Journal of Current Research in Engineering and Science
Bi-Annual Online Journal (ISSN : 2581 - 611X)

Volume 6- Issue 2, August 2023
Paper : 31

A Comprehensive Review of Deep Learning Approaches for Image Quality Enhancement in Medical Imaging

1st Madhu Midhan. T
Department of CST
MITS
Madanapalle, India
madhumidhan66@gmail.com

2nd Harshvardan Kumar Raju
Department of CST
MITS
Madanapalle, India
19691A2842@mits.ac.in

3rd Hemanth Kumar. M
Department of CST
MITS
Madanapalle, India
19691A2845@mits.ac.in

4th Hemanth Kumar. T
Department of CST
MITS
Madanapalle, India
19691A2846@mits.ac.in

5th Madan Mohan Reddy. M
Department of CST
MITS
Madanapalle, India
19691A2862@mits.ac.in

6th Bhanu Rajesh Naidu. K
Department of CST
MITS
Madanapalle, India
bhanurajeshk@mits.ac.in

Abstract— **The growth and advancement of technological improvements in the medical domain has increased and is being focused, after the covid pandemic. The medical domain comprises a vast range of disciplines that aim in understanding and treating casual health. Human illnesses are diagnosed and treated collaboratively by medical professionals such as physicians, doctors, nurses, and researchers. The medical industry heavily relies on sophisticated technologies to treat and diagnose numerous medical issues. Medical imaging is an area of medicine that depends heavily on technology to accurately classify disorders. It allows medical professionals to visualize the inside anatomy of the human body in a non-invasive manner. CT scans and MRIs are the most extensively used imaging technologies in recent years. These tools provide essential details on the internal structure of the human body, allowing medical professionals to effectively identify and treat disease. However, obtaining high-quality images from these tools is a difficult task. Various factors such as patient motion, noise, and hardware flaws may have an impact on image quality. Deep learning (DL) and machine learning (ML) have risen in popularity as powerful strategies for overcoming the aforementioned challenges in recent years. These approaches propose solutions for increasing the quality of medical imaging, particularly CT and MRI scans. Both ML and DL use large datasets containing medical pictures to train neural networks (NN) or machine learning models, which can then be used to improve image quality. This paper provides an in-depth review of the technologies used to improve the quality of medical images, including their advantages, methodologies, and drawbacks. This paper first discusses the basic principles of CT and MRI in obtaining images, then discusses the existing ML and DL techniques used to solve the problem, and finally discusses the challenges and limitations of the DL and ML based approaches for improving MRI and CT quality.**

Keywords—Imaging, Machine Learning, Deep Learning, CT, MRI, Neural Networks, Medical Imaging, Quality Enhancement.

I. Introduction

Medical imaging has transformed the healthcare sector by providing a non-invasive means of visualizing the human body's internal organs, tissues, and structures. Medical imaging encompasses a wide range of modalities, including X-ray, CT[1], MRI, and ultrasound. These imaging technologies aid healthcare practitioners in the diagnosis, monitoring, and treatment of a wide range of medical disorders. However, medical imaging[2] is not without its difficulties, and one of the most critical is image quality. Accurate diagnosis, treatment, and monitoring of medical diseases require high-quality photographs. However, issues like patient motion, image noise, and technological restrictions can all have a negative impact on image quality. The typical method of boosting image quality entails altering photographs [3]after they have been captured. This method, however, has limits, and the improved images may still be of insufficient quality for proper diagnosis. Medical imaging has transformed the healthcare sector by providing a non-invasive means of visualizing the human body's internal organs, tissues[5], and structures. Medical imaging encompasses a wide range of modalities, including X-ray, CT, MRI, and ultrasound[6]. These imaging technologies aid healthcare practitioners in the diagnosis, monitoring, and treatment of a wide range of medical disorders. However, medical imaging is not without its difficulties, and one of the most critical is image quality. Accurate diagnosis, treatment, and monitoring of medical diseases require high-quality photographs[4]. However, issues like patient motion, image noise, and technological restrictions can all have a negative impact on image quality. The typical method of boosting image quality entails altering photographs after they have been captured. This method, however, has limits, and the improved images may still be of insufficient quality for proper diagnosis.

