model

These limitations have created a growing demand for more intelligent, adaptive visualization tools that go beyond traditional rendering pipelines. In healthcare, neural rendering holds significant promise due to its ability to enhance visualization of complex anatomical structures through novel view synthesis and high-resolution rendering. It has capability of generating realistic synthetic medical data for data augmentation, addressing challenges associated to limited labeled datasets. By improving both utility and quality images, neural rendering has potential to assist clinicians, reduce patient burden, and open up new possibilities in personalized medicine and AI-assisted diagnosis.

The survey article aims to emphasize motivation, challenges, various applications in health care industry and limitations associated in implementing NeRFs for medical images. The main objective of the survey it offers better visualization of medical images, integration of Neural Rendering with AI-driven diagnosis and treatment planning, evaluation and validation of neural rendering in clinical and research settings and to assess the potential benefits of 3D rendering of medical images to improve healthcare.

The contribution of the work is outline as:

• The survey highlights the key objective and challenges related with applying NeRFs to medical images, finding out the important complication that has to overcome.

• The review emphasis on classifying and revising existing Nerf methodologies, highlighting their evaluation metrics.

• Additionally, the upcoming future work highlighting how

NeRFs when adopted in medical field can modernize diagnostic methods, pre-surgical planning and improvements in healthcare industry.

The remaining section of the article is structured as follows. Section 2 comprises of background and fundamentals of NeRFs. The methods adopted in NeRF are described in Section 3. The publically available datasets for NeRFs in medical images are summarized in Sections 4. We talk about the future direction in Section 5 and conclusion of the paper in Section 6.

2. BACKGROUND

Xin Wang et al[1] have emphasized on through the creation of 3D representations from 2D pictures. Neural Radiance Fields (NeRF) hold the prospective to transform medical images. Four primary issues are identified in the paper: color density significance, inner structure needs, object boundary definitions, and imaging principles.

Mingyuan Yao et al [2] focused on providing a comprehensive review of Neural Radiance Fields (NeRF), highlighting its advancements in computer vision and graphics. The key points include NeRF's role in human body reconstruction, 3D scene understanding and perspective synthesis.

Khadija Iddris et al [3] focused that in order to improve medical diagnosis and treatment planning; the study addresses developments in 3D MRI imaging. It emphasizes how precise 3D reconstructions from 2D MRI slices can be developed using neural radiance fields (NeRF), which eliminates necessitates for lengthy scan acquisitions. With the potential to reduce motion artifacts and scan delays, this technique seeks to enhance the visualization and study of anatomical structures. The author Faisal Mahmood et al [4] suggests that the article discusses the challenges in applying deep learning to medical images due to limited annotated data, particularly for rare conditions. The authors present a technique which utilizes cinematically rendered data to improve the generalization of a synthetic data-driven model for exact depth estimation in real tissue.

Focusing on drawbacks of conventional methods, the motivation of adopting neural approaches in healthcare industry is improved data visualization, having insights into diagnosis and improved pre-surgical plan.

3. METHODOLOGY

The neural rendering approach has found increasing application in medical imaging, where rendering high-quality, informative visualizations from limited data are clinically valuable. The most basic neural rendering techniques are explained in figure 1 as shown below.

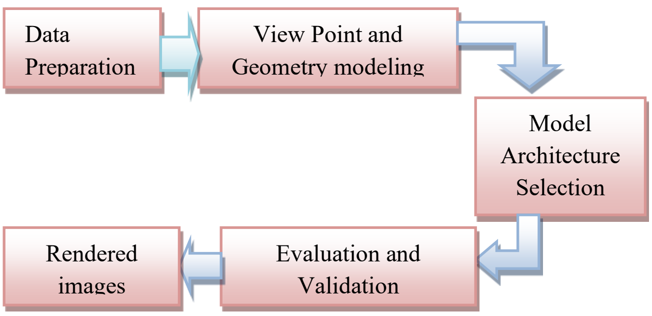

Fig 2: Steps for creating Nerf model

3.1 Data Preparation:

Collect the data CT, MRI or X-ray in (DICOM format). Perform the preprocessing such as normalize intensity values, resize or crop to consistent dimensions and augmentation of data.

3.2 View Point and Geometry modeling:

The pose estimation becomes essential when working with multiple views, such as stacks of CT or MRI slices. This step involves determining the spatial relationships between different image acquisitions. Define intrinsic/extrinsic parameters for neural radiance fields (NeRF-like models) to accurately model how each 2D image maps into 3D space.

3.3 Model Architecture Selection:

Choose an appropriate neural rendering framework suitable for implementation. The various neural rendering frameworks are explained below:

3.3.1 Implicit Neural Representations

The Implicit Neural Representation (INR) models encode 3D information (such as geometry, color, or density) adopts neural network, classically a Multi-Layer Perceptron (MLP). They adopt the concept of storing data as voxel grids or meshes, the MLP learn a continuous mapping from spatial coordinates to physical properties like color or density. This approach is memory-efficient and provides high-resolution reconstruction [9].