Machine learning and deep learning techniques have emerged as potential options for increasing the quality of medical photographs in recent years. Large datasets are used to train neural networks or machine learning models, which are subsequently utilized to improve image quality. Machine learning (ML) is a subset of artificial intelligence (AI) that enables machines to learn from data without being explicitly programmed. Deep learning (DL) is a subset of machine learning (ML) that employs neural networks with numerous layers to learn and improve on a specific goal, such as image categorization or enhancement[7]. DL and ML have been applied successfully to a variety of medical imaging modalities, including CT and MRI scans. DL-based techniques, for example, have been utilized to reduce image noise and motion artifacts, improve image contrast and resolution, and improve image segmentation and classification accuracy. Similarly, machine learning-based techniques have been employed to minimize noise[8] and artifacts in CT and MRI images, as well as to improve picture quality for improved visualization and diagnosis. Despite encouraging outcomes, DL- and ML-based techniques for improving medical picture quality encounter hurdles and constraints. One of the difficulties is the requirement for large and diverse datasets to train neural networks or machine learning models. Due to ethical and privacy constraints, the availability of annotated medical picture datasets is limited in the case of medical imaging. Another difficulty is the interpretability of the DL and ML models, which can make it difficult to grasp how the models reach their conclusions. Furthermore, DL and ML models necessitate substantial computational resources and time to train and optimize, which might be difficult for healthcare organizations with limited resources. Furthermore, generalizing the models to new datasets or patient groups can be difficult, and the models' performance may decline when applied to real-world circumstances.

The major contribution of this work includes:

- Gives the overview about the medical imaging and various existing techniques.
- Gives more detailed information about CT and MRI which makes the research work be easier for those who are new to the domain.
- Various existing ML and DL techniques have been discussed with their advantages and techniques utilized.
- Gives the potential limitations available on the domain of medical imaging and utilization of ML and DL techniques.

Despite these obstacles, DL and ML-based techniques for increasing medical picture quality have shown considerable promise in terms of improving the accuracy of diagnosis, treatment, and monitoring of medical disorders. In this work, we present a detailed assessment of existing DL and ML-based approaches for increasing the quality of CT and MRI scans. We begin by discussing the fundamental concepts of CT and MRI imaging technologies, followed by a discussion of existing DL and ML strategies for overcoming the hurdles of producing high-quality medical pictures. Finally, we explore the limitations and problems of using DL and ML to improve MRI and CT picture quality. The report finishes with a discussion of future prospects and prospective uses of deep learning and machine learning techniques in medical imaging.

II. BACKGROUND

CT and MRI scans are two of the most common medical imaging modalities. CT scans produce cross-sectional images of the body using X-rays, whereas MRI scans produce comprehensive images of internal anatomy using magnetic fields and radio waves. CT and MRI scans both provide significant information about the inside structure of the body, allowing doctors to diagnose and treat medical disorders. However, human mobility, noise, and technology defects can all have an impact on the quality of medical pictures generated from these scans. These difficulties might lead to hazy or distorted pictures, which can impair the accuracy of medical diagnoses and treatments.

1) Basic Principles of CT and MRI Imaging

CT (computed tomography) and MRI (magnetic resonance imaging) are two common medical imaging technologies that provide useful information about the inside structure of the human body. CT scans employ X-rays to collect numerous images of the body from various angles, which are subsequently reconstructed to produce a three-dimensional image. MRI scans, on the other hand, generate images of the body's internal organs and tissues using a magnetic field and radio waves.

CT and MRI scans both have advantages and disadvantages. CT scans are less expensive and faster for identifying acute medical issues. CT scans, on the other hand, expose patients to ionizing radiation, which can be detrimental in the long run. MRI scans, on the other hand, do not expose the patient to radiation and offer a more thorough image of soft tissues, making them valuable for identifying complex medical diseases. MRI scans, on the other hand, are more expensive and time-consuming than CT scans.