3.3.2 Neural Radiance Fields (NeRF)

The NeRF can be defined as a neural volume rendering method that synthesizes photorealistic novel views of a 3D scene using only 2D input images. It learns a function that maps a 3D point and viewing direction to volume density and emitted radiance. In medical applications, NeRF variants like MedNeRF and Neural AD are being explored for 3D organ reconstruction, volumetric visualization, and view synthesis from limited-angle scans [10].

3.3.3 Generative Adversarial Networks (GANs)

GANs consist of a generator and a discriminator competing in a mini-max game to produce realistic images. The task of generator is creation of fake images and a discriminator that distinguishes real from fake ones. The concept of CycleGAN is adopted for cross modality image synthesis i.e. converting MRI to CT and vice versa. It is applicable for obtaining super resolution and performing data augmentation. GANs are widely used in medical image synthesis, where paired data are scarce. [11].

3.3.4 Diffusion Models

Diffusion-based rendering leverages diffusion models to generate images or volumes through a gradual denoising process. In the context of rendering, diffusion models are adapted to synthesize novel views, modalities, or enhanced versions of images from learned distributions. The working of diffusion model is described in two step model forward and reverse process. One common example of diffusion in medical rendering is Medfusion and Conditional 3D Diffusion [12].

3.3.5 Transformer-Based Rendering

Transformer-based models are being explored for applications like view synthesis, modality translation, and volume reconstruction—especially when working with complex or sparse data. Transformers can be used to integrate information from different views and generate novel views by modeling the spatial relationships between them. Example: A transformer model learns to generate synthetic PET images from paired MRI scans [13].

3.4 Evaluation and Validation

Adopt quantitative metrics such as PSNR, SSIM and qualitative analysis. In order to ensure generalization across patients makes use of cross validation techniques and finally real time rendered image is obtained.

The table 1 mentioned below comprises of existing methods of NeRF, the dataset utilized and the results obtained.

Table 1: Existing methods of NerF

Sl.no	Author	Organ	Methodology	Imaging Principle	Dataset	Results
1.	Khadija Iddris et al [3]	Brain	Convolution Neural Networks (CNN) for feature extraction and cubic interpolation for slice interpolation.	MRI	BRATS dataset	PSNR-25.01 ± 1.17 SSIM-0.879 ± 0.07
2.	Faisal Mahmood et al [4]	Stomach (colon)	Cinematic rendering and Graphical rendering	CT	Synthetic image dataset	Relative error – 0.364 Average log10 Error (log10) – 0.221 Root mean square error – 2.153
3.	Nicholas Bien et al [5]	Knee	CNN and Logistic regression	MRI	Real time data collected from Stanford University Medical Centre	Accuracy – 0.920 Specificity - 0.933 Sensitivity – 0.906
4.	Yuanhao Cai et al [6]	Chest	Line Segment-based Transformer method.	X-ray	X3D dataset	Average PSNR – 12dB Average SSIM - 0.9535
5.	Yukun Zhou et al) [7]	Retina of Eye	Vision Transformer as an encoder and CNN.	CT	Moorfields Diabetic image dataset.	Sensitivity – 0.7 Specificity – 0.67 AUROC – 0.794

4. DATASETS AND EVALUATION METRICS

Datasets are absolutely crucial in neural rendering. They act as a fuel for neural engine. The creation of NeRFs in medical imaging is greatly aided by public datasets, which provide a richness of unique and annotated data that is crucial for algorithm developing and validating.

4.1 Digitally Reconstructed Radiographs(DRR):

DRRs serve as bridge among 3D CT data and 2D X-ray imaging, enabling the development of AI models for diagnosis, treatment planning, and disease classification. The main aim of DRRs is to simulate 2D X-ray images from 3D CT scans. The DRRs provide good assistance in creating reference projections to match with real-time 2D X-rays, enabling better accuracy and real-time updates. The synthetic data produced by DRR provide a benchmark to the researcher as they are implementing on ground truth data. The primary advantage of using DRR technology is it facilitates the reduction in additional diagnostic X-ray examination, thereby minimizing exposure of patient to ionizing radiation [14]. The figure 2 shows the procedure of generating synthetic data.

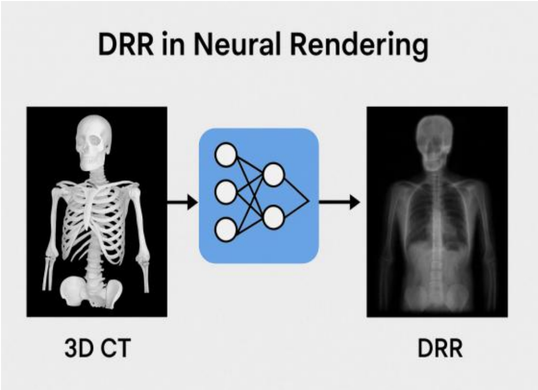

Fig 2: The conversion of 3D image to DRR is performed by neural network. Left: original CT scan image, Mid: neural network processing 3D data, Right: generated DRR image

4.2 Public Dataset

4.2.1 MedNeRF dataset:

The dataset is publically available in GitHub repository which comprises of 20 chest CT scans and in addition 5 knees CT scans. The concept of DRR is adopted, in order to create synthetic images with a resolution of 128 × 128 at five-degree intervals; the DRR production procedure simulates the rotation of an imaging panel and radiation source around the vertical axis. As a result, 72 unique DRRs were generated by each item [15, 16, 17, 18].