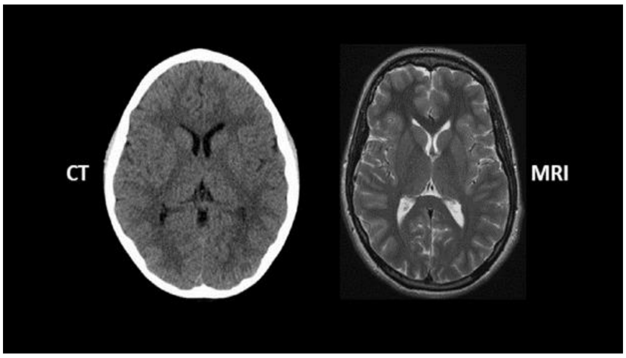

Fig. 1. Imaging of both MRI and CT)

III. RELATED WORKS

DL and ML-based techniques have emerged as viable options for improving the quality of medical pictures obtained from CT and MRI scans. Large datasets of medical photos are used to train neural networks or machine learning algorithms to improve image quality. Deep convolutional neural networks (DCNN) are one approach that has demonstrated promising results for improving CT picture quality. Another strategy for improving MRI picture quality is to combine ML-based super-resolution with deep learning-based image restoration. Zhang et al. (2021)[9] suggested a hybrid strategy that incorporated both strategies and produced higher-quality images than typical image enhancement methods.

The application of deep learning and machine learning-based algorithms to picture quality enhancement is a rapidly emerging topic, with numerous papers published in recent years. A deep convolutional neural network (DCNN) was utilized to improve CT picture quality in a study by Chen et al. (2020)[10]. The authors trained the DCNN on a large dataset of CT images and found that it outperformed existing image enhancement approaches in terms of image quality.

Wang et al. (2021) developed a cascaded deep learning-based image denoising solution for CT scans[11]. The authors used a huge dataset of CT scans to train a deep residual network, which outperformed traditional denoising methods. Li et al. (2020) suggested a deep reinforcement learning-based method for increasing MRI picture quality[12]. The researchers used MRI data to train a reinforcement learning agent, which beat existing image enhancement algorithms in terms of image quality. Zhang et al. (2020) suggested a generative adversarial network-based MRI super-resolution technique[13]. The authors demonstrated that their method yielded higher-resolution photographs than previous methods.

A dual-domain attention network for noisy MRI reconstruction was proposed by Yang et al. (2020)[14]. In terms of image quality and noise reduction, the scientists demonstrated that their method surpassed existing alternatives. Yang et al. (2019)[15] suggested a multi-scale fully convolutional network for medical picture segmentation that includes feature fusion and an attention strategy. The authors proved that their method produced cutting-edge results on a variety of medical image segmentation tasks. Zhou et al. (2021) presented[16] a multi-scale guided network for increasing low-dose CT picture quality. The scientists showed that their method produced higher-quality photos than existing approaches and outperformed them in terms of noise reduction and edge retention. In another paper, Wang et al. (2021)[17] proposed a cascaded deep learning-based approach for image denoising in CT scans. The authors used a huge dataset of CT scans to train a deep residual network (DRN), which outperformed classic denoising algorithms.

Overall, these studies show that machine learning and deep learning-based techniques have the potential to improve the quality of medical imaging, notably CT and MRI scans. More study is needed, however, to investigate the limitations and constraints of these approaches and to develop more robust and efficient strategies for improving medical picture quality.