4.2.2 LIDC-IDRI dataset:

The LIDC-IDRI [19] is publically available dataset contains 1018 helical thoracic CT scans gathered from seven institutions, ensuring a diverse range of scanner models and technical parameters. These scans were anonymized to eliminate protected health information (PHI) in compliance with HIPAA guidelines. The dataset includes a variety of lesions, with 7371 lesions identified, but only 1940 lesions had complete agreement among four radiologists on their categorization.

4.3 Evaluation Metrics

Variety of techniques has been implemented to estimate the effectiveness of NeRFs in medical imaging such as Peak to Signal Noise Ratio (PSNR), Structural Similarity Index (SSIM), Reprojection error[20], Learned perceptual image patch similarity (LPIPS) and Gradient magnitude similarity deviation (GMSD)[25].

4.3.1 The Peak to Signal Noise Ratio (PSNR):

It is primarily adapted to measure quality of an image. If the obtained PSNR value is higher, it conveys that generated image is more similar to original image. The major goal of PSNR is to quantify the variance between the actual and model-generated images [21].

4.3.2 The Structural Similarity Index Measure (SSIM):

The SSIM provides an inclusive evaluation technique that measures perceived quality by comparing structures in images. The SSIM considers factors such as luminance, structural integrity and contrast. The range of SSIM lies between SSIM € [0, 1]. The value ‘1’ defines a perfect match and ‘0’ defines as completely different [22].

4.3.3 The Reprojection error:

It is called as evaluation metric adopted in 3D reconstruction, camera pose estimation, view synthesis and neural rendering. The potential benefit of reprojection error [23] is to measure how far 3D point, when projected back onto the image, deviates from where it should appear. The value obtained in reprojection error should be lower which conveys that proper alignment between 2D to 3D representation. The higher value in the reprojection error suggests that misalignment between 3D and 2D representations. It is defined by a formula

Reprojection Error = ‖xobserved − xprojected ‖

4.3.4 Learned perceptual image patch similarity (LPIPS):

The LPIPS [25] compares deep features taken from neural networks to determine how original and rebuilt images are perceptually similar. Because it captures subtleties that pixel-wise measurements like PSNR or SSIM could miss, LPIPS is especially helpful in assessing how closely the reconstructed volume resembles the human perception of similarity.

4.3.5 Gradient magnitude similarity deviation (GMSD):

The GMSD [25] assesses how much the original and reconstructed images differ in gradient magnitude. Especially in areas with significant spatial variability, GMSD is useful for assessing how well edges and small features are preserved in the reconstructed volume, offering further information about the reconstruction's quality.

5. CONCLUSION

The conclusion conveys that, research into Neural Radiance Fields (NeRF) for medical imaging shows promise for improving early disease diagnosis, treatment planning, and diagnostic accuracy. In this article, the author has observed several challenges that are critical for medical analysis. The survey highlights the need for creative ideas that can overcome these challenges by carefully analyzing existing approaches and having a thoughtful conversation about the promise and constraints of NeRFs. The combination of NeRFs along with cutting-edge technologies and methodologies has potential to greatly advance medical imaging as we move forward, focusing the urgent need for ongoing research, teamwork, and creation of innovative strategies to fully realize NeRFs' potential to transform medical imaging. A comprehensive analysis of existing NeRF-based approaches reveals that while there is significant progress, many techniques are still in their early stages and require further refinement for clinical adoption.

6. FUTURE DIRECTION

In addition to addressing the constraints outlined above, we also notice a few significant future avenues for NeRFs in medical imaging that will get increased interest.

Real-Time Rendering for Surgery and Robotics: Future developments should emphasize on improving the speed of neural rendering models. Advanced algorithms could be designed to obtain more efficiency in real time rendering and adopt techniques such as FastNeRF, Instant-NGP (NVIDIA) and TensorRF. When real time rendering is incorporated with robotics, provides potential benefits in image-guided surgery, robotic interventions and AR/VR-assisted diagnostics.

Integration with new Advanced Techniques: Sometimes neural rendering models fail when applied to rare or unusual diseases such as cancer. The future NeRFs should lay more emphasis on significant advancements, especially with new techniques that deals with uncommon diseases. More data-efficient models has to be developed that can handle low-data regimes and out-of-distribution scenarios.

Data Scarcity and Better Synthetic Data: Diverse and authentic data is basic necessity in development of a research work. Medical data is often termed to be private, rare and expensive to label. Improvements have to be adopted in creating high quality synthetic datasets using DRR, GANs and diffusion models that reflect real world diversity.

Integrating with Explainable AI (XAI) Techniques: To enhance the trustworthiness of neural rendering in medical applications, Explainable AI (XAI) techniques are becoming essential. Provenance maps and feature attribution techniques, Grad-CAM and Integrated Gradients, can highlight which part of input data contribute to specific output regions.

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