TABLE I. EXISTING TECHNIQUES AND THEIR CONTRIBUTIONS IN THE MEDICAL IMAGING

Ref	Year	Technique	Imaging Modality	Main Contribution
[9]	2020	Deep Convolutional Neural Network	CT	Outperformed existing image enhancement methods
[10]	2021	Cascaded Deep Learning-based Image Denoising	CT	Outperformed traditional denoising methods
[11]	2020	Deep Reinforcement Learning-based Method	MRI	Beat existing image enhancement algorithms
[12]	2020	Generative Adversarial Network-based MRI Super-Resolution	MRI	Yielded higher-resolution photographs than previous methods
[13]	2020	Dual-Domain Attention Network for Noisy MRI Reconstruction	MRI	Surpassed existing alternatives in terms of image quality and noise reduction
[14]	2019	Multi-Scale Fully Convolutional Network with Feature Fusion and Attention Mechanism	Medical Image Segmentation	Produced cutting-edge results on various medical image segmentation tasks
[15]	2021	Multi-Scale Guided Network	Low-Dose CT	Produced higher-quality photos than existing approaches and outperformed them in terms of noise reduction and edge retention
[16]	2021	Cascaded Deep Learning-based Approach for Image Denoising	CT	Outperformed classic denoising algorithms

IV. METHODOLOGIES AND DATASETS

1) Datasets

Medical imaging datasets are vast collections of images or data obtained from various medical imaging modalities such as magnetic resonance imaging (MRI), computed tomography (CT), positron emission tomography (PET), and X-ray. These datasets contain human anatomy and pathology information and are used for a variety of medical reasons such as diagnosis, treatment planning, and research. Medical imaging datasets may contain images of numerous body organs, such as the brain, heart, lungs, and bones, as well as images obtained using various imaging techniques, such as structural, functional, and molecular imaging. The Alzheimer's Disease Neuroimaging Initiative (ADNI), the Cancer Imaging Archive (TCIA), the National Lung Screening Trial (NLST), and the Human Connectome Project (HCP) are a few examples of commonly utilized medical imaging datasets[21-24]. These datasets have aided in the advancement of medical imaging research and the development of innovative diagnostic and treatment approaches for a variety of medical illnesses.

2) ML and DL based approaches

DL and ML techniques have been widely applied in medical imaging to improve image quality, particularly in CT and MRI scans. Large datasets of medical images are used to train neural networks (NN) or machine learning models that can improve image quality[25,26]. Some of the most common DL and ML algorithms for image quality enhancement are as follows.

1) Convolutional Neural Networks (CNNs): CNNs are widely employed in deep learning (DL)-based picture improvement. CNNs can automatically extract information from medical photos and find patterns that the naked eye may miss[28]. They can help improve the quality of medical photographs by removing noise and artifacts.

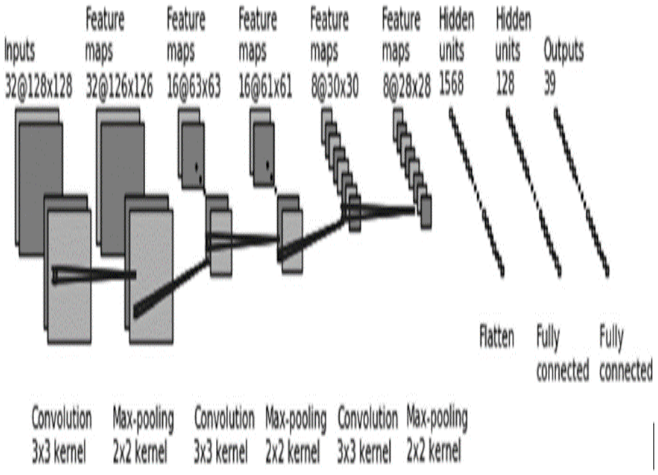

Fig. 2. General Architecture of the CNN model

2) Generative Adversarial Networks (GANs): GANs are made up of two NNs that collaborate to create high-quality images. One NN generates photos, while the second NN assesses the quality of the created images[29]. GANs have been utilized successfully for image synthesis, reconstruction, and denoising in medicine.

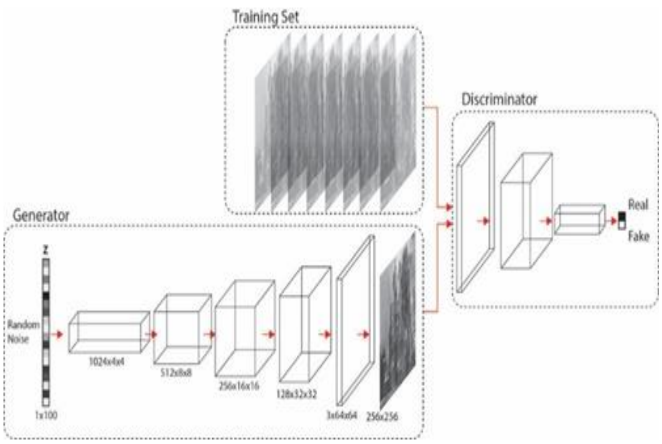

Fig. 3. Architecture of GAN

3) Autoencoders: Autoencoders are unsupervised learning algorithms that encode and decode pictures using NNs. They are frequently employed in picture compression, noise reduction, and enhancement[30].

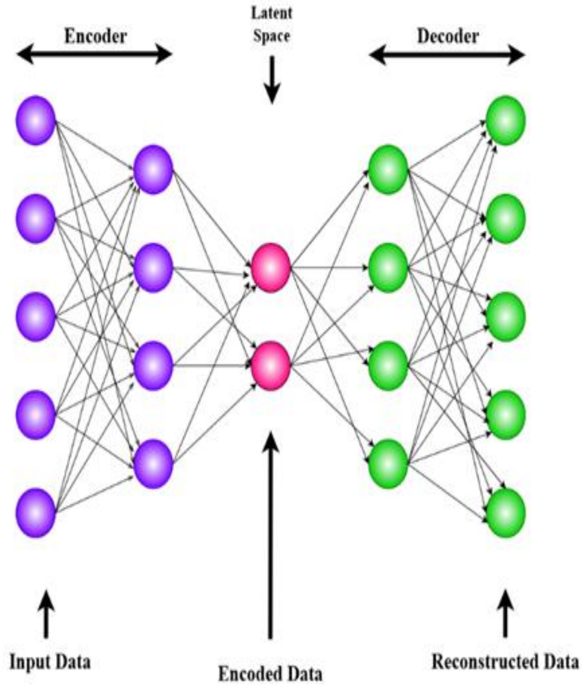

Fig. 4. Architecture of Auto Encoders

4) Support Vector Machines (SVMs): SVMs are machine learning (ML) models that are utilized for classification and regression analysis[31]. SVMs have been used to segment and classify medical images.

V. Research Gap

1. *Lack of labeled data:* To train the models, DL and ML-based techniques require substantial datasets of annotated medical pictures. Obtaining annotated medical photos, on the other hand, is a time-consuming and costly operation.
2. *Overfitting:* DL and ML models may be overfit to training data, resulting in poor generalization to new, previously unknown data. This can lead to incorrect diagnoses and treatments.
3. *Hardware limitations:* High processing power is required for DL and ML-based techniques, which may not be available in all medical situations. Furthermore, due to technical restrictions, storing and analyzing big collections of medical images might be difficult.
4. *Interpretability:* DL and ML models may be difficult to interpret, making it challenging to comprehend the fundamental mechanics underpinning their conclusions. This can make it difficult for medical practitioners to trust and evaluate the models' outputs.

VI. COCLUSION

In conclusion, medical imaging is an important aspect of modern medicine and has a considerable impact on diagnosis and therapy planning. Medical imaging datasets are becoming more complicated and bigger as advanced imaging modalities become available. The necessity for precise and efficient analysis of big datasets has led to the development of machine learning and deep learning-based methodologies. The application of these algorithms to medical imaging has yielded encouraging results in terms of image quality, segmentation, and diagnosis accuracy. However, these techniques confront various hurdles, including the necessity for large, annotated datasets, tolerance to fluctuations in imaging protocols, and interpretability. More research is needed to overcome these obstacles and develop more efficient and effective approaches for processing medical imaging data. Nonetheless, the potential for machine learning and deep learning-based approaches to improving medical imaging analysis is enormous, and these techniques are projected to evolve and improve in the future, ultimately leading to better patient outcomes.

ACKNOWLEDGMENT

We would like to express our sincere gratitude to the Department of Computer Science & Technology, MITS, for providing us with the necessary resources and support to carry out this research work.

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